The Impact of Prices on Boundedly Rational Decision Makers in Supply Chains

by

Stavrianna Dimitriou

A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy

The University of Warwick, Warwick Business School

June 2010

Volume 1 / 2

Table of Contents

List of Figures

List of Tables

Acknowledgements

I am indebted to many people for the help, advice and support that they have generously offered to me throughout the different stages of completing this thesis. I also had the unique opportunity to work with and learn from a number of outstanding researchers. First and foremost, I would like to thank my supervisor, Professor Stewart Robinson, for his invaluable guidance and, continuous encouragement over the past four years. Much of Stewart's enthusiasm, patience, optimism and never-ending creativity is mirrored in this thesis. Secondly, I am grateful to my second supervisor, Dr. Kathy Kotiadis, for her constructive comments and the enlightening conversations that we had over the last 4 years. I really appreciate the time that Kathy took to discuss with me my concerns and support me through occasional low-motivation periods. Thirdly, I am largely indebted to Professor Karen Donohue from Carslon School of Management, University of Minnesota, for accepting me in her seminar in "Behavioural Research in Operations Management", which took place at London Business School in summer 2009. Karen led intriguing discussions and posed challenging questions about existing experimental research in the Operations Management field. These discussions inspired much of the research that is presented in this thesis. I also enjoyed very much the stimulating conversations that we had with the other participants of the course both during and after the end of every seminar (*i.e.* Ahu, Chris and John). Fourth, I appreciate very much Prof. John Morecroft's invitation to the "Simulation Methods for Research" PhD seminar at London Business School in summer 2007; at the course of which he took the time and effort to discuss and contribute fresh ideas to my PhD research. I am also indebted to Dr. Duncan Robertson from the Marketing and Strategic Management group at Warwick Business School for passing on to me his enthusiasm about Agent Based Simulation modelling. Finally, special thanks must go to both my examiners, Professor Sally Brailsford and Dr. Katy Hoad for their constructive comments that really helped to improve the quality of this thesis.

My research would have been impossible without the support from various sources, including the financial support from the Operational Research and Management Sciences group, the Engineering and Physical Sciences Research Council, the Warwick Postgraduate Research Scheme and the Warwick Business School. I would like to thank these sources for funding me during the course of my doctoral studies. I also feel indebted to the student subjects who volunteered to participate in the two laboratory investigations of this study. Although their names are kept anonymous, I admit that without their impartial eagerness to contribute in my work this thesis would not have been possible. I am also grateful to the UK OR Society for funding my participation to a number of conferences that helped me gain a valuable insight into OR and its application.

This thesis would not have been completed without the support and encouragement from an amazing social environment. I want to thank my colleagues and fellow PhD students (Charoula, Chris, Christina, Kabir, Niran) and the staff members of the Operational Research and Management Sciences group, who created a unique work environment and over the years converged from colleagues to good friends. I also want to thank my friends outside academia for listening to my worries (Alexandros, Costas, Costis, Veni). Thanks also go to the secretaries of the Operational Research and Management Sciences Group, Sue Shaw and Racheal Monnington, for the animated chats and their support.

Most importantly, I want to mention my parents, Sophia and Emilios and my brother, Michalis, all of whom I love dearly and know that they love me too, because they have been supporting me with all possible ways during the different stages of completing this PhD thesis.

Declaration of Authorship

I, Stavrianna Dimitriou, declare that this thesis entitled:

"The Impact of Prices on Boundedly Rational Decision Makers in Supply Chains"

and the work presented are my own. I confirm that:

- This work was done wholly while in candidature for this research degree;
- This thesis contains no material which has been accepted for the award of any other degree or diploma in any university;
- I have acknowledged all main sources of help;
- The work described in this thesis has served the material for several published papers and conference presentations that are listed below.

Refereed Conference Proceedings

- DIMITRIOU S, Robinson S and Kotiadis, K "The Impact of Prices on Boundedly Rational Decision Makers: Evidence from simulating the Beer Distribution Game," *Simulation Workshop 10*.
- DIMITRIOU S, Robinson S and Kotiadis, K (2009). "The Impact of Human Decision Makers' Individualities on the Wholesale-Price Contract's Efficiency: Simulating the Newsvendor Problem," *Winter Simulation Conference 2009*.
- DIMITRIOU S, Robinson S and Kotiadis K (2008) "The Newsvendor Problem: An Agent Based Simulation Perspective," *EurOMA International Conference on Tradition and Innovation in Operations Management*.

- DIMITRIOU S (2008) "Investigating Agent-Based Simulation for the effective Alignment of Supply Chain Partners' Incentives," *Simulation Workshop 08*, pp. 325-329.
- DIMITRIOU S (2007) "The Use of Simulation in the Selection of effective Supply Chain Coordination Mechanisms," OR *Peripatetic Post-Graduate Programme 3 Conference*, pp. 197-209.

Conference Presentations

- DIMITRIOU S (2009). "Human Decision Makers' Bounded Rationality and the Resulting Efficiency of the Wholesale Price Contract," *Trans-antlantic Doctoral Conference 2009*, May 2009, London.
- DIMITRIOU S (2009). "The Effect of Human Decision Makers' Individualities: The Newsvendor Case," *Young OR 16*, March 2009, Warwick.
- DIMITRIOU S, Robinson S and Kotiadis K (2008). "Towards Developing Agent Based Simulation Models for effectively aligning Incentives of Supply Chain Partners," EIASM *1st Publishing Workshop* (presented at the *Journal of Operations Management* workshop), October 2008, Sophia-Antipolis.
- DIMITRIOU S, Robinson S and Kotiadis K (2008). "Towards Developing an Agent Based Simulation Model of the Newsvendor Problem," *The Operational Research Society 50*, September 2008, York.
- DIMITRIOU S, Robinson S and Kotiadis K (2008). "The Newsvendor Problem: An Agent Based Simulation Perspective," EurOMA *International Conference on Tradition and Innovation in Operations Management*, June 2008, Gröningen.
- DIMITRIOU S (2008). "Investigating Agent-Based Simulation for the effective Alignment of Supply Chain Partners' Incentives," *Spring Doctoral Conference*, April 2008, Warwick.
- DIMITRIOU S (2007). "Using simulation to facilitate Supply Chain Coordination: a conceptual framework", *Young OR 15*, March 2007, Bath.

Thesis Abstract

This PhD thesis was motivated by the simple observation that the objectives of distinct supply chain managers are often conflicting. This problem is usually addressed via *supply chain contracts* that are designed to align the incentives of the different supply chain partners to the overall benefit of the entire supply chain, when seen as a whole. In this way, the long-term prosperity and viability of all the firms that participate in the supply chain can be ensured. In order to study the efficiency of different *supply chain contracts* in attaining the theoretical optimum performance, there exist a number of standard normative models that predict the decisions of perfectly rational decision makers. But supply chain partners might in reality not make the perfectly rational decisions that these theoretical models predict. This may be because they may lack the required information, or experience cognitive limitations and individual preferences or have only a finite amount of time available. For this reason, they might have to settle at *satisficing* choices. The result of these 'boundedly rational' decisions is a real world of different than expected interactions.

Since in this world the standard normative models retain limited predictive power, this PhD thesis aims to explore the true *efficiency* of the simplest *supply chain contract* that can exist, namely, the *wholesale price contract*. In addition, this PhD thesis provides some useful recommendations that aim to help supply chain managers make price and order quantity decisions that would be better aligned with the interests of the overall supply chain.

To this end, this study applies an original approach that supplements experiments with human subjects with Agent Based Simulation experiments. In greater detail, informal pilot sessions with volunteers were first conducted, during which knowledge of the underlying decision making processes was elicited. Appropriate Agent Based Simulation models were subsequently built based on this understanding. Later on human subjects were asked to interact with specially designed versions of these Agent Based Simulation models in the laboratory, so that their consecutive decisions over time could be recorded. Statistical models were then fitted to these data sets of decisions. The last stage of this approach was to simulate in the corresponding Agent Based Simulation models all possible combinations of decision models, so that statically accurate conclusions could be inferred. This approach has been replicated for both the simple newsvendor setting and the beer distribution game.

The results that are obtained indicate that the overall *efficiency* of the *wholesale price contract* differs significantly from the theoretical prediction of the corresponding standard normative models. It varies greatly and depends largely on the interplay between the pricing and ordering strategies that the interacting supply chain partners adopt. In view of this, real world echelon managers are advised to use prices as an effective mechanism to control demand and, also, keep their total supply chain profits in mind when making their respective decisions.

Chapter 1

Introduction

This PhD thesis was motivated by the simple observation that the objectives of distinct supply chain managers are often conflicting. This is exactly what constitutes the underlying cause of incentive misalignment in supply chains. Supply chain incentive misalignment has numerous negative consequences and can even hurt the long-term prosperity and viability of all the firms that participate in a supply chain (these are defined as the distinct *supply chain partners*). This problem is usually addressed via *supply chain contracts* that *intend* to align these objectives to the overall benefit of the entire supply chain. In respect to this, there is some analytical evidence. Nevertheless, there still remains some anecdotal practical evidence that comes in stark contrast with the analytical expectations. In order to explain this deviation, this PhD thesis identifies the over-simplifying assumptions that are inherent with the existing analytical models and, thus, recognises the limited degree to which these analytical models can predict the decisions of human supply chain managers. To this end, it builds on the acknowledgment that human supply chain managers may not in practice be in a position to make perfectly rational decisions and accommodates their need to make heterogeneous decisions that are specified by their own individual *intention*s, *actions* and *reactions*. In this regard, it introduces the notion of *bounded rationality* and explores the effect that *bounded rationality* may bring in supply chain decision making. Building on this, this PhD thesis presents an original and novel contribution to knowledge in a number of different aspects that are highlighted in the remainder of this chapter.

In greater detail, this chapter introduces the topic of this PhD thesis and sets the background of the work that is undertaken, as explained in the following chapters. It also presents the issues that are inherent with decision making in supply chains and the associated complications that *bounded rationality* may introduce. This chapter serves to provide some principal definitions. It also briefly explains the reasoning that was behind this study and discusses the initial thoughts that stimulated it.

This chapter is organised as follows. *Section 1.1* summarises the effect of misaligned objectives in supply chains, while *Section 1*.2 explains how *supply chain contracts* serve to address this problem. The notion of *bounded rationality* and the effect that it may bring in supply chain decision making are discussed in *Section 1.3*. All the above are brought together in *Section 1.4* that discusses what this PhD thesis is really about. Finally, an overview of the contents of this PhD thesis is provided in *Section 1.5*.

1.1 The Effect of Misaligned Objectives in Supply Chains

A supply chain is defined as an integrated system of firms that are involved, through upstream and downstream linkages, in the different activities that are required to produce the final product, which is delivered to the end consumer (*e.g*. Chopra and Meindl, 2007; Simchi-Levi *et al*, 2008). In respect to this definition, any supply chain consists of multiple firms, each of which is managed by different managers. Based on the information that is locally available to each of these individuals, they make their respective pricing and purchasing decisions, which jointly determine the overall supply chain performance. In case these individuals share the common goal to optimize the system-wide performance, then they behave as a 'team' and aim to lead the entire system to its optimum performance. In the opposite case, their objectives may come into conflict and, thus, prevent the overall supply chain from attaining its optimum performance. Allowing each organization to implement locally "optimal" policies, thus, may lead to overall supply chain performances that are much inferior to the optimum (Lee, 2004; Narayan and Raman, 2004; Li and Wang, 2007).

The latter can sometimes have results that are even catastrophic for the entire supply chain's prosperity. For example, "Wall Street still remembers the day it heard that Cisco's much-vaunted supply chain had snapped" (Narayan *et al*, 2004: pp. 94). This was due to demand forecasts that were over-exaggerated by $2.5 billion, which is almost half as its sales in the quarter of spring 2001. Furthermore, "in the summer of 1997, movie fans flocked to their local Blockbuster video stores eager to rent *The English Patient* and *Jerry Maguire*, only to find that all available copies of it had already been checked out" (Cachon and Lariviere, 2001: pp. 20). The results were customer frustration and lost sales.

But providing managers with the appropriate incentives that induce optimal decisions is a non-trivial task, given the complications that the interactions between numerous decision makers generate. The reason that the "world's largest network-equipment provider" (Narayan *et al*, 2004: pp. 94) suffered from such huge losses was the vast amounts of assembly boards and semiconductors that Cisco's suppliers had stockpiled in their warehouses and over which Cisco had to assume responsibility. Cisco's suppliers ordered inconsistently with the sudden decrease in demand that occurred in the economic downturn of 2001, because they were rewarded only for delivering supplies quickly and did not assume any of the cost that was associated with excess inventory. In other words, the suppliers' objectives came in direct conflict with Cisco's.

As for the problems with the video rental industry, they were that the cost of a video tape was traditionally high relative to the price of a rental and the peak popularity of a title did not last for very long. The result was that acquisition of a sufficient number of copies could not be justified and, so, the initial peak demand could not be entirely covered (Cachon and Lariviere, 2005).

In summary, the objectives of distinct supply chain managers are often conflicting. In order to align these objectives to the *team overall optimal* benefit, 'contracts' or else '*transfer payment scheme*s' are extensively used. The section that follows briefly introduces how *contracts* are designed to operate in supply chains.

1.2 Supply Chain Contracts

A *supply chain contract* or else a *transfer payment scheme* fully determines the terms of trade and the payment agreements that take place between adjacent supply chain partners (Tsay *et al*, 1999; Cachon, 2003). A *contract* or *transfer payment scheme* is said to *coordinate* a supply chain if it forces the aggregate channel performance to coincide with the *first-best case*[1] *optimum* performance

---

[1]The term "*first-best case*" is adapted from the term "first best" that is used by Lee and Whang (1999) to reflect the overall channel performance that would be attained, if the *team optimal solution* was adopted by all echelon managers (Chen, 1999) or there was a central planner (*i.e*. headquarters) that had access to all sites' inventory-related information and made all decisions for the entire system (Lee and Whang, 1999). The reason that this term is used is to reflect the fact that this is the absolute optimum

(Cachon, 2003). In respect to this, its *efficiency* is assessed in regard to whether it produces an aggregate channel performance that is not inferior to the *first-best case* optimum performance that would be achieved in the case that the distinct echelon[2] managers behaved as a *team* (Lariviere, 1999; Tsay *et al*, 1999).

In this regard, the existing contracting literature concentrates on either assessing a *contract*'s *efficiency* or proposing *contracts* that may induce the *first-best case* optimum performance. The simplest *contract* that can exist is the *wholesale price contract*, according to which there is only one incentive that may *coordinate* the distinct echelon managers' decisions to the *team optimal* solution, that is, the *wholesale price*. But this contract has been since long analytically established as *inefficient* (Lariviere and Porteus, 2001; Cachon, 2003). In greater detail, its inability to attain the *first-best case* optimum performance is confirmed via standard normative models that are built on the assumption of perfectly rational decision makers, who are exclusively interested in optimizing their

---

performance that can be attained by the entire channel when seen as a whole (*e.g*. Cachon, 2003; Cachon and Netessine, 2004).

[2]The term "echelon" is used in accordance with Clark's (1958) definition (as found in Clark and Scarf, 1960) to reflect a site, in which the inventory for which it is accountable consists of: *i.* the inventory that exists in this site, *ii.* the inventory that is in transit to this site and *iii.* the inventory that is on hand at a lower site [Source: Clark, A. 1958, A dynamic, single item, multi-echelon inventory model, RM-2297, Santa Monica, California, The RAND Corporation].

respective individual objectives and, to this end, are assumed to have access to perfect symmetric information[3].

In order to overcome the *inefficiency* of the simple *wholesale price contract* a number of more sophisticated *transfer payment schedules* have been suggested. These proven as *efficient supply chain contracts* force the *team optimal* solution to be adapted and, in this way, the *first-best case* optimum performance to be attained. Some indicative examples are the *buyback contract* (Pasternack, 1985; Lau *et al*, 2007), the *revenue sharing contract* (Cachon and Lariviere, 2005), the *quantity discount contract* (Moorthy, 1987; Kolay *et al*, 2004), the *responsibility tokens* of Porteus (2000) and the *simple linear transfer payment schemes* of Cachon and Zipkin (1999). The *supply chain contracts* that are of relevance to this PhD thesis are reviewed in *Sub-section 2.3.1*. The majority of these *transfer payment schemes* are built on a number of over-simplifying assumptions, such as, for example: that the *team* optimum solution is common knowledge to all partners; or that there is one firm that presumes the responsibility of compensating the other firms and, thus, adequately allocating the costs between them; or that all echelon managers are always willing to share all private information with their supply chain partners without the need for being compensated for doing so; or that the interacting firms are deprived the ability to

[3]The term "perfect symmetric information" is used in accordance with Cachon and Netessine's (2004) use to reflect the fact that exactly the same information is available to all interacting supply chain partners. The term comes in opposition to "information asymmetry", a popular term in economics and contract theory, according to which one party has more accurate or better information [Source: http://en.wikipedia.org/wiki/Information_asymmetry , last accessed: 29/08/2010].

make some profit of their own. For detailed surveys of all the above contracts and reviews of the analytical results that are acquired so far the interested reader is referred to Tsay *et al*. (1999), Cachon (2003) and Simchi-Levi *et al*. (2008).

In spite of the aforementioned *contracts' efficiency*, there is some anecdotal evidence that the *wholesale price contract* remains more popular among supply chain managers, especially in industries such as the publishing and movie rental industries (Cachon and Lariviere, 2001; Narayan and Raman, 2004; Cachon and Lariviere, 2005). The practical prevalence of the *wholesale price contract* over the *efficient transfer payment schemes* remains paradoxical. There are certainly some important benefits associated with its implementation, such as, for example, it is much simpler to be put in force, easier to administer and it only requires one transaction to take place between each interacting party. But are these benefits the only reasons that explain its wide popularity? Could perhaps its true *efficiency* be significantly different from its corresponding theoretical prediction? These are some intriguing questions that this PhD thesis aims to explore. To this end, this PhD thesis recognises that supply chain managers might in reality not make perfectly rational decisions. The section that follows discusses how the notion of *bounded rationality* could affect the true *efficiency* that the *wholesale price contract* can in practice attain. Although this PhD thesis restricts attention to the simple *wholesale price contract*, similar ideas are also applicable to the other, more complicated *supply chain contracts* as well. In this regard, their true *efficiency* may be significantly different from their corresponding theoretical predictions.

1.3 Boundedly Rational Decision Makers

Supply chain managers, like all decision makers, might in reality not make perfectly rational decisions. There are three different reasons that explain why supply chain managers might need to compromise at non-perfectly rational decisions, namely 'boundedly rational' decisions. *First,* they may lack the required information, as in practice access to perfect symmetric information might not always be possible in supply chain settings. The underlying reason is that most supply chain partners would not be willing to share their private information with their partners, at least not without being compensated in some way for doing so (*e.g*. Cachon and Fisher, 2000; Chen, 2003). *Second*, supply chain managers may "experience limits in formulating and solving complex problems and in processing information" (Simon 1957 in Williamson 1981: pp. 553), and, thus, suffer from limited knowledge and finite cognitive abilities (Sterman, 1989; Simon, 1996; North and Macal, 2007; Gilbert, 2008). *Last*, supply chain managers might only have a finite amount of time available to make their respective decisions. That is why they might have to settle at reasonable, thus *satisficing*, choices.

For these reasons, supply chain partners might not be in a position to search the entire solution space and, thus, identify the optimal decisions; they are *boundedly rational* (Simon, 1996; North and Macal, 2007; Gilbert, 2008). Since, in view of their *bounded rationality*, the standard normative models that are built on the assumption of optimizing objectives lose their accuracy, the notion of *bounded rationality* complicates the decision making that takes place in supply chains further.

In greater detail, different decision makers seem to be characterised by individual preferences, limited knowledge and finite cognitive abilities, which are in turn responsible for the behavioural biases that influence significantly their respective decisions (Camerer, 1995; Loch and Wu, 2007; Gino and Pisano, 2008). In other words, not all supply chain managers are anticipated to have exactly the same priorities, knowledge and abilities. Further to this, their preferences, information and limitations are expected to vary to a great extent. Therefore, their respective decisions are expected to deviate from the perfectly rational decisions to varying degrees. The result is that different supply chain managers exhibit different degrees of *bounded rationality* or else are perceived as *heterogeneously boundedly rational*. Thus, a “richer real world environment” (Holmstrom and Milgrom, 1987) of different than expected interactions is anticipated to emerge.

In this emerging richer world, interactions become very different from their corresponding analytical expectations. As different supply chain managers appear to have different priorities and abilities, they adopt different strategies and, thus, make significantly different decisions. Hence, the theory – driven, standard normative models retain little power to predict supply chain partners’ decisions. In a similar way, their predictions of a contract’s resulting *efficiency* may also become out of date. In respect to this, the *wholesale price contract* might perform significantly differently than theoretically predicted. It is also possible that it leads to the *first-best case* optimum performance. As such, the *wholesale price contract*’s practical *efficiency* would offer an additional important explanation for its wide practical popularity, beyond just its simplicity. It would also justify its dominance over contracts that are analytically proven as *efficient*, especially since their true performances might also be significantly different than predicted. This constitutes the reason that this PhD thesis aims at exploring the true *efficiency* of the *wholesale price contract* under conditions of real human interactions. *Section 1.4* sheds light on what exactly the object of this PhD thesis is.

1.4 What is this thesis about?

The purpose of this PhD thesis is to explore the true *efficiency* of the *wholesale price contract* in human supply chain managers' interactions, that is, given the *heterogeneous bounded rationality* that is inherent with their decision making. Hence, the main question that drives the research that is undertaken in this thesis is:

"Could the *wholesale price contract* in practice generate the *first-best case maximum performance* of a supply chain setting and if so, under which specific conditions?".

The reason that this is an interesting question is because it can explain the paradoxical wide popularity of the *wholesale price contract* in a variety of different settings. As for the conditions under which the *wholesale price contract*'s *efficiency* could be attained (that is provided that this *efficiency* is feasible), these conditions could reveal some important managerial insights. These favourable conditions would also highlight some recommendations that would help supply chain managers to ensure the *efficiency* of their interactions under the *wholesale price contract*.

In respect to this research question, the main objectives that drive this PhD thesis can be formulated as follows:

1. To develop a methodology that revisits the over-simplifying assumptions of the existing theory-driven, standard normative models. This methodology needs to be apt to predict accurately the decisions of human supply chain decision makers.

2. To assess how different the decisions of human supply chain decision makers are to the corresponding predictions of the standard normative models when the *wholesale price contract* is assumed to be in force.

3. To investigate the *efficiency* of the *wholesale price contract* when human supply chain decision makers interact with each other.

4. To consider the impact that different pricing strategies have on the *wholesale price contract*'s *efficiency*.

In order to address these questions, this PhD thesis uses as computational frameworks two distinct settings: the *Newsvendor Problem* and the *Beer Distribution Game*. The *Newsvendor Problem* is the simplest supply chain setting that can exist, where there is only one supplier and one retailer that interact with each other. The reason that this setting is studied is because it constitutes the fundamental building block of any supply chain configuration. The *Beer Distribution Game* represents a periodic review production-distribution supply chain with serial echelons, which operates in a *de-centralised fashion*. The reason that this setting is chosen to be studied is it mimics the material, information and financial flows of any general type, serial multi-echelon supply chain. The reason that these two settings are selected is because, combined, they provide a broader view of the way that general type, serial multi-echelon supply chains operate. The exact specifications of the *Newsvendor Problem* and the *Beer Distribution Game* are provided in *Sub-sections 2.1.1* and *2.2.1*, respectively.

The work carried out in this PhD thesis is considered to be an original and novel contribution to knowledge for a number of reasons. *First*, it develops and applies a novel approach to answer the main research question and, also, address the research objectives. The reason that this approach is considered novel is because it is the first study in the field that supplements the laboratory experiments with simulation experiments. The corresponding simulation models have been calibrated via the results from the laboratory experiments, which were run with human subjects. In this way, the requirements of multiple interactions, prolonged interaction lengths and multiple replications, which would not have been possible if only experiments with human subjects were run, could be simultaneously addressed. The end result of this novel approach is that it successfully addresses the existing literature gaps, which are identified in *Section 2.4* (*s.* Table 2.5).

Second, this PhD thesis extends for the first time the *wholesale price contract* to a more complicated supply chain setting than the *Newsvendor Problem*. It applies for the first time the *wholesale price contract* to the *Beer Distribution Game*, which is an accurate representation of any general type, serial multi-echelon supply chain. In spite of the contract's simplicity, only complicated *transfer payment scheme*s have as yet been implemented in the *Beer Distribution Game* setting. In this way, it proves the distinctively different way that the *wholesale price contract* operates in the *Newsvendor Problem* and the *Beer Distribution Game* settings and, thus, introduces an issue of scalability for most existing analytical and experimental studies that exclusively study this contract in the *Newsvendor Problem* setting. Following this, a deeper understanding of the way that the *wholesale price contract* operates in any serial multi-echelon supply chain is gained.

Last but not least, this PhD thesis contributes some counter-intuitive and interesting results about the practical *efficiency* of the *wholesale price contract*. The results that concern the *Newsvendor Problem* are reported in *Chapter 5*, while the results that concern the *Beer Distribution Game* are reported in *Chapter 8*. The common managerial implications and insights that can be inferred from these results are discussed in greater detail in *Chapter 9*, while some general lessons about supply chain settings are offered in *Chapter 10*.

1.5 Overview of Thesis

The remainder of this thesis is organized as follows:

Chapter 2 defines the *Newsvendor Problem* and the *Beer Distribution Game* settings and also determines the arrangements of different *supply chain contracts* that have been enforced in these two settings. It also reviews the standard normative models that correspond to these two settings and also explores which of their simplifying assumptions have been revisited by existing laboratory – based investigations. The chapter concludes by summarising the remaining literature gaps.

Chapter 3 describes and justifies the approach that this PhD thesis adopts to address the existing literature gaps. This approach enables one to investigate the effect that different, prolonged interactions between dynamic, autonomous and heterogeneous decision makers can have on the *wholesale price contract*'s overall *efficiency*.

Chapter 4 adapts this approach to the needs of the *Newsvendor Problem*, while *Chapter 5* reports on the results that are obtained. A brief discussion and a reflection on the managerial implications and practical significance of these results is also provided.

Chapter 6 introduces the new version of the *Beer Distribution Game* where the *wholesale price contract* becomes the basis of any interaction that takes place between adjacent supply chain partners. This new version of the game is named the "Contract Beer Distribution Game". The chapter also develops the standard normative models that are associated with the *Contract Beer Distribution Game*, namely, makes provision for the inclusion of prices in them.

Chapter 7 adapts the approach that is proposed in this PhD thesis to the needs of the *Beer Distribution Game*. *Chapter 8* reports on the results that are obtained. A brief discussion and a reflection on the managerial implications and practical significance of these results is provided.

Chapter 9 discusses, explains and justifies the differences that are observed between the results of the *Newsvendor Problem* and the *Beer Distribution Game*. It also critically reflects on the common themes that seem to emerge from these two settings.

Building on these common themes, *Chapter 10* proceeds to the general lessons about serial multi-echelon supply chain settings that can be gained from this study. In addition, *Chapter 10* reflects on whether the objectives of this study have been satisfied, summarizes the main contribution of this PhD thesis, recognises its main limitations and proposes directions for future research.

Chapter 2

Supply Chain Models and Contracts: Analytical and Experimental Results

The purpose of this chapter is two-fold: The first objective is to define the two settings that are used as computational frameworks in this PhD thesis; namely, the *Newsvendor Problem* and the *Beer Distribution Game*, and also determine how the arrangements of different *supply chain contracts* can be applied in these two settings. The second objective of this chapter is to review the existing research in the area. In this regard, the standard normative models that correspond to the aforementioned two settings and the *supply chain contracts* are first described. These are built on the assumption that all supply chain managers are perfectly rational in their respective decisions, namely they are exclusively interested in optimizing their individual objectives; to this end, they are assumed to almost ignore their partners' corresponding decisions and their surrounding environment. Since these common assumptions of the existing standard normative models are over-simplifying, subsequently the experimental studies that have explored how different the real human decisions that are observed in the laboratory are from these theoretical predictions are reviewed. The main focus is to highlight which of these assumptions are successfully revisited. The experimental protocols that are followed, as well as the key findings are additionally presented.

The chapter is organised as follows: First, the *Newsvendor Problem* is outlined (*Section 2.1*). Later on the *Beer Distribution Game* is discussed (*Section 2.2*). Last but not least, the *supply chain contracts* that have been applied to the

Newsvendor Problem and the *Beer Distribution Game* are separately presented (*Section 2.3*). In each of these three distinct sections, the extant analytical results are first summarised, while the relevant behavioural studies are subsequently reviewed.

2.1 The Newsvendor Setting

In this section the typical newsvendor setting is considered. First presented by Whitin (1955), it is still receiving increasing attention, mostly due to diminishing product lifecycles and dominance of pure service and mixed retail/service industries, for which it is particularly applicable (Khouja, 1999). For a review of the existing analytical results and the extensions that have been applied to it so far the interested reader is referred to Khouja (1999), Lariviere (1999) and Cachon (2003).

In *Sub-section 2.1.1* the standard normative models of the typical newsvendor setting are described. First is outlined the case, where there is only one decision maker involved, namely an *integrated newsvendor* who replenishes stock to satisfy customer demand. This *centralised operation* mimics the material, information and financial flows of a system that has access to all available information and, thus, is in a position to optimize the system-wide performance or else to attain the *first-best case maximum* profit. Attention is subsequently turned to the case that the setting operates in a *de-centralised operation* fashion; the problems that the manufacturer and the retailer face are then discussed separately. Since neither of them takes into account the effect of his/her individual decisions on the other's profit, a deviation occurs between the *first-best case maximum* profit and the aggregate profit that is achieved, when the two partners make their decisions independently. This phenomenon is known as the "double marginalization problem" (Spengler, 1950) and is subsequently discussed.

In *Sub-section 2.1.2* the laboratory investigations of decisions that human decision makers make in the laboratory are reviewed. The assumptions of the standard normative theories that are revisited by these experimental studies are first summarised; the experimental protocols that are applied are subsequently outlined; their key findings are last delineated.

2.1.1 Standard Normative Models

The Centralised Operation

The typical *integrated newsvendor* setting is illustrated in Figure 2.1. Well in advance of each time period *t*, this *integrated newsvendor* needs to specify the order quantity q that he/she chooses to satisfy customer demand. This entire quantity is assumed to be instantaneously delivered to the *integrated newsvendor* at a constant marginal cost of *c* per unit. The retail price is fixed at *p* per unit, which is determined by market competition, as is usual for commodity products (Hirschey *et al*, 1993; Chopra and Meindl, 2007). The product under study can only last for one selling season and no left-over inventories at the end of a season can be carried over from one period to the next. For each unit of demand that is not satisfied, a goodwill penalty cost of *g* is incurred. It is also assumed that the stochastic customer demand *x* follows a continuous distribution *F(x)* on the non-negative reals with density *f(x)*. *F* is invertible, strictly increasing and differentiable with a continuous derivative $f'(x)$ and *F*(0) = 0. Also let $\bar{F}(x) = 1 - F(x)$; $\mu = E(x)$ and $\sigma^2 = Var(x)$.

In summary, the following notation is used throughout this sub-section:

x	customer demand, a random variable
$f(x)$	probability density function of x
$F(x)$	cumulative distribution function of x
p	selling price per unit
c	manufacturing cost per unit
g	lost sales (goodwill) penalty cost
C_o	unit overage cost = c
C_u	unit underage cost = $p+g-c$
q	order quantity

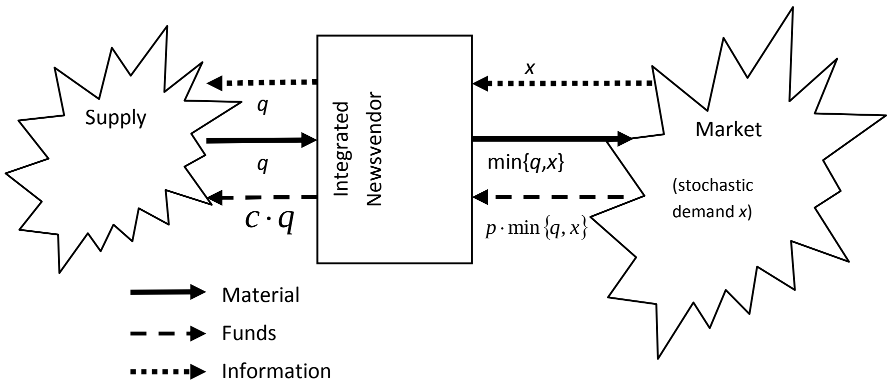


Figure 2.1: The *integrated newsvendor* problem

It is also assumed that all the above information is common knowledge to the *integrated newsvendor*. Based on this, the *integrated newsvendor*'s profit per period is given by:

$$\pi_{int} = \begin{cases} (p-c) \cdot q - g \cdot (x-q), if\ x \geq q \\ p \cdot x - c \cdot q, if\ x < q \end{cases}$$

Simplifying and taking the expected value of π_{int} gives the following expected profit:

$$\Pi_{int} = p \int_0^q xf(x)dx - c \int_0^q qf(x)dx + (p+g-c) \int_q^\infty qf(x)dx - g \int_q^\infty xf(x)dx$$

which can be easily transformed as follows:

$$\Pi_{int} = E(\pi_{int}) = pS(q) - cq - gB(q)$$

$$\text{or else: } \Pi_{int} = (p+g)S(q) - cq - g\mu \tag{2.1}$$

S(*q*) represents the expected sales quantity and *B*(*q*) the unsatisfied customer demand, in the case that an order quantity of *q* is placed.

Let the superscript * denote optimality. Application of the Leibnitz's rule about differentiation under the integral sign (Kaplan, 2002) for the derivatives of first and second order demonstrates that Π_{int} is concave and, thus, there is a unique q_{int}^* that maximises Π_{int}. As proven by Khouja (1999) and Lariviere (1999) the sufficient optimality condition that would maximise the perfectly rational *integrated newsvendor*'s expected profit $\prod_{int}$ is given by formula (2.2):

$$q_{int}^* = F^{-1}\left(\frac{p+g-c}{p+g}\right) = F^{-1}\left(\frac{C_u}{C_o+C_u}\right) \tag{2.2}$$

The De-centralised operation

The manufacturer-retailer setting is illustrated in Figure 2.2 that follows. The simplest contract that can exist is assumed to be in force, *i.e*. the *wholesale price contract*. According to this, there are only two pieces of information exchanged between the interacting manufacturer and retailer: *i.* the price that the manufacturer charges to the retailer and *ii.* the order quantity that is placed by the retailer (Lariviere and Porteus, 2001; Cachon, 2003). The events in each time period *t* unfold as follows: Well in advance of each time period *t*, the manufacturer needs to specify the wholesale price *w* that he/she wishes to charge to the retailer. In response to that, the retailer must choose an order quantity *q*. The manufacturer is assumed to instantaneously deliver to the retailer any quantity that he/she places an order for. The retailer is, in turn, responsible for satisfying customer demand. The retailer sells each unit of product at the price of *p*; the manufacturer has to incur a unitary production cost of *c*.

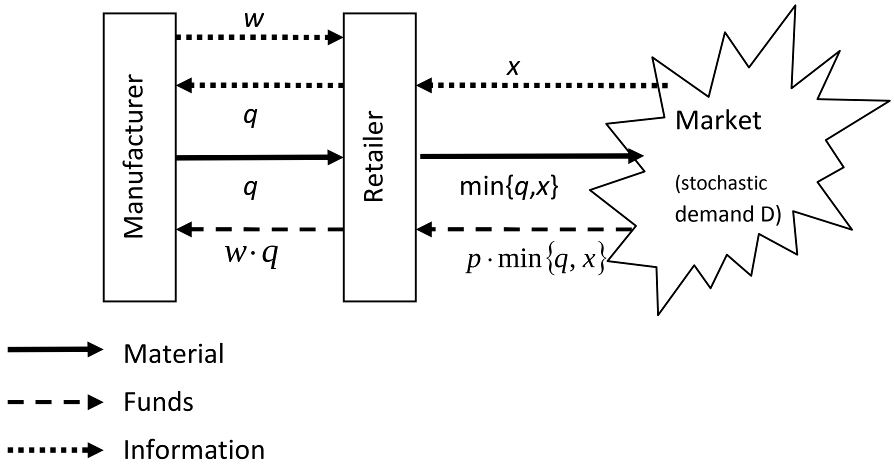


Figure 2.2: The *de-centralised operation newsvendor* problem

As in the *de-centralised operation*, the product under study can only last for one selling season and no left-over inventories at the end of a season can be carried over from one period to the next. The notation that is used in the previous section is also used throughout this sub-section.

The problem that the retailer is facing is now studied. The retailer's profit per period π_{int} is given by:

$$\pi_r = \begin{cases} (p-w)\cdot q - g\cdot(x-q), if\ x \geq q \\ p\cdot x - w\cdot q, if\ x < q \end{cases}$$

The same rationale applied for the *integrated newsvendor*'s problem is again followed to get the retailer's expected profit:

$$\Pi_r = E(\pi_r) = pS(q) - gB(q) - wq \Rightarrow$$

$$\Pi_r = \tag{2.3}$$

$$\int_0^q xf(x)dx - w\int_0^q qf(x)dx + (p+g-w)\int_q^\infty qf(x)dx -$$

$$g\int_q^\infty xf(x)dx$$

or else: $\Pi_r = (p+g)S(q) - g\mu - wq$

From this the order quantity (q_r^*) that the rationally optimizing retailer would order to maximise his/her expected profit Π_r can be easily calculated:

$$q_r^* = F^{-1}\left(\frac{p+g-w}{p+g}\right) = F^{-1}\left(\frac{p+g-w}{C_o+C_u}\right) \tag{2.4}$$

Now the manufacturer's problem is studied. Acting as the Stackelberg leader (Stackelberg, 1934 in: Cachon and Netessine, 2004), the manufacturer initiates any interaction and is, thus, the first who determines the preferred wholesale price *w*. While making this decision, the manufacturer correctly anticipates the retailer's response order quantity to this price, namely the retailer's demand curve $q_m^*(w)$. In this regard, the manufacturer's profit per period $\pi_m(w)$ is given by the following formula, according to Lariviere and Porteus (2001) and Cachon (2003):

$$\pi_m = (w - c) \cdot q_m(w)$$

Therefore, the manufacturer's expected profit becomes:

$$\Pi_m = E(\pi_m) = (w - c) \cdot q_m(w) \tag{2.5}$$

A rationally optimizing manufacturer would charge as much (w*) as would maximise his/her expected respective profit, namely:

$$\prod_m^* = max\{\Pi_m(w)\} = (w^* - c) \cdot q_m^*(w^*) \tag{2.6}$$

In equation (2.6) q_m^* represents the order quantity that the rationally optimizing retailer would place in response to this price $w*$, or else $q_m^* = \arg\left[\max \prod_{\mathrm{m}}(w^*, q)\right] = F^{-1}(\frac{p+g-w^*}{p+g})$, according to (2.4). According to this, equation (2.6) gets transformed to (2.7):

$$\prod_m^* = (w^* - c) \cdot F^{-1}(\frac{p+g-w^*}{p+g}) \tag{2.7}$$

Equation (2.7) can be used to calculate the rationally optimizing manufacturer's maximum profit that would be attained if he/she charged w*. But (2.7) does not provide the actual w*-price that the rationally optimizing manufacturer needs to charge in order to achieve this maximum profit. In order, thus, to estimate this rationally optimizing price $w*$ Lariviere and Porteus' (2001) approach is followed. According to this, instead of concentrating on the retailer's demand curve $q_m^* = F^{-1}(\frac{p+g-w}{p+g})$, the retailer's inverse demand curve, which is:

$w(q_m^*) = (p+g)\bar{F}(q_m^*) = (C_o + C_u)\bar{F}(q_m^*)$, is looked at. From Leibnitz's rule and the derivative of (2.5) of first order the manufacturer's sufficient optimality condition is calculated for the case of a demand distribution that has an increasing generalised failure rate (IGFR):

$$w^*(q_m^*)\left(1 - q\frac{f(q_m^*)}{\bar{F}(q_m^*)}\right) = c \qquad (2.8)$$

Lariviere and Porteus (2001) define a distribution's generalised failure rate as: $g(x) = x\frac{f(x)}{\bar{F}(x)}$. In this regard, a distribution is said to have IGFR if $g'(x) > 0$ for all x on the non-negative reals that $f(x)$ is defined. In the case of any such distribution (2.8) becomes the sufficient optimality condition of the manufacturer's maximum profit and can be used to estimate the rationally optimizing manufacturer's $w*$ - price. In addition, Lariviere and Porteus (2001) describe the elasticity of retailer's response orders as: $v(x) = \frac{1}{g(x)}$, which allows for transformation of the first-order optimality condition (2.8) to the following, much simpler form:

$$w^*(q_m^*)\left(1 - \frac{1}{v(q_m^*)}\right) = c$$

The above form is preferred to (2.8), because it can be used more easily to infer managerial insights (Lariviere and Porteus, 2001).

In the sub-section that follows attention is turned to overall supply chain performances, in the two distinct cases of *centralised operation* and *de-centralised operation* of the *newsvendor setting*.

Supply Chain Performance

As already seen in the previous sub-sections, in the case of *centralised operation* the maximum profit, or else the *first-best case maximum profit* of the overall channel can be attained, that is: $\Pi_c^* = \Pi_{int}^*$. In the case where the rationally optimizing manufacturer and retailer interact with each other, the manufacturer would charge w^* (making, thus, a profit of $\prod_m^*$), while the retailer would order q_r^* (making, in turn, a profit of $\prod_r^*$). When these decisions are combined, they generate an aggregate channel profit of $\prod_{\mathrm{c}} = \prod_m^* + \prod_r^*$. The overall supply chain performance is in this case assessed via the "efficiency score" that is attained. The closer an *efficiency score* is to one, the better the overall supply chain performance is, or else the more of the *first-best case maximum* profit is attained by the manufacturer – retailer channel that is studied. The *efficiency score* is defined according to relation (2.9):

$$Eff. = \frac{\prod_c^*}{\prod_{int}^*} \tag{2.9}$$

Without loss of generality and in order to demonstrate how the *double marginalization problem* arises, a simple numerical example is hereby cited. It is assumed that: p=250 *m.u.* (*i.e.* monetary units)*;* c=50 *m.u.*; g=1 *m.u* and that customer demand follows the truncated at zero normal distribution with μ=140 and σ = 80, because it more closely reflects real cases, where limited information about the distribution of customer demand is available (Gallego and Moon, 1993; Son and Sheu, 2008; Ho *et al*, 2009). Because of this truncation at zero, demand mean and variance need to be modified according to Barr and Sherrill (1999)'s recommendations to μ'≈147 and σ' ≈ 65. For simplicity the example of a single demand observation *D*=140 is taken. Under these circumstances the rationally optimizing *integrated newsvendor* would order $q_{int}^{*} = 202$ units and only incur the manufacturing cost $w_{int}^{*} = c$, leading the entire channel to the *first-best case maximum* profit of $\prod_{\mathrm{int}}^{*} = 24{,}900$ *m.u.* As for the rationally optimizing manufacturer, not taking into account the effect of his/her own decision on the retailer's profit, he/she would charge *w**=184 *m.u.*, leading the retailer to place an order of *q**=106 units. The result of this allocation of profits (*i.e.* $\prod_{m}^{*} = 14{,}204$ *m.u.* and $\prod_{\mathrm{r}}^{*} = 6{,}962$ *m.u.*) would be an aggregate channel profit of $\prod_{\mathrm{c}}^{*} = 21{,}166$ *m.u.*, which is significantly lower than $\prod_{int}^{*}$. This phenomenon where neither partner would take into account the effect of his/her own decision on the other's profit is known as the "double marginalization" problem (Spengler, 1950). The result is that the overall *efficiency score* attained would be: $Eff = \frac{\Pi_{\mathrm{c}}^{*}}{\Pi_{\mathrm{int}}^{*}} = 0.85$. The fact that Eff<1 signifies the *wholesale price contract's inefficiency*.

Let's now consider the case that the manufacturer charges *w*=150<184= *w** and the retailer orders *q*=125<130=*q**(*w*). The interaction of these two decisions would generate an aggregate channel profit of $\prod_{\mathrm{c}} = 24{,}985 \approx 24{,}990$ *m.u.*, which is the *first-best case maximum* profit and also ensures a more equitable allocation of profits between the manufacturer and the retailer (*i.e.* $\prod_{m} = 13{,}500$ *m.u.* and $\prod_{\mathrm{r}} = 11{,}485$ *m.u.*). In practical terms, a sacrifice on the part of the manufacturer of only *34 m.u.* per unit sold and *704 m.u.* in total would increase the retailer's profit share by 4,523 *m.u.* and the aggregate channel profit by 3,824 *m.u.* But the fact that neither the manufacturer nor the retailer take into account the effect of their own decisions on the aggregate channel profit causes the *double marginalization* problem.

Yet, very seldom in reality would human decision makers follow the above decisions (*e.g*. Benzion *et al*, 2008; Bolton and Katok, 2008; Bostian, Holt and Smith, 2008), leading the *newsvendor setting* to overall performances that are significantly different from the ones that are theoretically predicted. In *Sub-section 2.1.2* that follows the experimental research that has already been conducted in the newsvendor area is reviewed. This field of research establishes the systematic divergence of human newsvendors' order quantities from the quantities that are predicted by the standard normative models; this field of research additionally investigates the individual behavioural biases that could be held responsible for this deviation. That is why this existing field of research is here named as the "behavioural newsvendor".

Since interactions of human manufacturers that on average charge significantly different prices from w^* and human retailers that order quantities, which on average diverge significantly from q_r^* give rise to widely fluctuating *efficiency scores*, the *efficiency scores* that are attained overall can in practice deviate significantly from the above theoretical prediction (which for this particular numerical example becomes equal to 0.85). That is why it becomes interesting to explore the true *efficiency scores* that the *supply chain contracts* attain in the laboratory and compare them with their respective theoretical predictions. In this regard, although laboratory investigations of *supply chain contracts* are still scarce, there is already a number of papers that are concerned with exploring the predictive success of the existing supply chain contracting theories. These are reviewed in *Sub-section 2.3.2* that limits attention to the existing laboratory investigations of *supply chain contracts*.

2.1.2 The Behavioural Newsvendor

Carlson and O'Keefe (1969) and Fisher and Raman (1996) constitute the first papers that perform controlled human experiments of the newsvendor problem. Even though for Carlson and O'Keefe (1969) the *newsvendor problem* only represents a sub-set of participants' allocated decision task, both the innate ability of some participants to make reasonably good decisions without being taught a formal rule and the tendency of other participants to make "almost every kind of mistake" (p. 483) are recognised. Fisher and Raman (1996) conduct an industrial experiment at a fashion apparel manufacturer's site that enforces a 'Quick Response' system (*i.e.* they allow placing orders only after and in response to initial demand observations). Under these conditions, Fisher and Raman (1996) ascertain that managers order quantities that are systematically inferior from the quantities that are calculated by their exact Lagrangian decomposition - based algorithm. Neither Carlson and O'Keefe (1969) nor Fisher and Raman (1996) are concerned with either explaining this observed behavioural bias or reflecting on its potential persistence at different settings. The reason is it was not until relatively recently that a systematic behavioural perspective was brought to the field of operations management and, thus, to the newsvendor problem (Bendoly *et al*, 2006; Loch and Wu, 2007; Gino and Pisano, 2008). In this regard, these two papers are not considered in the account of existing experimental research on the *newsvendor setting* that follows. In this elaborate account the assumptions of the standard normative theories that that are revisited are addressed, along with the experimental protocols that are applied and the experimental evidence that is collected.

Assumptions Revisited

In order to review the assumptions that are revisited so far by laboratory experiments, the *Analysis of Assumptions* framework is followed, as applied by Bendoly *et al*. (2006). According to this, the models' assumptions are classified in the following three broad categories: *Intention*s, *Actions* and *Reaction*s. In the paragraphs that follow these are defined and the papers that revisit each of these assumptions are reviewed.

Intentions refer to the accuracy of the studied model in reflecting the actual goals of the decision maker under study (Bendoly *et al*, 2006). In this regard, the standard normative models that are presented in *Sub- section 2.1.1* are built on the common assumption that any decision maker would be exclusively interested in maximising his/her own individual net profit. But in reality, a decision maker might display a variety of different objectives: For example, he/she could weigh profits and/or underage (*i.e*. $p+g-c$) and overage (i.e. c) costs in an un-even fashion, that is, assign different priorities to the different sub-objectives (*i.e*. factor weighting). Alternatively, he/she might not be risk-neutral, as assumed by the aforementioned models that are built on expected value calculations, but instead adopt a risk seeking (*i.e*. he/she might prefer a choice with a lower expected value but a higher risk) or a risk averse attitude (*i.e*. he/she might be reluctant to choose an alternative with a lower expected value but a higher risk). He/she could also exhibit different concerns, of a more social nature, for example an inclination to sustaining justice or fairness towards his/her remaining partners, an interest in maintaining trust and good prior relationships with them, altruistic concerns or group, rather than individual, goals.

Building on the seminal paper by Eeckhoudt *et al*. (1995) that is the first that applies the expected utility function approach in the newsvendor setting, Schweitzer and Cachon (2000) make provision for a variety of different retailers' *intentions*:

i. *Risk-seeking*: a risk-seeking attitude implies that human retailers would prefer to order quantities that include a higher uncertainty, although they might be associated with a lower expected value. Risk-seeking retailers would prefer to order higher quantities than risk-neutral profit maximising retailers, as predicted by the standard normative models (q_r^*).

ii. *Risk-aversion*: a risk-averse attitude implies that human retailers would prefer to order quantities that include a lower uncertainty; therefore, they would prefer to order lower quantities than risk-neutral profit maximising retailers, as predicted by the standard normative models (q_r^*).

iii. *Reference-dependence*, according to Prospect theory (Kahneman and Tversky, 1979): reference-dependent preferences would tend to reproduce human retailers' risk aversion over the domain of gains and risk seeking over the domain of losses. As a result, retailers acting according to prospect theory preferences would order less than q_r^*, when for all possible order quantities they would strictly make profits, while they would order more than q_r^*, when for all possible order quantities they would strictly make losses. For the cases that both profits and losses would be possible for all the order quantities of their choice, they could maximise their respective expected utility function by ordering either less or more than q_r^*.

iv. *Loss-aversion*: a loss averse preference reflects those human retailers that are reluctant towards ordering quantities that might generate losses, namely they would prefer to order quantities that would be expected to generate only gains to their current wealth status.

v. *Waste-aversion*: a waste averse attitude represents retailers' particular dislike of holding excess inventory at the end of a time period (Arkes, 1996). Waste aversion is modelled via an additional penalty that occurs for each unit of inventory not sold during the time period. Waste averse retailers would tend to order less than the rationally optimizing retailer q_r^*.

vi. *Stock-out aversion*: a stock-out averse attitude represents retailers' particular dislike of lost customer sales; it is modelled via an additional goodwill penalty that occurs every time customer demand appears, but there is no sufficient inventory in stock to satisfy this demand. Stock-out averse retailers would tend to order more than the rationally optimizing retailer q_r^*.

vii. *Opportunity costs under-estimation*: an attitude towards under-valuing opportunity costs occurs when a retailer discounts the marginal value of forgone sales. *Opportunity costs* arise when there are forgone sales, namely when there is unsatisfied customer demand. Retailers that under-estimate *opportunity costs* would tend to order less than q_r^*.

viii. *Ex-post inventory error minimisation*: the *ex-post inventory error* is defined as the difference between the order quantity and the actual demand (Bell, 1982; 1985). So, an attitude towards minimisation of *ex-post inventory error* reflects the high significance that some retailers assign to minimising this difference. This priority most probably stems from retailers' potential disappointment from not choosing the realised demand (*i.e. psychology of regret*: Camerer, 1995; Loch and Wu, 2007) and can be modelled via an additional penalty that occurs every time a human retailer's chosen order quantity differs from realised demand.

Schweitzer and Cachon (2000) formally prove that for the cases of demand, of which cumulative distribution functions are symmetric about the mean μ, human newsvendors' *intention* to minimise *ex-post inventory error* generates a systematic *too low/too high* pattern. This *too low/too high* pattern signifies human retailers' tendency to order quantities that are lower than q_r^* for products of the high profit type and higher than q_r^* for products of the low profit type. This phenomenon is known as the "pull-to-centre effect" (Bostian *et al*, 2008).

In addition, Schweitzer and Cachon (2000) revisit the standard normative models' assumptions about human *intentions* by building their laboratory experiments on the postulation that human retailers aim at minimising *ex-post inventory error*. Kremer *et al*. (2008) further explore their subjects' individual and psychological biases that drive this *intention*. Following the same rationale, Bostian *et al*. (2008) empirically collect data and fit different models to this data, among which there is a quadratic regret error term that encapsulates the *intention* that is relevant to minimising *ex-post inventory error*, as recognised by

Schweitzer and Cachon (2000). Subsequently, Bostian *et al*. (2008) further extend this decision rule by incorporating dynamic parameters: namely, they let the degree by which inventory errors influence subsequent order decisions to vary over time.

Actions refer to the rules or implied behaviour of human decision makers (Bendoly *et al*, 2006). The inherent assumption of the standard normative models that are presented in *Sub-section 2.1.1* is that all human newsvendors are perfectly rational in their decisions. This assumption pre-supposes that all human decision makers possess both the required perfect symmetric information and the cognitive and processing abilities to do so. But in practice, human retailers might not be aware of the true customer demand distribution (*e.g*. Gallego and Moon, 1993), or even if they are, they might not be willing to share this private information with their partners, at least not without being compensated in some way for doing so (*e.g*. Cachon and Fisher, 2000). But provision of related incentives would completely distort the analytical results of the *Newsvendor Problem* setting that are presented in *Sub-section 2.1.1* (Chen, 2003). In addition, human decision makers might lack the processing means and the time to search the entire solution space and identify the optimal decisions (Chen, 2003). In summary, they might "experience limits in formulating and solving complex problems and in processing information" (Simon 1957 in Williamson 1981: pp. 553) and, for this reason, might need to settle at reasonable, thus *satisficing*, choices (Sterman, 1989; Simon, 1996; North and Macal, 2007; Gilbert, 2008). For this reason, the standard normative models need to remove these over-simplifications and, thus, be adapted to accommodate *bounded rationality* (Simon, 1996).

In order to address human retailers' *bounded rationality*, Schweitzer and Cachon (2000) make provision for appropriate modifications of Kahneman *et al*.'s (1982) "anchoring and insufficient adjustment" heuristic to govern their decisions. In accordance with this heuristic, participants would initially choose an order quantity ("anchor") and subsequently modify or insufficiently adjust this order quantity ("insufficiently adjust") towards a desired stock level. From the available anchors, namely the expected demand, the initial, pre-determined order quantity and past demand realizations, Schweitzer and Cachon (2000) consider mean demand and prior order quantity, according to the following two heuristics:

i. *Mean anchor*: the mean anchor heuristic implies that a retailer would initially choose an order quantity according to mean demand, which is his/her *anchor* and subsequently *insufficiently adjust* towards the profit maximising quantity q_r^*.

ii. *Demand chasing*: the demand chasing heuristic implies that a retailer would initially *anchor* on a prior order quantity and thereafter *insufficiently adjust* towards prior demand realizations.

Schweitzer and Cachon (2000) also demonstrate that the *mean anchor* heuristic reproduces the same *pull-to-centre* systematic *too low/too high* pattern that is caused by human retailers' *intention* to minimise *ex-post inventory error*.

After Schweitzer and Cachon (2000) applied the Kahneman *et al*.'s (1982) *anchoring and insufficient adjustment* heuristic to the *Newsvendor Problem* setting a number of subsequent papers further investigate its presence: Benzion *et al.* (2008), Bolton and Katok (2008), Bostian *et al*. (2008) and Kremer *et al*. (2008) explore whether participants would tend to order quantities that would follow the *mean anchor* decision rule, while Benzion *et al.* (2008), Kremer *et al*. (2008), Bostian *et al*. (2008) and Lurie and Swaminathan (2009) seek for further evidence in favour of the *demand chasing* decision rule.

Nevertheless, except for Kahneman *et al.*'s (1982) *anchoring and insufficient adjustment* heuristic, there is a number of additional behavioural biases that might influence human decisions (Camerer, 1995; Loch and Wu, 2007). For this reason, a number of papers collectively model human decision makers' potential *bounded rationality*, instead of specifically identifying and, thus, directly addressing their distinct behavioural biases. Examples are Bostian *et al*. (2008) and Su (2008), who treat all possible order decisions as discrete choices and develop different models that would assign to each different possible choice a different probability of getting selected.

Bostian *et al*. (2008) develop a dynamic model of *bounded rationality*, learning and adjustment, which concretely represents the mental decision processes of human decision makers. According to this model, each possible order decision is assigned a different probability of being chosen, according to the studied participant's respective level of *rationality* and each possible choice's respective weight. The level of *rationality* varies from 1 to ∞, where 1 represents a decision maker who would make completely random choices (*i.e*. completely irrational) and ∞ indicates a decision maker who would make decisions perfectly in accordance with Bostian *et al*. 's learning and adjustment model (*i.e*. perfectly rational). As for the order quantity's relevant weight, Bostian *et al*. define this weight as the weighted sum of two distinct components: *i*. the weight that is assigned to this order decision in the last round and *ii*. the counter-factual profit that would have been generated by this order decision in the last round, given the demand realization that has been truly observed. Each of these two components' respective weight is determined by each decision maker's respective memory bias, namely his/her tendency to ignore or not historical performances of different order decisions. This consideration of historical performances incorporates the learning that human decision makers experience during the course of the game. As for the counter-factual profit that would have been generated by true customer demand in the last round, Bostian *et al*. make provision for participants to either consider the counter-factual profits of alternative choices or not, according to their implicit reinforcement bias. This reinforcement bias encapsulates participants' degree of adjustment to the results of previous choices.

Su (2008) develops a quantal choice[4] behavioural model, according to which different order decisions are assigned different probabilities of being chosen, according to their respective expected utility function values. It is ensured that alternatives with higher expected utility function values are chosen more often. Su considers expected utility function values, which are equal to the expected profits q_r^* that are calculated by the standard normative models. In this model, decision makers' *bounded rationality* varies from 0 to ∞, with 0 reflecting a perfectly rational decision maker who would only choose the order quantities

[4]The classic "quantal choice" theory (*s*. Thurstone, 1927; Luce, 1959) postulates that people may not make the best decisions all the time, but make good decisions more often than worse ones. [Sources: 1. Thurstone, L. 1927. A law of comparative judgement. *Psychological Review* 34, 273-286; 2. Luce, R. 1959. *Individual choice behaviour: a theoretical analysis*. Wiley, New York].

that would generate the highest expected utility function value and ∞ representing a completely naive decision maker who would randomize over the possible alternative order quantities with equal probabilities.

Both Bostian *et al*. (2008) and Su (2008) validate subsequently their respective *bounded rationality* models by fitting to them data that they have collected empirically.

Reactions refer to human players' response to model parameter changes. They might include implied rules for how decisions makers learn, perceive and process feedback information or are influenced by environmental factors (Bendoly *et al*, 2006). The standard normative models that are presented in *Sub-section 2.1.1* embed the assumption that people do *not* react to changes going on around them and, since they make perfectly rational decisions, they do not need to use the information that is available to them to further improve their decisions. Yet, this is seldom the case in practice: human decision makers may react to the changes that occur around them. Since, in addition, there is potential for them to improve their imperfect decisions, they may learn from available past information. In this regard, the existing experimental research addresses well the behavioural newsvendor's *reactions* to learning (Schweitzer and Cachon, 2000; Schultz and McClain, 2007;Benzion *et al*, 2008; Bolton and Katok, 2008; Bostian *et al*, 2008), environmental changes (Schultz and McClain, 2007; Bolton and Katok, 2008; Bostian *et al*, 2008; Kremer *et al*, 2008; Lurie and Swaminathan, 2009) and feedback information (Bolton and Katok, 2008; Lurie and Swaminathan, 2009).

Learning is mostly treated as the gradual convergence of participants' order quantity to the rationally optimizing quantity q_r^*, that is predicted by the standard normative models. In view of this, Schweitzer and Cachon (2000) test the existence of learning in participants' decisions, as exhibited over 30 rounds. Benzion *et al.* (2008) extend the period to 100 decision rounds and, additionally, investigate exactly how participants' previous round's decision affect their subsequent decisions. Bolton and Katok (2008) explore whether decision makers' increased experience helps them to enhance their realised profits. Bostian *et al*. (2008) recognise that different decision makers' learning attitudes could vary from complete ignorance to high prioritization of historical performances and, as a result, incorporate this range in their dynamic model via a memory bias parameter. For Schultz and McClain (2007) human retailers' learning is associated with the environmental set-up and, for this reason, they investigate whether explicit statement of *opportunity costs* would improve participants' learning.

Schultz and McClain (2007) are also among the first studies that investigate the environment's effect on participants' observed decisions. They explore whether the framing of the decision task, namely whether the emphasis is put on losses or gains, affects participants' order quantities. A number of subsequent papers follow a similar rationale: Kremer *et al*. (2008) test whether and how the framing and the complexity of the decision task influences participants' tendency to follow the *mean anchor* and the *ex-post inventory error minimising* decision rules. But instead of treating the framing of the decision task in terms of whether the emphasis is put on losses or gains, they manipulate it by means of the information related to customer demand that is provided to participants. Kremer *et al*. (2008) also treat task complexity by the number of quantity choices that are available to participants and the magnitude of the space of true customer demand. Bolton and Katok (2008) investigate whether and how the framing and the complexity of the decision task influence the profits that are attained by human participants. In this regard, they treat the framing of the decision task in terms of whether information about forgone options is provided to participants. They control for decision complexity by reducing: *i*. the number of decision options that are available to participants and *ii*. the number of distinct decisions that are required. Lurie and Swaminathan (2009) investigate whether decision complexity affects participants' order decisions and their respectively realised profit. To this end, like Bolton and Katok (2008), they treat complexity via the number of distinct decisions they ask participants to make. Finally, Bostian *et al*. (2008) incorporate environmental impact in their already discussed dynamic model via the reinforcement bias parameter. This reinforcement bias parameter relates well to the environmental impact, because it encapsulates participants' degree of adjustment to the respective results of previous choices.

Providing information about forgone options is a form of feedback information. That is why we consider Bolton and Katok (2008) to address the impact of feedback information on participants' attained profits. But Lurie and Swaminathan (2009) are more directly concerned with investigating the effect of presentation and frequency of feedback information on participants' decisions and resulting profits.

The Protocols Applied

In all papers reviewed in this sub-section, human participants are asked to determine their newsvendor order quantity decisions facing stochastic customer demand in computerized simulation games. They are expected to enter these order quantity decisions in specifically designed computer interfaces. These interfaces ensure that participants would only have access to the information that is dictated by the research questions being addressed. Human newsvendors are asked to iteratively make quantity decisions over 30 (Schweitzer and Cachon, 2000; Bostian *et al*, 2008; Kremer *et al*, 2008; Lurie and Swaminathan, 2009), 40 (Schultz and McClain, 2007) or 100 (Benzion *et al,* 2008; Bolton and Katok, 2008; Su, 2008) rounds. Customer demand is assumed to follow the uniform (Schweitzer and Cachon, 2000; Schultz and McClain, 2007; Benzion *et al,* 2008; Bolton and Katok, 2008; Bostian *et al*, 2008; Kremer *et al*, 2008; Su, 2008; Lurie and Swaminathan, 2009) or normal (Benzion *et al*, 2008) distributions. Most studies pay participants a flat minimum participation fee and, in addition, a variable rate that is determined by the profits that they have realized in a randomly selected round of the experiment (Schultz and McClain, 2007; Benzion *et al*, 2008; Bolton and Katok, 2008; Kremer *et al*, 2008; Su, 2008).

Key Findings

Most studies of the behavioural newsvendor confirm the existence of the *pull-to-centre effect*, namely provide evidence for the *too low/too high* systematic pattern of human newsvendors' order quantities (Schweitzer and Cachon, 2000; Benzion *et al*, 2008; Bolton and Katok, 2008; Bostian *et al*, 2008). Schweitzer and Cachon (2000) find support for both the *ex-post inventory error* minimisation and *demand chasing* decision rules; Benzion *et al.* (2008) reproduce the *demand chasing* and the *mean anchor* decision rules; while Kremer *et al*. (2008) corroborate the existence of *ex-post inventory error* minimisation, *demand chasing* and *mean anchor*. In addition, Kremer *et al.* (2008) establish that the information that is available to participants may have a significant effect on their respective tendencies to follow any of these three decision rules: *ex-post inventory error* minimisation, *demand chasing* and *mean anchor*.

Although Schultz and McClain (2007) could not support participants' learning through increased experience, Benzion *et al.* (2008) and Bolton and Katok (2008) establish the effect of experience-based learning, as human newsvendors' decisions would move closer to the rationally optimizing quantities q_{r}^{*}. In addition, average profits per period would increase with the number of decision rounds that the game is played. Furthermore, Schultz and McClain (2007) do not find the alternative framing of the required decision task (with the emphasis on losses or gains) to have any significant effect on the participants' order decisions and realised profits. In accordance to this, Bolton and Katok (2008) could not find support for the notion that any additional information about foregone profits would increase profits. Yet, reducing the number of decisions required from participants does seem to have the potential to increase the profits. Lurie and Swaminathan (2009) establish that offering feedback information too frequently to decision makers would degrade their profits and diverge their respective order quantities away from optimal quantities q_{r}^{*}.

Bostian *et al*. (2008) compare the predictive power of their learning, adjustment and *bounded rationality* model with that of the *mean anchor* and *demand chasing* decision rules. Su (2008) assesses the goodness-of-fit of his *bounded rationality* model in respect to the predictions of the standard normative theories. Both papers base their evaluations on the Schwarz or Bayesian Information Criterion (BIC) (Schwarz, 1978), because they follow the maximum likelihood procedure and fit a different number of independent variables in each model (McCulloch *et al*, 2008; Fox, 2008). These comparisons confirm confidence in the explanatory potential of these models.

2.1.3 Summary

Section 2.1 presents the main analytical results that are known for the *Newsvendor Problem* setting; it also reviews the true decisions that human newsvendors have been observed to make in the laboratory. In this regard, Table 2.1 provides a breakdown of the articles that revise the common behavioural assumptions of the standard normative newsvendor models. Following the organisation of *Sub-section 2.1.2*, this table is structured according to the *Analysis of Assumptions* framework, as applied by Bendoly *et al*. (2006).

It is evident from Table 2.1 that the systematic divergence of human newsvendors' order quantities from the quantities that are predicted by the standard normative models is established (Schweitzer and Cachon, 2000; Schultz and McClain, 2007; Benzion *et al*, 2008; Bolton and Katok, 2008; Bostian *et al*, 2008; Kremer *et al*, 2008; Su, 2008; Lurie and Swaminathan, 2009). These observed deviations are attributed to a number of individual behavioural biases, such as for example:

- *risk-seeking* (Schweitzer and Cachon, 2000),

- *risk-aversion* (Schweitzer and Cachon, 2000),
- *reference-dependence* (Schweitzer and Cachon, 2000),
- *loss-aversion* (Schweitzer and Cachon, 2000),
- *waste-aversion* (Schweitzer and Cachon, 2000),
- *stock-out aversion* (Schweitzer and Cachon, 2000),
- *opportunity costs under-estimation* (Schweitzer and Cachon, 2000),
- *ex-post inventory error minimisation* (Schweitzer and Cachon, 2000; Bostian *et al*, 2008; Kremer *et al*, 2008),
- *mean anchor* (Schweitzer and Cachon, 2000; Benzion *et al,* 2008; Bolton and Katok, 2008; Bostian *et al*, 2008; Kremer *et al*, 2008),

Table 2.1: Distribution of behavioural papers in the context of the *Newsvendor Problem* by assumption type

Research Paper	**Behavioural assumptions**	**Key Findings**
Intentions: decision makers' actual goals might be different from maximisation of the aggregate channel's profit		
Schweitzer and Cachon (2000)	*Risk-seeking*; *risk-aversion*; *reference-dependence*; *loss-aversion, waste-aversion*; *stock-out aversion*; *opportunity costs under-estimation*; *ex-post inventory error minimisation*	*Ex-post inventory error minimisation*

Research Paper	**Behavioural assumptions**	**Key Findings**
Bostian *et al*. (2008)	*Ex-post inventory error minimisation*	No systematic evidence
Kremer *et al*. (2008)	*Ex-post inventory error minimisation*	*Ex-post inventory error minimisation*
Actions: decision makers' behaviour might differ from the behaviour that is specified by their respective *intention*s		
Carlson and O'Keefe (1969)	No systematic account of observed deviations	Existence of systematic deviations of participants' decisions from the order quantities that would maximise the newsvendor's profit
Fisher and Raman (1996)	No systematic account of observed deviations	Systematic difference between supply chain managers' true decisions and corresponding exact optimal solution
Schweitzer and Cachon (2000)	*Mean anchor*; *demand chasing*	*Pull-to-centre effect*; *demand chasing*
Benzion *et al.* (2008)	*Mean anchor*; *demand chasing*	*Pull-to-centre effect*; *mean anchor*; *demand chasing*
Bolton and Katok (2008)	*Mean anchor*	No systematic evidence
Bostian *et al*. (2008)	*Mean anchor*; *demand chasing*; learning; adjustment; *bounded rationality*	Learning, adjustment and *bounded rationality* model
Kremer *et al*. (2008)	*Mean anchor*; *demand chasing*	*Demand chasing*; *mean anchor*
Su (2008)	*Bounded rationality*	*Bounded rationality* behavioural model

Research Paper	**Behavioural assumptions**	**Key Findings**
Lurie and Swaminathan (2009)	*Demand chasing*	No systematic evidence
Reactions: decision makers might learn, process feedback information and react to environmental changes		
Schweitzer and Cachon (2000)	Learning	No systematic evidence
Schultz and McClain (2007)	Learning; framing of decision task	No systematic evidence
Benzion *et al*. (2008)	Learning	No systematic evidence
Bolton and Katok (2008)	Learning; framing and complexity of decision task; presentation of feedback information	Simplification of required decision task would improve decisions
Bostian *et al*. (2008)	Learning; environmental impact	Learning, adjustment and *bounded rationality* model
Kremer *et al*. (2008)	Framing and complexity of decision task	Impact of relevant information provided
Lurie and Swaminathan (2009)	Decision complexity; presentation and frequency of feedback information	Too frequent information would degrade decisions

- *demand chasing* (Schweitzer and Cachon, 2000; Benzion *et al*, 2008; Bostian *et al*, 2008; Kremer *et al*, 2008; Lurie and Swaminathan, 2009).

The aforementioned individual behavioural biases are also collectively characterised as *bounded rationality* (Bostian *et al*, 2008; Su, 2008). Last but not least, the impact of environmental factors is also accounted for (Schweitzer and Cachon, 2000; Schultz and McClain, 2007; Benzion *et al*, 2008; Bolton and Katok, 2008; Bostian *et al*, 2008; Kremer *et al*, 2008; Lurie and Swaminathan, 2009).

2.2 The Beer Distribution Game

In this section the typical *Beer Distribution Game* setting is considered. Since first used by Sterman (1989) as an experimental framework, the *Beer Distribution Game* is still very popular in supply chain management classes all over the world (Sterman, 1992; 2000) and is also still extensively used in experimental research (*e.g*. Steckel *et al*, 2004; Croson and Donohue, 2006; Wu and Katok, 2006). The reasons for its popularity are that it is sufficiently simple for human subjects to quickly understand and learn how to play, but also retains key features of real supply chains. The *Beer Distribution Game* mimics the material, information and financial flows of a *de-centralised operation*, periodic review production-distribution supply chain with a number of serial echelons.

Participants in the game are asked to minimise total inventory holding and backlog costs. Although they would attain the *first-best case minimum* cost by simply ordering as much as they are themselves requested to deliver (Chen, 1999; Lee and Whang, 1999), human decision makers are naturally inclined to pass on to their respective suppliers orders that are of amplified size and variance, when compared to their incoming orders (Lee *et al*, 1997a; b). This tendency of orders to increase in magnitude and variance as one moves upstream away from the customer to the manufacturer is defined as the '*bullwhip effect*', or else 'Forrester effect' (Forrester, 1958; 1961). Figure 2.3 presents an indicative example of a supply chain configuration with three serial echelons, where the *bullwhip effect* takes place. The relevant evidence is provided by the fact that orders magnify in size and variance upstream, that is, from the retailer to the wholesaler to the manufacturer. Since the *bullwhip effect* increases inventory holding and backlog costs (Chen *et al*, 1999; Dejonckheere *et al*, 2003; Sucky, 2009) and, thus, further augments overall supply chain *inefficiencies*, a common pre-occupation of researchers of the *Beer Distribution Game* is to establish its persistence. To this end they have resorted to both analytical models and laboratory experiments.

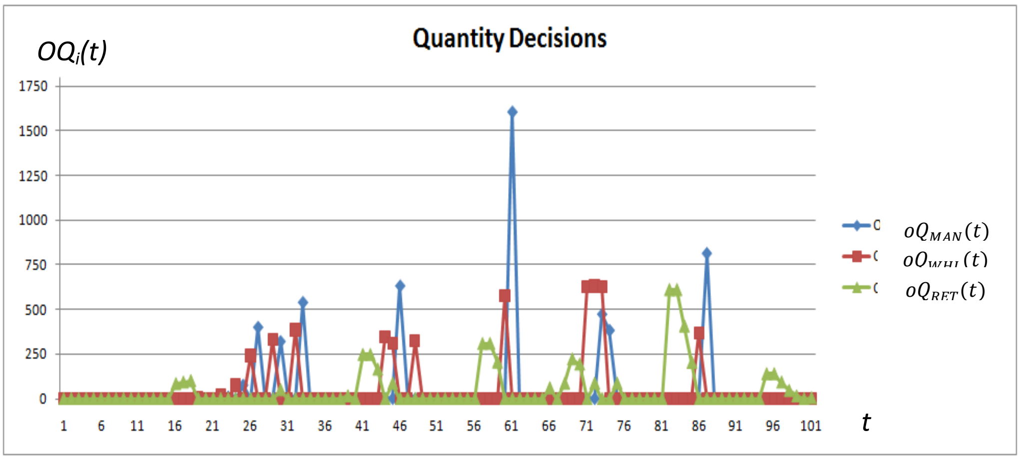


Figure 2.3: The *bullwhip effect*

Sub-section 2.2.1 concentrates on the relevant standard normative models, after the game set-up has been described and some basic notation has been introduced. *Sub-section 2.2.2* focuses on existing experimental research. The exact assumptions of the standard normative models that these experimental studies *intend* to revisit are first summarised. The experimental protocols are then outlined and the key findings are finally presented.

2.2.1 Standard Normative Models

Figure 2.4 illustrates the typical *Beer Distribution Game* setting. Customer demand arises at echelon i=1; echelon i=1 replenishes its stock from echelon i=2, echelon i=2 from i=3 etc., and echelon N(=3) from a perfectly reliable outside supplier (N+1=4). Customer demand is assumed to be stationary and independent across periods. For reasons of simplicity Steckel *et al*.'s (2004) experimental setup is followed, according to which there are three serial echelons (namely N=3), that is, the retailer (i=1), the wholesaler (i=2) and the manufacturer (i=3). At the beginning of each period t, each echelon's manager decides how much to order from echelon i+1, therefore places an order quantity $OQ_i(t)$, with i=1,..,N. Information in the form of replenishment orders flows from downstream to upstream (*i.e*. from i to i+1), while material flows in the opposite direction: from upstream to downstream(*i.e*. from i to i-1).

The set-up is additionally complicated by order processing and production/shipment delays that occur between each manufacturer/customer pair. As Figure 2.5 demonstrates, these respectively represent the time required to receive, process, produce/ship and deliver orders. In greater detail, once an order is placed from site i, a constant information lead time (l_i = 2) of two time periods occurs before the order actually arrives to the supply site i+1, while when an order is filled by the supply site i+1 a fixed transportation lead time (L_i= 2) of two time periods passes before the shipment gets delivered to site i. The total lead-time is M_i=l_i + L_i. At the highest echelon level (i=3) production requests represent production quantities. Since the external supplier is assumed to receive and satisfy orders from the manufacturer instantaneously (*i.e*. l_N=1), a total of M_N = 3 periods are required to process and manufacture an order. This is why the manufacturer, not facing any supply uncertainty, is illustrated in Figure 2.5 to receive all placed production requests after exactly M_3 = 3 time periods.

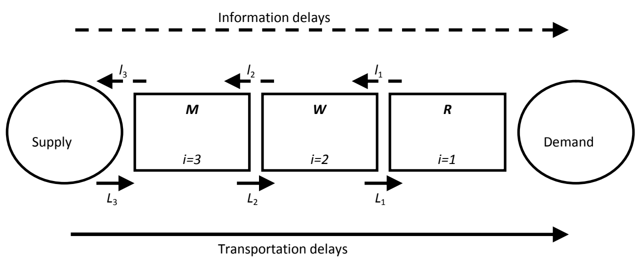


Figure 2.5: Lead times in the *Beer Distribution Game*

It is also assumed that each echelon i needs to satisfy as much of outstanding orders from the downstream customer i-1 as possible from available on-hand inventory. But in case *i* runs out of stock, *i* backlogs the unsatisfied portion of customer orders and incurs a backlog penalty of b_i =1 *m.u.* for every unit of unsatisfied demand; echelon *i* subsequently treats this as an outstanding order from downstream customer *i*-1. Each echelon *i* also has to incur linear inventory holding cost of h_i =0.50 *m.u.* for every unit of product that is kept in inventory for one period. Finally, the retailer sells each case of beer at the fixed selling price of *p* = 3 *m.u.* and the manufacturer produces each case of beer at the fixed manufacturing cost of *c* = 0.50 *m.u.*

For clarity, a convention that is typically accepted in the field is here also followed: It is assumed that all replenishment activities occur at the beginning of the period. Therefore, the significant events for each echelon *i* unfold as follows: *1.* the shipment from the upstream manufacturer $S_{i+1}(t - L_i)$ is received, *2.* If there is any backlog, it is filled, *3.* the incoming order from the downstream customer $oQ_{i-1}(t - l_{i-1})$ is received, *4.* as much of the incoming order as possible is filled and shipped to the downstream customer i-1, namely $S_i(t)$, that is provided that there is any inventory left in warehouse; in addition, in case there are any outstanding orders, these are added to the existing backlog and last, *5.* an order is placed with the upstream manufacturer $oQ_{\mathrm{i}}(t)$.

In summary, for every site *i*=1,...,*N* the following notation is used:

x customer demand, a random variable

$f(x)$ probability density function of *x*

$F(x)$	cumulative distribution function of *x*
p	selling price per unit
c	manufacturing cost per unit
b_i	lost sales (goodwill) penalty cost
h_i	inventory holding cost
$oQ_i(t)$	order quantity of site *i* in time period *t*
$S_i(t)$	shipment sent from site *i* to site site *i*-1 in time period *t* (*i.e.* site *i*-1 will receive this shipment in period t+L_{i-1})
$IN_i(t)$	net inventory position of site *i* in time period *t* (a site's net inventory position is given by its on-hand inventory position minus the backlogged orders from the downstream customer, or backlogged customer demands for the case of the retailer)
L_i	production/transportation lead-time from site *i*+1 to site *i*
l_i	information lead-time from site *i* to site *i*+1
M_i	total lead-time $M_i = l_i + L_i$
$\mathcal{L}_i$	downstream information lead-time $= \sum_{j=1}^{i-1} l_j$ with $\mathcal{L}_1 = 0$

Based on the above notation and assumptions, it is evident that any echelon *i* sends to its respective downstream customer *i*-1 the portion of backlogs, if any, and incoming orders that can be satisfied, depending on *i*'s available inventory, that is:

$$S_1(t) = min\{D(t), max\{IN_1(t-1) + S_2(t-L_1)\ ,0\}\} \tag{2.10}$$

$$S_i(t) = min\left\{oQ_{i-1}(t-l_i)\ , max\{IN_i(t-1) + S_{i+1}(t-L_i)\ ,0\}\right\} \tag{2.11}$$

Following this, any echelon's *i* inventory increases by the shipments that it receives from its upstream manufacturer *i*+1 (in turn given by relations (2.10) and (2.11)) and decreases by the incoming orders that it receives from its downstream customer *i*-1. Therefore, the following inventory balance equations can be deduced:

$$IN_1(t) = IN_1(t-1) + S_2(t-L_1) - D(t) \tag{2.12}$$

$$IN_i(t) = IN_i(t-1) + S_{i+1}(t-L_i) - oQ_{i-1}(t-l_i) \text{ for } i = 2,3 \tag{2.13}$$

Centralised operation

The ultimate objective of the game under the hypothetical scenario of *centralised operation* is to attain the *first-best case minimum* cost, namely, minimise the total inventory holding and backlog costs. Each site *i* has to incur a total inventory and backlog cost of $IC_i(t)$, as given by equation (2.14) :

$$IC_i(t) = h_i \cdot [IN_i(t)]^+ + b_i \cdot [IN_i(t)]^- \tag{2.14}$$

($[x]^+ \stackrel{\text{def}}{=} max\{x, 0\}$ and $[x]^- \stackrel{\text{def}}{=} max\{-x, 0\}$.).

The result is that the total supply chain inventory holding and backorder cost in period *t* is given by:

$$IC_c(t) = \sum_{i=1}^{N} [h_i \cdot [IN_i(t)]^+ + b_i \cdot [IN_i(t)]^-] = \sum_{i=1}^{N} [h_i \cdot A + b_i \cdot B] \tag{2.15}$$

Hence, the total supply chain costs through to period *T* become:

$$\sum_{t=1}^{T} IC_C(t) = \sum_{t=1}^{T}\sum_{i=1}^{N}[IC_i(t)] \tag{2.16}$$

It is obvious from (2.16) that since customer demand is stationary and independently distributed across periods, the stochastic game reduces to a sequence of similar single period games, under the assumption of a stationary inventory policy. For this reason, it suffices to minimise overall supply chain costs in period t $IC_C(t)$ in order to minimise $\sum_{t=1}^{T} IC_C(t)$ (Federgruen and Zipkin, 1984; Axsäter, 2003). The set of decision making strategies that would generate the *first-best case minimum* cost IC^*_t constitutes the *team optimal solution* $IC_O(t)$.

Although most analytical papers explore this *team optimal solution* for multi-echelon inventory systems without provision for information lead-times (*e.g*. Clark and Scarf, 1960; Federgruen and Zipkin, 1984; Chen and Zheng, 1994), Lee and Whang (1999) and Chen (1999) are the exceptions and do accommodate the presence of information lead-times. Lee and Whang (1999) are concerned with developing a *transfer payment scheme* that fairly allocates overall system costs to distinct echelon managers, but takes their optimum ordering policies for granted. Chen (1999) identifies the *team optimal solution* and, in addition, echelon managers' distinct ordering policies that would minimise their own respective inventory and backlog costs. Chen (1999) additionally estimates the penalties that should be charged to echelon managers in order for their distinct ordering policies not to deviate from the *team optimal solution*.

While Chen (1999) is evidently more closely connected with the aim here to recognise the *team optimal solution*, it differs from it in three aspects: *i*).

dissimilarly to Chen (1999), quantities in transit from one site to another as well as backlogged demands do not incur any inventory holding costs; *ii*). all sites (that is not only the retailer, like in Chen, 1999) incur a linear backlog penalty b_i for all non-immediately satisfied demands that they receive from their respective downstream customers; *iii).* in contrast to Chen (1999), no echelon incremental holding cost rates apply. The reason is that in the *Beer Distribution Game* no value adding activities take place. These differences originate from the attempt to keep the model formulation as consistent as possible with Sterman's (1989, 1992) original *Beer Distribution Game* set-up.

Chen (1999) relies on three optimality conditions to apply Chen and Zheng's (1994) procedure to identify and simplify Clark and Scarf's (1960) and Federgruen and Zipkin's (1984) optimum ordering policies. Although there is no reason for these optimality conditions not to hold in the case of the *Beer Distribution Game*, this has as yet not been confirmed. Therefore, it still remains to be formally proven that the *team optimizing* echelon managers in the *Beer Distribution Game* would follow Chen's (1999) decision rules.

At this point we consider noteworthy two details about these optimal decision rules: *First*, although Chen (1999) follows the exact same proof procedure with Chen and Zheng (1994), by making provision for information lead-times, he identifies *order-up-to level* policies $(Z_1^*, \dots, Z_N^*)$ as optimum for all firms and not for all but the retailer, like Chen and Zheng (1994). According to these *order-up-to level policies* $(Z_1^*, \dots, Z_N^*)$, all echelon managers *i* (=1,..., *N*) need to order as much as would keep their respective site's inventory level at Z_i^* (Johnson and Montgomery, 1974; Hopp and Spearman, 2001). If these *order-up-*

to level policies $(Z_1^*, \dots, Z_N^*)$ are followed by all distinct echelon managers, the *first-best case minimum* cost is attained by the entire supply chain of the *Beer Distribution Game* (Chen, 1999; Lee and Whang, 1999). It is very interesting that Lee and Whang (1999) also support the same *order-up-to level* policies as minimising the overall inventory cost.

Second, even though Clark and Scarf (1960), Federgruen and Zipkin (1984) and Chen and Zheng (1994) express the optimal decision rules in the form of echelon base stock policies, Chen (1999) and Lee and Whang (1999) transform these to installation stock levels. The difference between *installation stock levels* and *echelon base stock policies* is that the former are expressed in terms of a site's inventory level, while the latter comprises of the inventory levels of all subsequent sites until the retailer (Chen, 1999). Axsäter and Rosling (1993) demonstrate that the conversion of echelon base stock levels to installation stock levels does not alter overall costs. A difference occurs only in the case where initial echelon stock inventory positions are above the optimal *order-up-to* positions, for which the above installation-based stock policies may fail (Axsäter, 2003).

It is finally very interesting to note that in the case that distinct echelon managers are perfectly rational and exclusively interested in minimising the *team overall* cost, there is no *bullwhip effect*. The reason is that when they follow these optimal decision rules, they simply order as much as they are themselves requested to deliver to their respective customers. So, the variance of all incoming orders remains exactly the same.

But it is also very interesting to understand what happens when distinct echelon managers independently choose their order quantities and are exclusively interested in minimising their respective individual costs, that is, when they remain indifferent to the *team optimal solution*. Under this scenario of *de-centralised operation*, there are two important questions: *i.* whether the aggregate channel cost IC_c would differ from the *first-best case minimum* cost IC^*_t and *ii.* whether the *bullwhip effect* would arise. The sub-section that follows answers these questions.

De-centralised operation

Cachon and Zipkin (1999) prove that in the case of *de-centralised operation* the deriving aggregate cost IC_c is greater than the *first-best case minimum* cost IC^*_o, namely $IC_c > IC^*_o$. They also demonstrate that the aggregate channel cost IC_c differs in the case where echelon level or local inventory information is used. This potential gap that might exist between the aggregate channel costs $IC_C = \sum_{i=1}^{N} IC_i$ and the overall minimum backlog and inventory holding cost (or else the *first-best case minimum* cost) IC^*_0 is usually quantified via the 'competition penalty' (Cachon and Zipkin, 1999; Cachon, 2003), which is defined according to relation (2.17):

$$CP = \frac{IC_C - IC_0^*}{IC_0^*} \tag{2.17}$$

The closer to 0 a *competition penalty* is the better the overall performance of the multi-echelon inventory system under study and also the closer the cost that is incurred, IC_c, to the *first-best case minimum* cost IC^*_o. But Cachon and Zipkin's (1999) inventory system consists of only two echelons: a supplier and a retailer. Therefore, it still remains to be explored whether under *de-centralised operation* of the *Beer Distribution Game* there would be any difference between the *first-best case minimum* cost IC^*_o and the aggregate channel cost IC_c that would be incurred and also whether the *bullwhip effect* would persevere.

In order to decrease this aggregate channel cost IC_c and bring it as close as possible to the overall minimum backlog and inventory holding cost IC^*_o, a number of *transfer payment scheme*s between local firm managers have been proposed in a number of different multi-echelon inventory systems (*e.g*. Lee and Whang, 1999; Porteus, 2000; Cachon and Zipkin, 1999). These *transfer payment scheme*s determine all terms of trade between interacting partners. Contractual arrangements as they are, they are reviewed in the *Sub-section of 2.3.1* that is relevant to the *Beer Distribution Game* setting. Nevertheless, the question of exactly how the corresponding standard normative model would predict the performance of the *wholesale price contract* in the typical *Beer Distribution Game* setting has as yet not been explored.

Another interesting question is what happens in the case where there is at least one decision maker whose decisions are not dictated by perfect rationality. In this case, the standard normative models cannot predict human decisions. As a result, discrepancies between the resulting aggregate channel cost IC_c and the *first-best case minimum* cost IC^*_o drastically change. In addition, since human decision makers might make significantly different decisions than their perfectly rationally optimizing counterparts, it is likely that the *bullwhip effect* might occur. The investigation of the real decisions that human participants in the *Beer Distribution Game* really make constitutes the object of the sub-section that follows.

2.2.2 Behavioural Studies of the Beer Distribution Game

Forrester (1958; 1961) is the first that revealed the *bullwhip effect*, along with its negative consequences. Since then a number of researchers are pre-occupied with demystifying its underlying causes. The *Beer Distribution Game*, both in its board-based (Sterman, 1989; 1992) and computer versions (Kaminsky and Simchi-Levi, 1998; Simchi-Levi *et al*, 2008) provide the most usual experimental framework for such studies.

Although it was not until relatively recently that a systematic behavioural perspective has been brought to the operations management literature (Croson and Donohue, 2002; Bendoly *et al*, 2006; Loch and Wu, 2007; Gino and Pisano, 2008), Sterman's (1989) seminal paper describes the first behavioural experiment that is conducted within the *Beer Distribution Game* setting. This paper demonstrates individuals' *bounded rationality* and, hence, limited ability to understand and control systems with lagged, indirect and non-linear feedbacks. In this regard, Sterman paves the way for a number of subsequent laboratory investigations that further confirm the presence of behavioural complexities in human decisions that are related to the *Beer Distribution Game*. The assumptions of the standard normative models of *Sub-section 2.2.1* that are revisited by this behavioural research are first reviewed. The experimental protocols that are applied are subsequently summarized and finally the main findings are outlined.

Assumptions Revisited

In order to review the assumptions that are revisited so far the *Analysis of Assumptions* framework, as applied by Bendoly *et al*. (2006), is followed.

The standard normative models that are discussed in *Sub-section 2.2.1* are built on the common assumption that all interacting decision makers would be interested in minimising either the *team* overall or own individual backlog and inventory holding costs (Chen, 1999; Lee and Whang, 1999). All the laboratory investigations of the *Beer Distribution Game* ask participants to play as members of a *team*; each *team* consists of the supply chain configuration to which participants have been allocated. These studies subsequently explore whether participants' decisions, when combined, give rise to the *first-best case minimum* cost IC^{*}_{t} or, else, the *team* overall minimum backlog and inventory holding cost, as predicted by the standard normative models (*e.g.* Kaminsky and Simchi-Levi, 1998; Steckel *et al*, 2004). Laboratory experiments also investigate whether participants' decisions, when combined, generate the *bullwhip effect* (*e.g.* Croson and Donohue, 2006; Wu and Katok, 2006; Croson *et al*, 2007). The main focus is so far placed on the *bullwhip effect,* because it is considered to be the lead cause of all cost amplifications. By comparing participants' aggregate results with the *team optimal solution's*, these studies aim at either confirming or refuting the existence of behavioural complexities or else individual biases in participants' decision making. These behavioural complexities or individual biases are then used to explain the deviation between the analytical predictions of the standard normative models and the phenomena that are observed in the laboratory. Therefore, minimisation of overall costs is still considered by the plethora of these papers as the ultimate objective of all participating players. As such, the assumption about *team minimising* cost *intentions* of decision makers, as prescribed by the standard normative models, has as yet not been revisited.

The only minor exception is the relatively small stream of experimental research that is concerned with how human subjects perform in comparison to or in collaboration with artificial agents (*e.g*. Kimbrough *et al*, 2002; Hieber and Hartel, 2003; Nienhaus *et al*, 2006). In these papers, artificial agents are fully pre-programmed to act according to the following *intentions*: complying with pre-determined genetic algorithm rules that would approximate minimum overall supply chain backlog and inventory holding costs (Kimbrough *et al*, 2002); ordering according to either the base stock policy (Hieber and Hartel, 2003; Nienhaus *et al*, 2006) or the economic order quantity (Hieber and Hartel, 2003); ordering as much as they are requested to provide (Hieber and Hartel, 2003) or as much as would reproduce a moving average of their own history orders (Hieber and Hartel, 2003; Nienhaus *et al*, 2006). A *base stock policy* ensures that a firm's inventory level would never fall below the specified target level, while the *economic order quantity* represents the inventory level that minimises total inventory holding and ordering costs (Johnson and Montgomery, 1974; Hopp and Spearman, 2001). These *intentions* differ from aggregate cost minimisation, as prescribed by the standard normative models. By comparing participants' aggregate results with the artificial agents' and, thus, establishing human decision makers' systematic under-performance, these studies serve to confirm the existence of behavioural complexities or individual biases in participants' decision making.

But behavioural complexities or individual biases imply that decision makers' *actions* might differ from their *intentions*. This recognition about *actions* is exactly what constitutes the main difference of most behavioural studies to the standard normative models. In this regard, Croson and Donohue (2006), Wu and

Katok (2006) and Croson *et al*. (2007) establish that the *bullwhip effect* persists, even after removal of all its operational causes, as recognised by Lee *et al*. (1997a; b). In this way, Sterman's (1989) earlier finding that the behavioural complexities are the phenomenon's lead causes is confirmed.

A number of papers attempt to identify among the individual biases that are suggested by Camerer (1995) and Loch and Wu (2007) the precise ones that are responsible for these observed divergences between real and predicted decisions. Sterman (1989) explores whether participants tend to apply the Kahneman *et al*. (1982) *anchoring and insufficient adjustment* heuristic in their decision making logic. According to this heuristic, participants would initially choose their order quantities ("anchor") based on the current stock levels and subsequently make insufficient adjustments ("insufficiently adjust") towards desired stock levels. Sterman (1989), Kaminsky and Simchi-Levi (1998), Croson and Donohue (2003; 2005; 2006) and Croson *et al*. (2007) further explore whether subjects would tend to "under-weight" their supply line in their realised decisions. Participants *under-weight* their supply line, if for every new order quantity decision they make they seem to almost ignore their outstanding orders (*i.e*. orders that they have placed but not yet received), but instead over-value their current inventory positions.

Other papers are mostly interested in revealing new behavioural biases that can exist in the *Beer Distribution Game* and, for this reason, turn to systematically exploring their respective impact on participants' decisions and the resulting occurrence of the *bullwhip effect*. Wu and Katok (2006) define 'organizational learning' as the interaction between role-specific and system-wide training and communication and investigate whether its lack could be one of the main behavioural biases leading to the *bullwhip effect*. Croson *et al*. (2007) perceive 'coordination risk' as the lack of: *i*. trust in other partners' actions and *ii*. common knowledge about the *team optimal solution*. They propose this to be a potential trigger for the subjects' tendency to *under-weight* their supply line. Su (2008) considers as the lead cause of the *bullwhip effect* supply chain members' need to safeguard against potential biases that may be inherent in other partners' decisions. For this reason, he offers an analytical framework to quantify the above defined *coordination risk* of Croson *et al*.'s

But the existing experimental research on the *Beer Distribution Game* setting is not exclusively concerned with revealing the behavioural complexities that cause the *bullwhip effect*. Another significant segment of this research methodically investigates the behavioural benefits, or else improvements to human decisions, that can be achieved, if institutional or structural simplifications are applied to the original game setup. Namely, a number of papers explore decision makers' *reactions* to environmental changes. Indicative examples are time lag reduction (Kaminsky and Simchi-Levi, 1998; Kimbrough *et al*, 2002; Steckel *et al*, 2004), sharing of additional information between players (Kaminsky and Simchi-Levi, 1998; Croson and Donohue, 2003; Steckel *et al*, 2004; Croson and Donohue, 2005; Croson and Donohue, 2006; Nienhaus *et al*, 2006), or other more drastic changes, such as *centralised operation* management of the entire supply chain by one player (Kaminsky and Simchi-Levi, 1998) or provision for storing extra inventory or public awareness of the *team optimum* policy (Croson *et al*, 2007).

Kaminsky and Simchi-Levi (1998) and Steckel *et al*. (2004) investigate the effect of reducing the required lead times between shipment and delivery.

Kimbrough *et al*. (2002) introduce lead time uncertainty by forcing lead times to follow a uniform distribution that ranges from 0 to 4 and explore the effect of this additional complexity on the overall supply chain performances that are attained by their artificial agents. Kaminsky and Simchi-Levi (1998), Croson and Donohue (2005), Croson and Donohue (2006) and Nienhaus *et al*. (2006) address the question of whether making all participants' inventory information publicly known to all of them would improve overall performance. Kaminsky and Simchi-Levi (1998) additionally publicize customer demand information to all participants of the game. Croson and Donohue (2003) and Steckel *et al*. (2004) limit their attention to only making Point-Of-Sales (POS) demand information available to all participants. In addition, Kaminsky and Simchi-Levi (1998) study whether the *centralised operation* management of the entire *Beer Distribution Game* supply chain by a sole player would enhance the overall performance attained. Last but not least, Croson *et al*. (2007) explore the effect of two more drastic changes to the usual experimental setup of the *Beer Distribution Game*: They make provision for their participants' extra possibility to hold excess inventory (which they call *coordination stock*), in order to be protected against *coordination risk*. They also inform all their participants what their inventory management policy should be in order to generate the *team optimal* solution or else not exceed the corresponding *first-best case minimum* cost. This policy seems to severely reduce the extent of the *bullwhip effect*.

The Protocols Applied

In Sterman's seminal paper (1989) human participants are asked to interact over the board version of the game (Sterman, 1992). In all the remaining papers reviewed in this sub-section, human participants are asked to determine their order quantity decisions in computerized simulation games of the *Beer Distribution Game* setting, according to the specifications that are provided by Kaminsky and Simchi-Levi (1998) and Simchi-Levi *et al*. (2008). Steckel *et al*. (2004) apply the implementation of the *Beer Distribution Game* with 3 players, while all other papers (*e.g*. Kimbrough *et al*, 2002; Croson and Donohue, 2003; Hieber and Hartel, 2003; Croson and Donohue 2005; Croson and Donohue, 2006; Nienhaus *et al*, 2006; Wu and Katok, 2006; Croson *et al*, 2007) explore the 4 echelons implementation. Kaminsky and Simchi-Levi 's (1998) and Hieber and Hartel ‘s (2003) participants interact with automated responses that simulate all remaining three roles' policies; the number of pre-simulated responses that Nienhaus *et al*.'s (2006) participants face vary from 0 to 3. Players of all other studies interact with and against each other via network (Steckel *et al*, 2004; Wu and Katok, 2006; Croson *et al*, 2007) or web-based (Croson and Donohue, 2003; Croson and Donohue, 2005; Croson and Donohue, 2006; Nienhaus *et al*, 2006) implementations of specifically designed computer interfaces. These interfaces ensure that participants would only have access to the information that is specified by the exact research questions addressed.

Kimbrough *et al*. (2002), Hieber and Hartel (2003) and Nienhaus *et al*. (2006) only resort to laboratory investigations to compare human decisions to artificial agents' performances and subsequently base all their conclusions on their simulation and ‘what-if' analyses results. Nonetheless, all remaining papers infer their conclusions from the decisions that the human participants are observed to make in the laboratory (*e.g*. Kimbrough *et al*, 2002; Croson and Donohue, 2003; Hieber and Hartel, 2003; Steckel *et al*, 2004; Croson and Donohue 2005; Croson and Donohue, 2006; Nienhaus *et al*, 2006; Wu and

Katok, 2006; Croson *et al*, 2007). Steckel *et al*. (2004) is the only paper that reports on restricting the time that each participant has to make a decision in each round (to 90 seconds).

Participants in the *Beer Distribution Game* are asked to iteratively make order quantity decisions over 25-50 (Kaminsky and Simchi-Levi, 1998), 35 (Kimbrough *et al*, 2002), 36 (Sterman, 1989; Steckel *et al*, 2004), 48 (Croson and Donohue, 2003; 2005; 2006; Wu and Katok, 2006; Croson *et al*, 2007), 50 or 100 rounds (Hieber and Hartel, 2003). Researchers avoid end-of-game effects by hiding from all participants the true length of the experiment (Croson and Donohue, 2003; Steckel *et al*, 2004; Croson and Donohue, 2005; 2006; Wu and Katok, 2006; Croson *et al*, 2007).

Some studies also require players to participate in some additional activities at the beginning or the end of the game, which also prove to play a rather significant role in the results that are obtained. In order to ensure that the participants have an in-depth understanding of the game dynamics and inherent complexity, Steckel *et al*. (2004) make provision for an additional 8 trial rounds to be run before the start of the actual game. The result from these rounds do not count toward the calculations of final outcomes. To the same end, Croson *et al*. (2007) invite participants to complete a test on the game rules and the meaning of customer demand, before starting to record their decisions and results. Because of the exact research questions addressed by Wu and Katok (2006), they additionally make *training* and *study* sessions possible, before the beginning of the actual game, in accordance with the research questions addressed. A *training* session would enable participants to practice for 20 periods in either a specific role or all roles of the game, while a *study* session would encourage participants to study the instructions, finish a quiz and reflect upon strategies to be implemented during the actual game for 10 minutes. After the end of the game, Croson *et al.* (2007) ask participants to complete a quiz that encourages them to reflect on the results obtained and their overall experience.

Sterman (1989) considers customer demand to follow a simple step-up function, according to which customer demand is fixed at 4 units for the first 4 weeks and increases to 8 units in week 5 and remains fixed at 8 units thereafter. Kaminsky and Simchi-Levi (1998), Kimbrough *et al*, (2002), Hieber and Hartel (2003), Nienhaus *et al*. (2006) and Steckel *et al*. (2004) follow Sterman's (1989) simple step-up demand function. Steckel *et al*. (2004) additionally study the case of *S*-shaped demand patterns with and without noise.

Lee *et al*. (1997a; b) identify the following four as causes of the *bullwhip effect* for the case of perfectly rational decision makers: *i.* demand signal processing (*i.e*. transformation of current demand information into future demand forecast), *ii.* shortage games (*i.e*. allocation of manufacturers' limited resources to competing partners), *iii.* order batching (*i.e*. ordering less frequently than once per time period) and *iv.* price fluctuations (discounts and promotions that usually encourage forward buying). From these, it naturally follows that Sterman's (1989) step-up demand function does not control for demand signal processing. In order, thus, to remove all operational causes of the *bullwhip effect*, Croson and Donohue (2006), Wu and Katok (2006) and Croson *et al*. (2007) assume that customer demand in each period follows the uniform distribution ranging from 0 to 8 units. In addition, they inform all participants of this demand distribution, as suggested by Chen and Samroenraja (2000). Kimbrough *et al*. (2002) force customer demand to follow the uniform distribution that ranges from 0 to 15. In order to remove all demand-related uncertainty, Croson *et al*. (2007) keep customer demand fixed at 4 units and again announce this to all players prior to the beginning of the game. Hieber and Hartel (2003) prefer to keep customer demand fixed at 8 units per period.

Most studies offer to participants financial incentives to make better decisions. Wu and Katok (2006) and Steckel *et al*. (2004) pay their participants according to their *team* performance, that is irrespectively from other *teams*' cumulative costs. In greater detail, Wu and Katok (2006) initially provide each *team* with an endowment of 5,000 tokens. All backlog and inventory holding costs incurred by all members of the *team* are then subtracted from the tokens that are initially made available to the *team*. The tokens that are at the end of the game still available to the *team* represent the total team earnings and are split equally among all *team* members. Steckel *et al*. (2004) pay all participants a flat minimum participation fee and, in addition, a variable rate that is determined by the total cumulative costs that are incurred at the end of the game by their own *team*. Meanwhile Sterman (1989), Croson and Donohue (2003), Croson and Donohue (2005), Croson and Donohue (2006) and Croson *et al*. (2007) incorporate an additional element of competition between different *teams*, by compensating them in relation to how their total costs rank among the other teams' overall costs. Sterman (1989) asks all participants at the beginning of the game to place a $1 bet to a kitty. At the end of the game the *team* with the lowest overall costs receives all bets placed and splits all bets equally to all members of the *team*. Croson and Donohue (2003), Croson and Donohue (2005), Croson and

Donohue (2006) and Croson *et al*. (2007) pay participants according to a continuous incentive scheme, that consists of two separate elements, that is, a minimum participation fee and a fee that is based on the difference between the lowest cumulative costs incurred and the *team*'s own cumulative costs.

Table 2.2 summarises the different experimental protocols that the papers reviewed in this sub-section apply. Since Sterman's (1989) original game set-up constitutes the base for all subsequent investigations, it is shaded in grey colour and separated from all other papers in this table by a line.

Key Findings

Kimbrough *et al*. (2002), Hieber and Hartel (2003) and Nienhaus *et al*. (2006) observe their participants to systematically *under-perform*, when compared with fully pre-programmed artificial agents. In this way, these three papers further confirm the prevalence of individual biases in human decision making in the *Beer Distribution Game* setting. The latter is additionally reported by a significant number of laboratory investigations (Sterman, 1989; Kaminsky and Simchi-Levi, 1998; Croson and Donohue, 2003; Croson and Donohue, 2005; Croson and Donohue, 2006; Wu and Katok, 2006; Croson *et al*, 2007).

In greater detail, Sterman (1989) mostly attributes the supply chain's excess total costs and the *bullwhip effect* to Kahneman *et al*.'s (1982) *anchoring and insufficient adjustment* heuristic. He demonstrates that participants in the *Beer Distribution Game* initially choose their order quantities ("anchor") based on initial stock levels and subsequently make insufficient adjustments ("insufficiently adjusted") towards desired stock levels.

Table 2.2: Distribution of experimental protocols applied in the *Beer Distribution Game* setting

Research Paper	Game Setup	Customer demand	Changes and Information Sharing	Incentives	Basis of Analysis
Sterman (1989)	• 4 echelons • 36 rounds • Board-based version	• Step –up increase • No relevant information is provided to participants	• Base for all subsequent investigations	• Bet placed by all *teams* • Bet earned by the lowest cost incurring *team*	• Experiments with human subjects
Kaminsky and Simchi-Levi (1998)	• 4 echelons • 25-50 rounds • Computer-based version • 3 automated partners' responses • *Centralised* control	• Step –up increase • Real-time information about customer demand is common knowledge	• Real-time information about inventory status is shared • Reduction of transportation and information lead-times	• Not reported	• Experiments with human subjects
Kimbrough *et al.* (2002)	• 4 echelons • 35 rounds • Computer-based version	• Step –up increase • Uniform [0,15]	• Reduction of transportation and information lead-times	• Not reported	• Results from simulation experiments with: ▪ lead-times distributed acc. to: uniform [0,4] ▪ network with 8 roles

Research Paper	**Game Setup**	**Customer demand**	**Changes and Information Sharing**	**Incentives**	**Basis of Analysis**
Croson and Donohue (2003)	• 4 echelons • 48 rounds • Interactive web-based simulation game • Participants unaware of true game duration	• Uniform [0,8] • Demand distribution is common knowledge	• Real-time information about demand is common knowledge	• Continuous incentive scheme that consists of a minimum participation fee and a variable fee according to team's rank of cost overall performance	• Experiments with human subjects
Hieber and Hartel (2003)	• 4 echelons • 50 and 100 rounds • Computer-based version • 3 automated partners' responses	• Step –up increase • Deterministic [8]	• Not reported	• Not reported	• Results from 'what-if' simulation runs
Steckel *et al*. (2004)	• 3 echelons • 36 rounds • Interactive simulation game • Participants unaware of true game duration • 8 trial periods	• Step –up increase • S-shaped demand pattern without noise • S-shaped demand patterns with random noise	• Reduction of transportation and information lead-times	• Continuous incentive scheme that consists of a flat participation fee and a variable fee according to team's overall cost	• Experiments with human subjects

Research Paper	Game Setup	Customer demand	Changes and Information Sharing	Incentives	Basis of Analysis
Croson and Donohue (2005)	• 4 echelons • 48 rounds • Interactive web-based simulation game • Participants unaware of true game duration	• Uniform [0,8] • Demand distribution is common knowledge	• Real-time information about upstream inventory status is shared • Real-time information about downstream inventory status is shared.	• Continuous incentive scheme that consists of a minimum participation fee and a variable fee according to team's rank of cost overall performance	• Experiments with human subjects
Croson and Donohue (2006)	• 4 echelons • 48 rounds • Interactive web-based simulation game • Participants unaware of true game duration	• Uniform [0,8] • Demand distribution is common knowledge	• Real-time information about inventory status is common knowledge	• Continuous incentive scheme that consists of a minimum participation fee and a variable fee according to team's rank of cost overall performance	• Experiments with human subjects

Research Paper	**Game Setup**	**Customer demand**	**Changes and Information Sharing**	**Incentives**	**Basis of Analysis**
Nienhaus *et al*. 2006	• 4 echelons • Computer-based version • Against varying (0-3) automated partners' responses	• Step –up increase	• Not reported	• Provision of financial incentives not clearly reported	• Comparison of decisions observed in the laboratory with artificial agents' decisions
Wu and Katok (2006)	• 4 echelons • 48 rounds • Interactive simulation game • Participants unaware of true game duration • Provision of *training* and *study* sessions at the beginning of the game	• Uniform [0,8] • Demand distribution is common knowledge	• Not reported	• Participants are paid the difference between their team overall inventory holding and backorder costs and their initial endowment of tokens	• Experiments with human subjects

Research Paper	**Game Setup**	**Customer demand**	**Changes and Information Sharing**	**Incentives**	**Basis of Analysis**
Croson *et al.* (2007)	• 4 echelons • 48 rounds • Interactive web-based simulation game • Participants unaware of true game duration • Before the start of the game provision for a quiz that tests the participants' understanding of the game rules • At the end of game provision for a quiz that asks participants to reflect on their results and game experience	• Deterministic [4] • Customer demand is common knowledge	• *Team optimum solution* is common knowledge • Provision for storing extra inventory	• Continuous incentive scheme that consists of a minimum participation fee and a variable fee according to team's rank of cost overall performance	• Experiments with human subjects

Sterman (1989), Kaminsky and Simchi-Levi (1998), Croson and Donohue (2003; 2005; 2006) and Croson *et al*. (2007) establish subjects' tendency to *under-weight* their supply line in their realised decisions, that is, for every new order quantity decision they make, they assign higher significance to their current inventory position than to their outstanding orders (*i.e*. orders they have placed but have not yet received from their upstream manufacturers). Wu and Katok (2006) recognise the deficiency of *organizational learning*, training and communication as the main causes of the *bullwhip effect*. Croson *et al*. (2007) ascribe coordination risk as at least partly responsible for the *bullwhip effect* and discover that the participants' usual lack of awareness about the *team optimal solution* seems to have a more significant contribution on the extent of the *bullwhip effect* than the participants' lack of trust in other partners' decisions.

2.2.3 Summary

Section 2.2 discusses some standard normative models that are applicable to the *Beer Distribution Game*. *Section 2.2* also reviews the true decisions that human participants in the *Beer Distribution Game* are observed to make. In this regard, Table 2.3 provides a breakdown of the articles that revise the common behavioural assumptions of the standard normative models.

Table 2.3 is structured according to the *Analysis of Assumptions* framework, as applied by Bendoly *et al*. (2006). Table 2.3 demonstrates how the systematic divergence of human decisions from the standard normative models' predictions is confirmed in the laboratory (Sterman, 1989; Kaminsky and Simchi-Levi, 1998; Croson and Donohue, 2003; Steckel *et al*, 2004; Croson and

Donohue, 2005; Croson and Donohue, 2006; Wu and Katok, 2006; Croson *et al*, 2007).

This inability of human participants in the *Beer Distribution Game* to follow the standard normative models' predictions is explained by the presence of a number of individual behavioural biases, such as, for example:

- *anchoring and insufficient adjustment* heuristic (Sterman, 1989);
- *supply line under-weighting* (Sterman, 1989; Kaminsky and Simchi-Levi, 1998; Croson and Donohue, 2003; Croson and Donohue, 2005; Croson and Donohue, 2006; Croson *et al*, 2007);
- *organizational learning* (Wu and Katok, 2006); coordination risk (Croson *et al*, 2007);
- protection against other partners' biases (Su, 2008).

Table 2.3: Distribution of behavioural papers in the context of the *Beer Distribution Game* by assumption type

Research Paper	**Behavioural assumptions**	**Key Findings**
Intentions: decision makers' actual goals might be different from maximisation of the aggregate channel's profit		
Kimbrough *et al*. (2002)	Approximate minimisation of aggregate channel backlog and inventory holding costs, according to a specially designed genetic algorithm	Human decisions systematically deviate from these objectives; persistence of behavioural complexities

Research Paper	**Behavioural assumptions**	**Key Findings**
Hieber and Hartel (2003)	Satisfaction of *economic order quantity*; compliance with *base stock policy*; matching supply with demand; matching supply with a moving average of own history orders	Human decisions systematically deviate from these objectives; persistence of behavioural complexities
Nienhaus *et al*. (2006)	Compliance with *base stock policy*; matching supply with a moving average of own history orders	Human decisions systematically deviate from these objectives; persistence of behavioural complexities
<u>*Actions*: </u>decision makers' behaviour might differ from the behaviour that is specified by their respective *intention*s		
Sterman (1989)	*Anchoring and insufficient adjustment* heuristic; *supply line under-weighting*	Prevalence of individual biases in human decision making; *anchoring and insufficient adjustment* heuristic; supply line *under-weighting*
Kaminsky and Simchi-Levi (1998)	*Supply line under-weighting*	Prevalence of individual biases in human decision making
Croson and Donohue (2003)	*Supply line under-weighting*	Prevalence of individual biases in human decision making; *supply line under-weighting*
Croson and Donohue (2005)	*Supply line under-weighting*	Prevalence of individual biases in human decision making; *supply line under-weighting*

Research Paper	**Behavioural assumptions**	**Key Findings**
Croson and Donohue (2006)	*Supply line under-weighting*	Recognition of behavioural complexities as the *bullwhip effect*'s lead cause; *supply line under-weighting*
Wu and Katok (2006)	*Organizational learning*	Recognition of behavioural complexities and deficiency of *organizational learning*, training and communication as the *bullwhip effect*'s lead cause
Croson *et al*. (2007)	*Supply line under-weighting*; *coordination risk*	Recognition of behavioural complexities and *coordination risk* as the *bullwhip effect*'s lead cause; *supply line under-weighting*; participants' usual lack of awareness about the *team optimal* solution has a significant contribution on the perseverance of the *bullwhip effect*
Su (2008)	Protection against other partners' biases	Analytical framework to quantify Croson *et al.*'s (2007) *coordination risk*; formal proof of why the existence of at least one non-perfectly rational decision maker constitutes a necessary and sufficient condition for the *bullwhip effect*

Research Paper	**Behavioural assumptions**	**Key Findings**
Reactions: decision makers might learn, process feedback information and react to environmental changes		
Kaminsky and Simchi-Levi (1998)	Time lag reduction; public inventory information; *centralised* decision making	Time lag reduction reduces overall costs; benefits of *centralised* decision making
Kimbrough *et al*. (2002)	Time lag reduction; lead time uncertainty	Results not clearly reported
Croson and Donohue (2003)	Public POS information	Sharing POS data could significantly reduce the extent of the *bullwhip effect*, when all partners are aware of underlying customer demand
Steckel *et al*. (2004)	Time lag reduction; public POS information	Time lag reduction improves decision makers' order quantity decisions for the cases of noise-free demand distributions; sharing POS data could significantly reduce overall supply chain costs for the cases of customer demand patterns with single changes
Croson and Donohue (2005)	Public inventory information	Sharing downstream inventory information could eliminate order oscillation
Croson and Donohue (2006)	Public inventory information	Sharing inventory information could eliminate order oscillation
Nienhaus *et al*. (2006)	Public inventory information	Conclusions that can be generalised not clearly reported

Research Paper	**Behavioural assumptions**	**Key Findings**
Croson *et al.* (2007)	Possibility to hold *coordination stock*; information about inventory management policy that would generate the *team optimal* solution	Neither *coordination stock* nor common knowledge of the *team optimal* policy could eliminate the *bullwhip effect*

The results of these erroneous human decisions are *two*-fold: *i*. a persistent discrepancy between the resulting aggregate channel cost IC_c and the *first-best case minimum cost* IC^*_0 (Sterman, 1989; Kaminsky and Simchi-Levi, 1998; Steckel et al, 2004) and *ii*. a prevalence of the *bullwhip effect* (Sterman, 1989; Croson and Donohue, 2003; Croson and Donohue, 2005; Croson and Donohue, 2006; Wu and Katok, 2006; Croson *et al*, 2007). As already discussed, the *bullwhip effect* further magnifies overall supply chain costs (Chen *et al*, 1999; Dejonckheere *et al*, 2003; Sucky, 2009).

2.3 *Supply Chain Contracts*

In this section the *contracts* or *transfer payments schemes* that are proposed to *coordinate* supply chains are considered. A *contract* or *transfer payment scheme* is said to *coordinate* a supply chain if it forces the aggregate channel performance, namely, the aggregate channel profit Π_c or aggregate channel cost IC_c,, to coincide with the *first-best case maximum* profit Πo^* or the *first-best case minimum* cost IC^*_t, respectively (Cachon, 2003). This section starts by reviewing contractual agreements that are applicable to the simple *newsvendor* setting and later proceeds to outlining the *transfer payment schemes* that are suggested as appropriate for the *Beer Distribution Game* setting. The reasons that different contractual arrangements may be required in these two settings are due to the structural differences that exist between them. These differences concern the following five aspects:

i. Although in the *Newsvendor Problem*, there is no inventory, in the *Beer Distribution Game* setting there is inventory that is kept at each echelon level.

ii. Even though in the *Newsvendor Problem* all unsatisfied demand is lost, in the *Beer Distribution Game* any unsatisfied demand is backlogged.

iii. In contrast to the *Newsvendor Problem* setting, in which all orders get immediately processed, in the *Beer Distribution Game* setting there is a fixed information lead-time for all orders to get transmitted and processed.

iv. Dissimilarly to the *Newsvendor Problem*, in which all shipments get prepared and delivered immediately, in the *Contract Beer Distribution* Game, there are fixed, non-zero production and transportation lead-times.

v. Although in the *Newsvendor Problem* all associated partners deal with demand uncertainty only, in the *Beer Distribution Game* setting all partners face uncertainty from both the supply and demand sides.

Sub-section 2.3.1 outlines the way that the *supply chain contracts* are designed to operate under the assumption of perfectly rational decision makers in both the *Newsvendor Problem* and the *Beer Distribution Game* settings. *Sub-section 2.3.2* reviews the relevant behavioural research, which explores whether and how different human decisions are from the relevant predictions of the standard normative models. In this regard, the same organization with the preceding sections is followed. *Sub-section 2.3.2* starts by reflecting on how laboratory investigations update standard normative models' assumptions, in view of decision makers' *intentions, actions* and *reactions*; it then outlines the experimental protocols that these studies apply and finally presents their key findings. This sub-section also tries to answer the question of how do these observed divergences of humans' true decisions from perfectly rational decisions affect the true *efficiency* of the contract that is assumed to be in force; namely, whether this true *efficiency score* differs from its corresponding theoretical prediction.

2.3.1 Standard Normative Models

The Newsvendor Setting

Although a number of contracts are suggested to align the individual decision makers' incentives with the *integrated newsvendor's*, so that the *first-best case maximum* profit is attained (*e.g*. buy-back: Pasternack, 1985; Lau *et al*, 2007, quantity discount: Moorthy, 1987; Kolay *et al*, 2004, quantity-flexibility: Tsay, 1999, sales rebate: Taylor, 2002; Arcelus *et al*, 2007; Burer *et al*, 2008, revenue sharing: Cachon and Lariviere, 2005), only two of these, namely the *buy-back* and *revenue sharing contracts*, have been studied in the laboratory. Hence, attention is limited here to the way that these two contracts work. The reason that only these two contracts have so far been studied in the laboratory are two-fold: *first*, they are simple and *second,* they are widely used in a variety of industries, such as, for example, the publishing, movie rental, computer software, computer hardware and pharmaceuticals (Cachon and Lariviere, 2005; Katok and Wu, 2009). For detailed surveys of all the above *supply chain contracts* and reviews of the analytical results acquired so far the interested reader is referred to Tsay *et al*. (1999), Cachon (2003) and Simchi-Levi *et al*. (2008).

In the *buyback contract* the manufacturer pays the retailer a rebate b for every unit not sold or, else, that is in excess of realised demand at the end of the period. The contractual agreement between the manufacturer and the retailer in every time period, thus, consists of the buyback price b and the corresponding wholesale price w_{bb}. Therefore, the transfer payment between the retailer and the manufacturer becomes: $T(q,b,w_{bb}) = bS(q) + (w_{bb} - b)q$. The retailer's expected profit from an order quantity q is given by:

$$\Pi_r = (p+g)S(q) - g\mu - T(q,b,w_{bb}) = (p+g)S(q) - g\mu - bS(q) - (w_{bb} - b)q \Rightarrow$$

$$\Pi_r = (p+g-b)S(q) - (w_{bb} - b)q - g\mu \qquad (2.18)$$

with an optimal order quantity: $q_r^* = F^{-1}\left(\frac{p+g-w_{bb}}{p+g-b}\right)$, according to (2.4). The set of buyback parameters (w_{bb}, b) that satisfy any integer value λ with $0 \leq \lambda \leq 1$ is now considered:

$$p + g - b = \lambda(p+g)$$

$$(w_{bb} - b) = \lambda c$$

A comparison with the *integrated newsvendor's* profit, as given by equation (2.1), transforms the retailer's expected profit given by (2.18) as follows:

$$\Pi_r = \lambda(p+g)S(q) - \lambda cq - g\mu \Rightarrow$$

$$\Pi_r = \lambda \Pi_{int} \text{-} (1-\lambda)\, g\mu$$

which is an affine function [5]of the *integrated newsvendor's* profit. It follows immediately that $q_r^* = q_{int}^*$ for the retailer. Interestingly, this same order quantity coincides with the manufacturer's most preferred order quantity because the manufacturer's expected profit also proves to be an affine function of the *integrated newsvendor's* profit:

$$\Pi_m = E(\pi_s) = \Pi_{int} - \Pi_r = \Pi_{int} - \lambda\Pi_{int} - (1-\lambda)\, g\mu \Rightarrow$$

$$\Pi_m = (1-\lambda)\Pi_{int}^* - (1-\lambda)\, g\mu$$

As a result, both the manufacturer's and the retailer's decisions are aligned with the *integrated newsvendor*'s and, hence, when combined, generate the *first-best case maximum* profit. Hence, the buy-back contract can *coordinate* the *newsvendor problem* and, for this reason, is an *efficient* contract.

The *revenue sharing* contract is an alternative contractual arrangement that Cachon and Lariviere (2005) prove that it is completely equivalent to the *buy-back contract*. In the *revenue sharing contract* the retailer shares some of his/her revenue with the manufacturer, or else passes a fraction of the selling price to the manufacturer, namely (1-*r*)*p*. The contractual agreement between the manufacturer and the retailer in every time period, thus, consists of the revenue fraction *r* that the retailer keeps for him/her self and the corresponding wholesale price w_{rs}. Therefore, the transfer payment between the retailer and the

[5]The term "affine function" describes a function with a constant slope, which implies that the dependent variable may have a non-zero value when all independent variables take zero values [source: http://economics.about.com/cs/economicsglossary/g/affine.htm, last accessed: 29/10/2010].

manufacturer becomes: $T(q,r,w_{rs}) = (1-r)pS(q) + w_{rs}q$. The retailer's expected profit from an order quantity *q* is given by:

$$\Pi_r = (p+g)S(q) - g\mu - T(q,r,w_{rs})$$
$$= (p+g)S(q) - g\mu - (1-r)pS(q) - w_{rs}q \Rightarrow$$

$$\Pi_r = (rp+g)S(q) - w_{rs}q - g\mu \tag{2.19}$$

with an optimal order quantity: $q_r^* = F^{-1}\left(\frac{rp+g-w_{rs}}{rp+g}\right)$, according to (2.4). The set of revenue sharing parameters (w_{rs}, r) that satisfy any integer value λ with $0 \le \lambda \le 1$ is now considered:

$$rp + g = \lambda(p+g)$$

$$w_{rs} = \lambda c$$

Under these terms the retailer's expected profit given by (2.19) becomes:

$$\Pi_r = \lambda(p+g)S(q) - \lambda cq - g\mu \Rightarrow \Pi_r = \lambda\Pi_{int} \text{-} (1-\lambda)\, g\mu$$

which is an affine function of the *integrated newsvendor's* profit. It follows immediately that the retailer's order quantity becomes: $q_r^* = q_{int}^*$. For the same reasons with the *buy-back contract*, this same order quantity would also maximise the manufacturer's respective profit, namely $q_m^* = q_{int}^*$. The result is that the *revenue sharing contract* can generate the *first-best case maximum* profit and, therefore, can *coordinate* the *newsvendor problem*, *i.e*. it is *efficient*.

Albeit the *buyback* and *revenue sharing* contracts can attain *efficiency*, they are costly to administer and implement. They also require more than one transaction to take place between the manufacturer and the retailer: one at the delivery and receipt of any ordered quantity and one at the end of the season, after customer demand has occurred. In addition, they are built on the assumption that the retailer is willing to share with the manufacturer at the end of the period either his/her true inventory status or a portion of his/her revenues. But in case these goods are not required to be physically transported to the manufacturer's site, the manufacturer does not have any means to confirm the accuracy of the information that is provided by the retailer. In summary, there is a high administrative burden that is associated with the implementation of the above *coordinating contracts*. This could at least partially explain their relatively limited applicability in practice.

Nevertheless, the *wholesale price contract* may not *coordinate* the *newsvendor setting* and can still leave discrepancies between the *first-best case maximum* profit and the channel's aggregate profit, but it is the simplest to put in force and, in addition, only requires one transaction between the interacting manufacturer and retailer. Although this simplicity is an obvious and important reason for the *wholesale price contract's* wide popularity, it remains open to further exploration whether there is any additional reason associated with this: namely, it is interesting to inquire whether its true performance might in practice be better than theoretically predicted. As discussed in *Section 1.4,* this constitutes one of the questions that this PhD thesis aims to address.

The Beer Distribution Game

Most researchers are influenced by the way that the *buyback contract* operates in the *Newsvendor Problem* setting and propose relevant *transfer payment schemes* to take place between local firm managers in the *Beer Distribution Game* in order to force them to follow the *team optimizing* decision rules and, thus, lead the aggregate channel to attain the *first-best case minimum* cost IC^{*}_{0} (*e.g.* Lee and Whang, 1999; Porteus, 2000; Cachon and Zipkin, 1999). In this regard, in order to minimise the arising *competition penalty*, they force the manufacturers to assume their responsibility for any unsatisfied customer demand.

In greater detail, Lee and Whang (1999) force manufacturers to incur backlog penalties (*i.e.* shortage reimbursements), every time they fail to fully deliver the requested quantities. Lee and Whang demonstrate that given the properties of these non linear transactions schemes, the *intention* of echelon managers to minimise their own respective backlog and inventory holding cost IC_i leads to aggregate channel costs $IC_C = \sum_{i=1}^{N} IC_i$ that would not be different from the overall minimum backlog and inventory holding cost IC_0^{*}. With respect to the same objective, Chen (1999) calculates the exact penalties that distinct echelon managers should be forced to pay, in order not to deviate from the *team optimal* decision rules. Cachon (2003) proves the equivalence between Lee and Whang's (1999) and Chen's (1999) suggested schemes. Porteus (2000) further facilitates the execution of Lee and Whang's (1999) *transfer payment scheme*. In lieu of backlog penalties, Porteus proposes a responsibility token to be issued every time a manufacturer cannot meet incoming order quantities. In this way, the manufacturer assumes full responsibility of arising customer backlog. The result is that exactly the same effect with Lee and Whang 's (1999) *transfer payment scheme* is produced, but without the need to compute all consequences in advance. Furthermore, Cachon and Zipkin (1999) suggest simple linear *transfer payment scheme*s based on on-hand inventory and backlog information; these linear *transfer payment scheme*s would eliminate local firm managers' incentives to deviate from the *team optimal* decision rules. Although Cachon and

Zipkin's *transfer payment scheme*s might sometimes not lead to the *team minimum* cost, they are much simpler and, thus, easier to implement than Lee and Wang's. Finally, Cachon (2003) generalises these linear *transfer payment scheme*s.

Nevertheless, these *transfer payment schemes* are based on information about partners' on-hand inventories and backlogs (Cachon and Zipkin, 1999; Cachon, 2003) and true customer demand (Lee and Whang, 1999); information which they might not always be willing to share, at least not without being compensated via some form of incentive (Cachon and Fisher, 2000; Chen, 2003). In addition, they are built on the pre-assumption that either the *team optimal solution* is common knowledge to all partners (Cachon and Zipkin, 1999; Lee and Whang, 1999; Cachon, 2003) or there is one firm that presumes the responsibility of compensating the other firms and, thus, adequately allocating the costs between them (Chen, 1999; Lee and Whang, 1999). Last but not least, the participating firms are deprived the ability to make some profit of their own (Chen, 1999). These assumptions that are required to make the above *transfer payment scheme*s converge to the *team* optimum solution are considered as over-simplifying and, hence, unrealistic. This might be a good explanation for why echelon managers do not often resort to them in practice and insist on resorting to the simplest contractual agreement that can exist, that is, the *wholesale price contract* (*e.g*. Narayan and Raman, 2004). Nevertheless, the way that the *wholesale price contract* would work, if applied to the *Beer Distribution Game* setting, has as yet not been explored.

2.3.2 Behavioural Studies of Supply Chain Contracts

Although experimental research on *supply chain contracts* is still in its infancy, there is already a number of papers that are concerned with either confirming or refuting the analytical predictions of the *supply chain contracting* theories. These studies explore the true *efficiency scores* that *supply chain contracts* attain in the laboratory and subsequently compare them with their respective theoretical predictions. The *newsvendor* setting is already extensively used to assess supply chain contracts' true *efficiency*. This is, however, not the case for the *Beer Distribution Game* setting. This is exactly why there are no references to papers on the *Beer Distribution Game* in the paragraphs that follow. The reasons that the *Beer Distribution Game* has as yet not been used as a framework to explore the *efficiency* of different contractual arrangements are due to the structural complications of the setting.

In the sub-sections that follow the same organization with the preceding sections is followed. Namely, first the assumptions of the standard normative models that are updated by the different behavioural studies are outlined, later the protocols that are applied are summarized and last the key findings are presented.

Assumptions Revisited

All behavioural research on *supply chain contracts* revises the common assumption of the aforementioned normative contracting theories, where all manufacturers and retailers are considered as perfectly rational and exclusively interested in maximising their respective profits. In this regard, laboratory investigations of *supply chain contracts* extend previous laboratory investigations of the *Newsvendor Problem* (*e.g.* Schweitzer and Cachon, 2000; Schultz and

McClain, 2007; Benzion *et al,* 2008; Bolton and Katok, 2008; Bostian *et al*, 2008; Kremer *et al*, 2008; Su, 2008; Lurie and Swaminathan, 2009) in that they recognise human retailers' natural tendency to conform with individual biases (Keser and Paleologo, 2004; Katok and Wu, 2009; Kremer, 2008) or their own implicit *bounded rationality* (Su, 2008).

Building on this, they additionally explore whether this is also the case for manufacturers' decision making. In greater detail, by making provision for human manufacturers and retailers interacting with each other, Keser and Paleologo (2004) compare the true performance of the *wholesale price contract* with its theoretical prediction. Katok and Wu (2009) evaluate the practical improvement offered by the coordinating *buy-back* and *revenue sharing contracts* over the *wholesale price contract*, in terms of attained *efficiency scores.* For this reason, all participants in the experiments of Katok and Wu (2009) are asked to play two different games: one with the *wholesale price contract* and one with a *coordinating* contract, either the *buyback* or the *revenue sharing* contract. Each is assigned in a random way. Su (2008) aims to explain the resulting behaviour of these two *coordinating contracts* that is reported by Katok and Wu as worse than theoretically predicted. Last, Kremer (2008) explores whether participants would prefer the *buyback* or *revenue sharing contracts* over the *wholesale price contract*, namely in the case that they are offered the choice of transiting from the *wholesale price contract* to one of the other two. In summary, laboratory investigations of *supply chain contracts* revisit the standard normative models' assumptions about decision makers' *actions* being perfectly aligned with their respective *intentions*. There are as yet no research papers that revisit the standard normative models' assumptions about profit maximising *intentions* and lack of *reactions* to occurring changes.

The Protocols Applied

In most papers reviewed in this section customer demand is assumed to follow the uniform distribution (Keser and Paleologo, 2004; Kremer, 2008; Katok and Wu, 2009) and participants are offered different types of financial incentives. Keser and Paleologo (2004) pay their subjects according to a linear payment scheme that makes provision for a minimum participation fee and an extra fee that incorporates the percent cumulative profit realised by the participant that is higher than the average cumulative profit that is realised by all participants who play the same role. Katok and Wu (2009) pay their participants the actual earnings that are accumulated over the total duration of the two gaming sessions in cash. Kremer (2008) pays a random draw of approximately 4% of his participants their actual earnings and a minimum participation fee.

Nevertheless, these research papers apply different experimental approaches that vary from interactive simulation games to surveys. Keser and Paleologo (2004) randomly assign participants to the role of either the manufacturer or the retailer and match them in pairs in a random way. In their study anonymity is ensured in that participants are seated in isolation from each other and they do not know who their partner is. Participants who play the role of the manufacturer are asked to determine prices for 30 consecutive time periods, while participants who play the role of the retailer are asked to determine order quantities for the corresponding 30 periods. Each participant responds in real time to his/her partners' decisions. All subjects participate in the experiment via computer software, developed in *z*-tree (Fischbacher, 2007), a special purpose facility widely used to design and conduct experiments in economics. As soon as participants read the instructions of the experiment, they are asked to complete a questionnaire that tests their level of understanding of the rules of the game and the arising dynamics; only after all questions are correctly answered does the game start.

Katok and Wu (2009) ask each participant playing the role of either the manufacturer or the retailer to make 200 separate price or quantity decisions, respectively, against a computer simulated retailer or a computer simulated manufacturer that maximises his/her individual profit in a perfectly rationally manner. Under the *wholesale price contract* 100 periods' decisions are made; while under either the *buyback* or *revenue sharing contract*, whichever is randomly assigned, another 100 decisions are made. The participants playing the role of the manufacturer, before actually entering their final choice, are given information about their expected realised profits for each of their potential decisions, so that they can make as much of an informed decision as possible. No form of communication is allowed between different participants.

Kremer 's (2008) approach is very different; his study is the first and only behavioural research study encountered so far that bases the findings on a questionnaire. Participants are again randomly assigned the role of the manufacturer or the retailer and informed about their existing *wholesale price* contractual agreement. They are subsequently asked to choose whether they would prefer to keep the *wholesale price* contract currently in force or change to a pre-selected random choice between the *buyback* or the *revenue sharing contract*.

Key Findings

Keser and Paleologo 's (2004) manufacturers charge prices *w* that are on average significantly lower than their rationally optimizing counterpart's w^*. This is, however, not the case for Katok and Wu's (2009) manufacturers, who do not charge significantly different prices than w^*. As for retailers, Keser and Paleologo (2004) do not find any supporting evidence for the *pull-to-centre effect*, namely the *too low/too high* systematic pattern of order quantities (Schweitzer and Cachon, 2000; Bostian *et al*, 2008), as most of their human retailers order on average lower quantities than the corresponding quantities q^* that would represent their best possible replies to the manufacturers' prices. But Katok and Wu's (2009) human retailers reproduce the *pull-to-centre effect*. When the *wholesale price contract* is in force, their human retailers may order on average lower quantities than q^*, but the *anchoring and insufficient adjustment* decision rule still seems to apply. This is what explains the occurrence of the *pull-to-centre effect* in the case of the *wholesale price contract*. When any of the two *coordinating* contracts is in force, Katok and Wu's retailers order significantly more than when the *wholesale price contract* is in force; yet, they order in most cases quantities that are still significantly lower than their corresponding theoretical predictions q^*. For this reason, when the *buyback* or *revenue sharing contracts* are in force, Katok and Wu's retailers reproduce the *demand chasing* decision heuristic, which is what explains the presence of the *pull-to-centre effect* in these cases.

The aforementioned combination of observed behaviours for human manufacturers and retailers permits a more equitable allocation of profits between Keser and Paleologo's (2004) and Katok and Wu's (2009) subjects. Nonetheless, the average *efficiency scores* that are attained by the *wholesale price contract* in Keser and Paleologo's and Katok and Wu's experiments do not differ significantly from the theoretical prediction of the corresponding standard normative model. As far as the two *coordinating* contracts are concerned, Katok and Wu (2009) establish their superior performance over the *wholesale price contract.* Still, neither the *buyback* nor the *revenue sharing contract* could reproduce the *first-best case maximum* profit that is theoretically expected. Thus, both attain an *efficiency score* that is strictly lower than 1. Su (2008) builds on his quantal choice behavioural model, according to which different order decisions are assigned different probabilities of being chosen, to explain the two contracts' worse than theoretically predicted performance. He proves analytically that when manufacturers and retailers are characterized by the same degree of *bounded rationality*, none of the above *coordinating contracts* can give rise to the *first-best case maximum* profit.

Another question that can be explored in the laboratory is whether these two contracts are truly equivalent when real people use them as the basis of their interaction, as has been mathematically proven. In this regard, Katok and Wu (2009) establish that they are only equivalent in manufacturers' perceptions. Yet, this equivalence is not confirmed by Kremer (2008). As Kremer's manufacturers prove to be *risk-averse*, they tend to avoid assuming any substantial part of the risk that is associated with customer demand and for this reason, they prefer the *revenue sharing* and *buyback* contracts, in decreasing order. But Katok and Wu and Kremer agree that the *buyback* and *revenue sharing* contracts are not equivalent in human retailers' perceptions. Katok and Wu (2009) find support for retailers' average order quantities being significantly different under these two contracts, while Kremer (2008) establishes that retailers prefer the *buyback* and *revenue sharing* contracts, in decreasing order.

2.3.3 Summary

Section 2.3 presents the main analytical results that are known for the most popular *supply chain contracts* or *transfer payments schemes* that are applicable to the *Newsvendor Problem* and the *Beer Distribution Game* settings. *Section 2.3* also reviews how different human decisions, as observed in the laboratory, can be to the standard normative models' predictions. In respect to this, Table 2.4 summarises the papers that revisit the common behavioural assumption of the standard normative models of *supply chain contracts*. In this table there are only references to the *Newsvendor Problem* setting. The reason is that the *Beer Distribution Game* is as yet not used as a computational framework to assess the *efficiency scores* that *supply chain contracts* can attain in the laboratory, namely, when human participants are asked to interact with each other. It is also evident from Table 2.4 that all laboratory investigations of *supply chain contracts* aim to update the standard normative models' assumption about human *actions* being consistent with their *intention* to maximise their own profits (Keser and Paleologo, 2004; Katok and Wu, 2009; Kremer, 2008; Su, 2008). In greater detail, a number of different individual biases are identified as responsible for diverting human decisions away from their respective *intention*s to maximise their own profits. Examples are the *anchoring and insufficient adjustment* (Katok and Wu, 2009) and *demand chasing* (Katok and Wu, 2009) decision heuristics, as well as human decision makers' implicit *bounded rationality* (Su, 2008). But it is still assumed that all human decision makers *intend* to maximise their respective profits; therefore, the assumption of the standard normative models about decision makers' *intention* to maximise individual profits is still widely accepted.

The impact that environmental factors can have on human decisions and, hence, the overall *efficiency scores* that are attained by *supply chain contracts* is as yet not accounted for. Hence, Table 2.4 only contains papers that update the standard normative models' common assumption about *actions*. Although experimental research on *supply chain contracts* is still in its infancy, the divergence of contracts' observed *efficiencies* from the corresponding standard normative prediction is already well established.

Table 2.4: Summary of behavioural papers in the context of *Supply Chain Contracts*

Research Paper	**Behavioural assumptions**	**Key Findings**
Newsvendor Problem setting		
Actions: decision makers' behaviour might differ from the behaviour specified by their respective *intention*s		
Keser and Paleologo (2004)	Prevalence of individual biases in human decision making	Equitable allocation of profits between manufacturers and retailers; the *efficiency score* achieved by the *wholesale price contract* is comparable to its theoretical prediction

Research Paper	**Behavioural assumptions**	**Key Findings**
Katok and Wu (2009)	Prevalence of individual biases in human decision making	*Pull-to-centre effect*; *anchoring and insufficient adjustment* decision rule when the *wholesale price contract* is in force; *demand chasing* under operation of the *buyback* and *revenue sharing* contracts; the *efficiency* achieved by the *wholesale price contract* is comparable to its theoretical prediction; the *efficiency* achieved by the *buyback* and *revenue sharing* contracts is significantly lower than their corresponding theoretical prediction; the *buyback* and *revenue sharing contracts* are not perceived as equivalent by retailers
Kremer (2008)	Prevalence of individual biases in human decision making	Most popular contract for manufacturers is the *wholesale price*; the most popular for retailers is the *buyback*

Research Paper	**Behavioural assumptions**	**Key Findings**
Su (2008)	*Bounded rationality*	Formal proof of why the interaction of manufacturers and retailers characterised by the same degree of *bounded rationality* would keep *efficiency scores* to values that are strictly lower than 1

In this regard, it is already confirmed that the *wholesale price contract*, although still unable to coordinate the *Newsvendor Problem setting*, performs better in the laboratory than theoretically expected (Keser and Paleologo, 2004; Katok and Wu, 2009). This improved practical performance of the *wholesale price contract*, when combined with the zero risk that it carries on the manufacturers' part, might explain human manufacturers' preference for it, which comes in direct opposition with the predictions of the standard normative models (Kremer, 2008).

As for the *coordinating contracts*, *i.e*. the *buyback* and *revenue sharing contracts*, they still attain higher *efficiency scores* than the *wholesale price contract*. Nonetheless, in stark contrast to theoretical predictions, they prove unable to *coordinate* the *Newsvendor Problem* (Su, 2008; Katok and Wu, 2009). Since the two *coordinating contracts* allocate a portion of customer demand uncertainty to manufacturers, human manufacturers tend to perceive the *buyback* and *revenue sharing contracts* as equivalent (Katok and Wu, 2009) and, thus, risk-averse as they are, the least preferred (Kremer, 2008). On the contrary, human retailers seem to prefer sharing some of the inherent risk with their manufacturers and, for this reason, prefer the *coordinating contracts* over the *wholesale price contract* (Kremer, 2008). Nevertheless, they do not perceive them as equivalent (Katok and Wu, 2009) and, hence, prefer the *buyback* over the *revenue sharing* contract (Kremer, 2008).

2.4 Summary of Analytical and Experimental Results of Supply Chain Models and Contracts

This chapter demonstrates that there are two main operational *inefficiencies* that most supply chains tend to suffer from. *First*, when individual firm managers make independent decisions that optimize their own respective performances, the resulting aggregate channel performance tends to be inferior to the *first-best case optimum* performance that would have been achieved if there was a central planner that made all decisions in the supply chain under study. *Second,* while making purchasing decisions, individual firm managers tend to place orders of quantities that are higher in both size and variance than the ones that they are themselves requested to deliver. Therefore, they are inclined to generate the *bullwhip effect*, which, in turn, further amplifies performance discrepancies. In order to bridge the gaps between aggregate channel performances and the *first-best case optimum* performance and, in addition, eliminate the *bullwhip effect*, a number of *contractual arrangements* or else *transfer payments schemes* between interacting supply chain partners are proposed. The settings of the *Newsvendor Problem* and the *Beer Distribution Game* are both extensively used to assess the *performance* of these contracts. Their performance is quantified by the attained *efficiency score* in the case of the *Newsvendor Problem* setting and the *competition penalty* in the case of the *Beer Distribution Game* setting.

Chapter 2- Supply Chain Models and Contracts: Analytical and Experimental Results

The standard normative models prove that when the interacting manufacturers and retailers are exclusively interested in maximising their respective profits in the *Newsvendor Problem* setting, the resulting aggregate channel profit is inferior to the *first-best case maximum* profit that would be achieved if there was an *integrated newsvendor* who made all decisions. The reason is that neither partner takes into account the effect of his/her decisions on the other's profit and the overall profit, a phenomenon that is known as the *double marginalization* problem. Since the *wholesale price contract* attains an *efficiency score* that is strictly lower than one, it can be said to be unable to *coordinate* the *newsvendor* supply chain. Nevertheless, there are a number of other, yet more complicated and expensive to administer and implement contract types that can *coordinate* the *newsvendor* supply chain, such as, for example, the *buyback* and the *revenue sharing* contracts. These analytical results are built on a set of common assumptions about decision makers' *intentions*, *actions* and *reactions*: *First*, they assume that all decision makers *intend* to maximise their respective profits. *Second*, they postulate that all decision makers would *act* in perfect accordance with their *intentions*. *Last*, they take for granted that since decision makers are *a priori* perfectly rational, they do not need to *react* to the changes that go on around them, do not use the information that is available to them and do not learn from their previous experiences.

But in reality a human decision maker may be: *i.* concerned about a variety of different objectives, possibly other than exclusive profit maximisation, *ii.* unable, for various different reasons, to act according to his/her *intention*s and *iii.* influenced, in a variety of different ways, by occurring environmental changes and also learning. By revisiting the corresponding standard normative models' assumptions about human *newsvendors' intentions*, *actions* and *reactions*, experimental research demonstrates that human retailers' order quantities may differ significantly from their corresponding theoretical predictions. This systematic divergence is justified by a number of individual biases that may be present in human decision making, such as, for example *ex-post inventory error minimisation*, *mean anchor*, *demand chasing*, or collectively *bounded rationality*.

Following a similar rationale, laboratory investigations of *supply chain contracts*, as applied in the *Newsvendor Problem* setting, make provision for a number of individual behavioural biases that might influence all interacting firm managers' decisions. In this way, these laboratory investigations of *supply chain contracts* revisit the assumption of the standard normative models that human decision makers' *actions* are always aligned with their respective profit maximising *intentions*. Yet, they treat the sources of this inherent *bounded rationality* as standard and homogeneous, while individuals may in practice have varying preferences, priorities and cognitive limitations. These preferences, priorities and cognitive limitations might even differ to such a degree that would not allow for generalizations. What is even more important, decision makers may make their own independent decisions in a completely autonomous way.

Moreover, these experimental papers still consider the *contracting* theories' assumptions about decision makers' *intentions* and *reactions* as valid. But firm managers might in reality not be exclusively interested in maximising their own individual profits; they might also be concerned about aggregate channel performances and/or the fair and equitable allocation of profits between their partners and them, because that would enhance the long term sustainability of their partnerships. In addition, firm managers might react to the changes going on around them, use the information that is presented to them to improve their decisions and, thus, learn, especially when they interact for prolonged periods of time.

The findings of these laboratory investigations of *supply chain contracts* in the *Newsvendor Problem* setting are that not only human retailers' order quantities might differ significantly from their rationally optimizing counterparts', but also human manufacturers' pricing decisions' might be substantially different from their profit maximising prices. As a result, the *efficiency scores* that are attained by *supply chain contracts* in the laboratory are significantly different from their corresponding theoretical predictions. The *efficiency scores* quantify how close the aggregate channel profit is to the *first-best case maximum* profit. Namely, the *inefficient wholesale price contract*, although still *inefficient*, performs better than theoretically predicted, while the *coordinating buyback* and *revenue sharing contracts* prove in practice unable to *coordinate* the *newsvendor* supply chain. Whether there could be any manufacturer – retailer interactions that could make the *wholesale price contract efficient* remains open to further exploration.

The standard normative models that are applicable to the *Beer Distribution Game* setting are built on the same set of assumptions about decision makers' *intentions*, *actions* and *reactions*. These analytical models prove that when all supply chain partners are exclusively interested in minimising their own inventory holding and backlog costs, the resulting aggregate channel costs might be superior to the *first-best case minimum* cost that would have been achieved if all distinct partners were interested in attaining the *team optimal solution*. A number of complicated *transfer payment schemes* between adjacent supply chain partners have been proposed to bring the aggregate channel cost as close as possible to the *first-best case minimum* cost. Their respective success in bridging the gap between the aggregate channel cost and the *first-best case minimum* cost is assessed via the *competition penalty* that is attained. According to the relevant analytical models, the *competition penalty* can be maximised, when all supply chain partners adhere strictly to the *team optimizing* decision rules and, thus, order exactly as much as requested. If this is the case, there is an additional important benefit: there is no *bullwhip effect*. But in spite of the *wholesale price contract*'s wide practical popularity, there is as yet no standard normative model that predicts the effect that the *wholesale price contract* can have on cost discrepancies and the *bullwhip effect* in the *Beer Distribution Game*.

A number of laboratory investigations update the standard normative models' assumptions about the *intentions*, *actions* and *reactions* of supply chain partners' quantity decisions in the *Beer Distribution Game* setting. These establish that human decision makers make significantly different decisions from their corresponding theoretical predictions. There is evidence for a number of individual behavioural biases that could explain this systematic divergence of human decisions from the standard normative models' predictions, such as, for example the following decision heuristics: *anchoring and insufficient adjustment* heuristic, *supply line under-weighting*, *organizational learning* and *coordination risk*. These are recognised as responsible in great part for the persistence of the *bullwhip effect* in all laboratory investigations. Nevertheless, the existing experimental research does as yet not explore the divergence of human decisions from standard normative models' predictions, when a *transfer payment scheme* is in force. Hence, the true overall supply chain performance that can be attained in the laboratory when adjacent supply chain partners interact via a concrete contractual arrangement remains open to future investigation.

In summary, this chapter identifies a number of gaps that still exist in the analytical and experimental *supply chain contracting* literature. In greater detail, experimental research still needs to revisit standard normative contracting theories' assumptions about decision makers' *intentions* and *reactions*. It also needs to accommodate their possibly heterogeneous *bounded rationality* and further explore the effect that interactions between varying, independent and autonomous decision making strategies can have on a contract' s observed *efficiency* score or *competition penalty,* whichever is applicable. Moreover, the development of a version of the *Beer Distribution Game* where contractual arrangements between adjacent supply chain partners can take place will shed some additional light on the complex nature of real life supply chain transactions. Given the *wholesale price contract*'s simplicity, a reasonable start could be made from it. In this regard, a standard normative model that would predict the *competition penalty* of the *wholesale price contract* would further contribute to the field's understanding of complicated supply chain transactions. Following the already existing *contracting* theories that are applicable to the *Beer Distribution Game*, this standard normative model could be built on the assumption of perfectly rational supply chain partners that would always *intend* to maximise their own total profits and would not react to any occurring environmental changes.

Chapter 2- Supply Chain Models and Contracts: Analytical and Experimental Results

As already discussed in *Chapter 1*, this PhD thesis restricts attention to the *wholesale price contract*. In respect to this, Table 2.5 summarises the sub-set of the above literature gaps that this PhD thesis aims to address.

Table 2.5: Summary of the literature gaps that this PhD thesis aims to address

Literature Gap	Name	Code
Accommodation of potentially different from profit maximising human *intentions*	Human *intentions*	(G.1)
Accommodation of *boundedly rational actions* that may be heterogeneous	Human *actions*	(G.2)
Accommodation of human decisions that may *react* to environmental changes	Human *reactions*	(G.3)
Accommodation of independent and autonomous *decisions*	Human decisions	(G.4)
Development of a version of the *Beer Distribution Game* where the *wholesale price contract* is the basis of any transaction that takes place between any interacting pair of supply chain partners	*Contract Beer Distribution Game*	(G.5)
Development of a standard normative model that predicts the performance of the *wholesale price contract* in the *Beer Distribution Game* setting	*Contract Beer Distribution Game* 's standard normative models	(G.6)

Chapter 3 that follows describes the approach that this PhD thesis has adopted to address the literature gaps G.1-G.4 that are outlined in Table 2.5. The reason that the literature gaps about human *intentions*, *actions*, *reactions*, and *decisions* (*i.e*. G.1 – G.4) are discussed in *Chapter 3* is because they concern both the *Newsvendor Problem* and the *Beer Distribution Game* settings. As for the literature gaps that reflect the design of the

Contract Beer Distribution Game (*i.e*. G.5) and the development of the corresponding standard normative models (*i.e*. G.6), they are applicable only to the *Beer Distribution Game* setting. Therefore, they are discussed in *Chapter 6* that concerns specifically the implementation of the *wholesale price contract* in the *Beer Distribution Game*.

Chapter 3

Research Design: The Approach

As its title implies, this chapter describes the approach that this PhD thesis has adopted to address the gaps of the existing behavioural literature on human *intentions* (*i.e*. G.1), *actions* (*i.e*. G.2), *reactions* (*i.e*. G.3) and *decisions* (*i.e*. G.4), as presented in Table 2.5 (*i.e*. *Section 2.4*). Since these literature gaps concern both the *Newsvendor Problem* and the *Beer Distribution Game* settings, this approach has been applied to both of these settings. This chapter describes in some detail the main characteristics of the approach that are applicable to both settings. More specific details about each setting are provided in *Chapters 4* and *7*, respectively.

This chapter only addresses the literature gaps G.1 – G.4 that are presented in Table 2.5. The literature gaps G.5 and G.6 concern respectively: *i.* the development of a new version of the *Beer Distribution Game*, where the *wholesale price contract* determines all terms of exchange between any pair of interacting supply chain partners and *ii.* the foundation of the corresponding standard normative model. Therefore, both G.5 and G.6 are specific to the *Beer Distribution Game*. As a result, they are not addressed here, but in *Chapter 6* that introduces the *Beer Distribution Game*, along with its associated standard normative models.

3.1 Overview of Approach

The purpose of this chapter is to describe the approach that this PhD thesis has adopted to investigate the effect that the different possible interactions between dynamic, autonomous and heterogeneous decisions of supply chain managers can have on the *wholesale price contract*'s overall performance. In greater detail, this approach aims to accommodate: *i.* human *intentions* that might be different from profit maximisation or cost minimisation (*i.e*. G.1 of Table 2.5 in *Section 2.4*), *ii.* human *actions* that might differ from their corresponding *intention*s *(i.e. boundedly rational actions)* in possibly heterogeneous ways (*i.e*. G.2), *iii*. human *reactions* that might depend on changes occurring in their surrounding environments if any (*i.e*. G.3), *iv*. human decisions that might be *independent* and *autonomous* (*i.e*. G.4).

In this regard, running experiments with human subjects in the laboratory would be necessary to investigate human decisions. According to the existing tradition of behavioural operations management, as described in *Chapter 2*, this approach represents a way to capture the variety of different possible human *intentions*. Therefore, running experiments with human subjects would successfully address the literature gap that concerns human *intentions* (*i.e.* G.1) that is presented in Table 2.5. Yet, there are a number of limitations that are recognised as inherent with running experiments with human subjects alone. The most important of these is the risk that human subjects might lose their interest and, thus, let their levels of concentration decline during the course of the experiment (Camerer, 1995; Croson, 2002; Duffy, 2006). As a result, human subjects could not be asked to interact: *i.* with or against a number of different partners, *ii*. over prolonged session durations and *iii.* for a statistically accurate number of replications.

First, asking all human subjects to interact with the same response sets across all experimental sessions would eliminate the potential to study different interactions, that is, *heterogeneous* decisions. But this comes in contrast with the literature gap that concerns human *actions* (*i.e*. G.2) that is presented in Table 2.5. *Next*, asking human subjects to interact over limited periods of time would deprive one from the ability to capture the effect of subjects' increased experience and, thus, *learning*. But this is in opposition with the literature gap that concerns human *reactions* (*i.e*. G.3: Table 2.5). *Last*, asking human subjects to interact for only one replication would seriously reduce the accurateness of all inferred results. Thus, for the needs of multiple interactions, prolonged interaction lengths and multiple replications, another set of experiments "in silico"[6] (Bonabeau, 2002; Samuelson and Macal, 2006) are required; these experiments *in silico* would complement the laboratory experiments that would be run with human subjects in the laboratory. In addition, these experiments *in silico* would enable one to infer statistically accurate results. That is exactly why the approach used here is to simulate human interactions over a prolonged period of time. As for the exact simulation technique that has been selected it needs to be one that is adequate to model *autonomous* and *independent* decisions, so that the literature gap that concerns differing human *decisions* (*i.e*. G.4) can be addressed. More details about the chosen simulation technique and a discussion on the reasons for its choice are now provided.

3.2 Agent Based Simulation

Agent Based Simulation (ABS) provides a natural test-bed for modelling phenomena that are represented as systems of *autonomous* agents that follow

[6]The expression "in silico" originates from the latin expression "in vitro" (*i.e*. "in glass") that is used to refer to experiments in a test tube; in a similar manner, the expression "in silico" refers to experiments in computer simulation or virtual reality [source: http://en.wiktionary.org/wiki/in_silico#English, last accessed: 19/02/2010].

rules for any decision and transaction that they make (Casti, 2001; Axelrod, 2005; Samuelson and Macal, 2006; North and Macal, 2007; Gilbert, 2008) and where strong ‘emergent phenomena’ come into play (Casti, 1997; Holland, 1998; Bonabeau, 2002; Lyons, 2004). This is exactly the reason why ABS is in this PhD thesis proposed to complement the human experiments.

As Figure 3.1 illustrates, any ABS model is typically defined by (*i*) its constituting agents, (*ii*) the underlying environment and (*iii*) the combined evolution of its agents and the underlying environment (Choi *et al*, 2001). In view of this, the supply chain managers that interact in the *Newsvendor Problem* and the *Beer Distribution Game* settings would be modelled as distinct *agents*; while the industry in which the supply chain under study is active and all remaining model parameters, such as selling prices and manufacturing costs, whichever are applicable, would constitute the underlying environment. The paragraphs that follow define all distinct components of an ABS model and specify the equivalent ABS representation of the *Newsvendor Problem* and the *Beer Distribution Game* settings. These paragraphs also explain how each of these elements would help to address the literature gaps about human *intentions*, *actions*, *reactions* and *decisions*, namely G.1-G.4 of Table 2.5 (*s. Section 2.4*).

I. <u>Agents</u>

Agents are uniquely defined by their corresponding set of attributes and behaviours. The *attributes* define what an agent is, while the *behavioural characteristics* define what an agent does (North and Macal, 2007). Although *agents* may have widely varying characteristics, consensus has at least been reached in that the most important characteristics that are associated with *agents* are the following (Sanchez and Lucas, 2002; North and Macal, 2007; Gilbert, 2008; Macal and North, 2009):

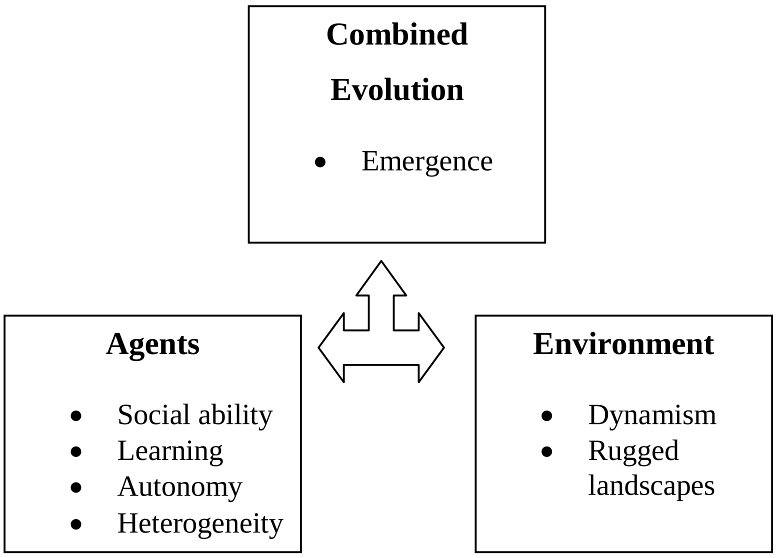


Figure 3.1: Fundamental Principles of an ABS model (adopted from Choi *et al*, 2001)

- *Social Ability* to communicate with each other and their surrounding environment,
- *Capability to learn*, modify and, thus, adopt their behaviours according to any occurring changes,
- *Autonomy*, that is separate and well determined goals to achieve and clearly defined internal logic rules that govern their actions, and
- *Heterogeneity*, namely differing *intention*s that force their respective decisions.

In this PhD thesis, the supply chain managers that are responsible for different firms have been modelled as agents. In this regard, supply chain managers have been treated as being able to communicate with each other only via the *wholesale price contract*, since the *wholesale price contract* has constituted the basis of any interaction that takes place in both the *Newsvendor Problem* (*Chapters 4*-5) and the *Beer Distribution Game* settings (*Chapters 6-8*). The exact set of attributes and behavioural characteristics that fully define the agents of the *Newsvendor Problem* and the *Beer Distribution Game* are presented in *Chapters 4* and *7*, respectively.

Since supply chain managers have been modelled as *agents*, they have also been treated as apt to learn and react to changes, able to make autonomous and independent decisions and also with differing characteristics, namely as heterogeneous. Their aptitude to learn and react to changes would enable one to address the literature gap that concerns human *reactions* (*i.e*. G.3 of Table 2.5 in *Section 2.4*). Moreover, supply chain managers' ability to make autonomous and independent decisions could accommodate the needs of the literature gaps that concern human *intentions* and *decisions* (*i.e*. G.1 and G.4 of Table 2.5). Last but not least, supply chain managers' heterogeneity would satisfy the needs of the literature gap that concerns *actions* that may not be consistent with their corresponding *intentions* (*i.e*. G.2 of Table 2.5).

II. Environment

The *environment* consists of the *agents* and their interconnections that have not been included within the boundaries of the model. The *environment* is mainly characterized by (Choi *et al*, 2001):

- dynamism, namely constantly recurring changes,
- rugged landscapes, namely if the function of the system's 'goodness' or 'fitness' is represented on a landscape, this would be uneven and it would, thus, become hard to distinguish the component combinations that would give rise to the overall system optimality.

In this PhD thesis for both the *Newsvendor Problem* and the *Beer Distribution Game* settings the environment is seen as dynamic in that customer demand is stochastic in nature and constantly evolving over time. If the supply chain's performance is represented on a landscape, overall optimality could be attained by a number of different, possibly surprising combinations. Identifying and justifying these combinations in both the *Newsvendor Problem* and the *Beer Distribution Game* settings constitutes one of the main purposes of this PhD thesis.

III. Combined evolution

The most important element of the combined evolution of *agents* and their underlying *environment* is *emergence*, which is defined as the arising of new, unexpected structures, patterns, properties, or processes that are not required to describe the behaviour of the underlying agents (Casti, 1997; Holland, 1998; Gilbert and Terna, 2000).

This PhD thesis aims at identifying whether 'globally good' performances could *emerge* from the interactions of 'locally poor' decisions in any or both of the *Newsvendor Problem* and the *Beer Distribution Game* settings. In case such *emergent* patterns are revealed, this PhD thesis aims at shedding light on the underlying reasons for these *emergent* phenomena. *Chapters 4* and *7* define exactly which performances are perceived as 'locally poor' and 'globally good' in the *Newsvendor Problem* and the *Beer Distribution Game* settings, respectively. *Chapters 5* and *8* report whether 'globally good' performances *emerge* from 'locally poor' decisions in any or both of the *Newsvendor Problem* and the *Beer Distribution Game* settings.

3.3 The Approach

It has so far been argued that running experiments with human subjects in the laboratory would enable one to investigate the effect of human decisions on the overall performances of the *wholesale price contract*. It has also been demonstrated that modelling supply chain managers as *agents* would allow one to address the literature gaps that concern human *intentions*, *actions*, *reactions* and *decisions* (*i.e*. G.1-G.4 of Table 2.5 in *Section 2.4*). Modelling the supply chain's activity as the underlying *environment* in the simulation model would enable one to identify possible *emergent phenomena*, where perhaps surprising combinations of 'locally poor' decisions could give rise to 'globally good' performances. Therefore, ABS would be useful to infer statistically accurate results about the effect that different prolonged interactions between dynamic, heterogeneous and autonomous decisions could have on the *wholesale price contract*'s overall performance. Via running adequate ABS models, a human's decision making strategies could interact with any number of other decision making strategies over any period of time and for any required number of replications. Therefore, the limitations of human experiments identified in *Section 3.1* could be overcome. To this end, instead of following the example of the seminal papers by Schelling (1978), Axelrod (1984) and Epstein and Axtell (1996) where human behaviour is not taken into account at all and all agents are assigned simple, adaptive learning rules based on intuition, in this PhD thesis the evidence gained from human experiments is used to calibrate the associated ABS models.

Figure 3.2 presents the approach that is followed in this PhD thesis for both the *Newsvendor Problem* and the *Beer Distribution Game* settings. In this way, knowledge on how human subjects make their decisions is elicited and the overall performance of all their possible interactions is assessed.

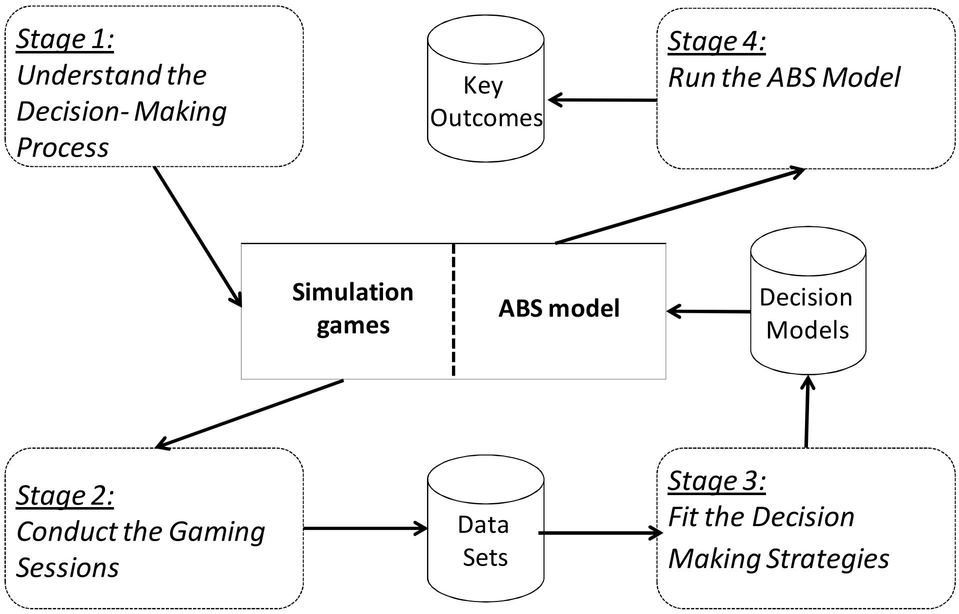


Figure 3.2: The Approach (adapted from Robinson *et al*, 2005)

This approach is based on the *Knowledge Based Improvement* methodology of Robinson *et al*. (2005) and consists of four distinct stages: that is, understanding the decision making process, conducting the gaming sessions, fitting the decision making strategies and running the ABS model. These four stages are represented within the dashed rectangles of Figure 3.2. The concrete outcomes of each stage are indicated within solid outer lines. As is evident from Figure 3.2, the focal element of this approach is the ABS model that corresponds to the *Newsvendor Problem* and the *Beer Distribution Game*, respectively. These ABS models are also adjusted to build the computer interfaces of the simulation games that the human subjects were asked to interact with. There are three reasons that explain the central importance of these ABS models. *First,* they are developed in the early stages of the approach; *next,* they are subsequently employed by almost all stages that follow; *last,* the final assessments of the overall performance of the *wholesale price contract* are based on these. Consequently, the conclusions on the research hypotheses that are of relevance to the *Newsvendor Problem* and the *Beer Distribution Game* settings (*i.e*. as formulated in *Sections 4.2* and *7.2*, respectively) are drawn on the basis of the corresponding ABS models. More specific details about the way that the simulation games were built based on the ABS models and the scenarios or response sets that the different participants in the *Newsvendor Problem* and the *Beer Distribution Game* were provided are given in *Sub-sections 4.3.2.* and *7.3.2*, respectively.

Figure 3.2 illustrates that the purpose of the first step (*Stage 1*) is to understand the underlying decision making process of each role that comes into play in the *Newsvendor Problem* and the *Beer Distribution Game* supply chains. To this end, the two settings ought to be first comprehended in some detail. The detailed specification of the *Newsvendor Problem* and the *Beer Distribution Game* settings, as well as the corresponding theory that is reviewed in *Sub-sections 2.1.1* and *2.2.*1 serve to recognise the decisions that each of the interacting partners in the two settings is entrusted with (or else the *decision variables*). But for each of these decisions to be made, a number of different factors (or else *decisions attributes*) need to be taken into consideration. Informal pilot sessions with volunteers, which were followed by interviews, enable one to identify the significant *decision attributes*. The objective is to identify among the information that is available to all volunteers the subset that is considerably taken into account by them. The ABS models that correspond to the *Newsvendor Problem* and the *Beer Distribution Game* settings could then be developed, building on the specification of the two settings and the *decision attributes* revealing as significant. These models are based on the activities that each agent needs to perform, their exact order and sequence, the conditions that trigger each activity, the decisions that each agent is responsible for and the corresponding *decision attributes*. The only information that is still missing from the ABS models, though, is the exact decisions that human participants in the two games truly make.

In order, thus, to capture human decisions, gaming sessions with human subjects are performed in *Stage 2*. To this end, volunteers have been randomly assigned to the different supply chain roles and asked to play these in simulation games in the laboratory. As is shown in Figure 3.2 the majority of the participants is asked to interact with appropriate modifications of the corresponding ABS model. More details about this correspondence are provided in *Sub-sections 4.3.2* and *7.3.*2, respectively. All their decisions over time are recorded. A separate data set is created for each participant's recorded decisions at the course of the simulation game, which can be seen as the concrete outcome of *Stage 2* in Figure 3.2. Each participant is assumed to follow his/her own decision making strategy, namely it is assumed that there is a unique relationship between each of the participant's *decision variables* and the corresponding *attributes* (*e.g*. the *decision variable* price is associated, for example, with the *decision attributes* past order quantity and realised profit). In order to determine a participant's specific decision making strategy, *Stage 3* is subsequently performed.

The object of *Stage* 3 is to determine the decision model of each participant in the *Newsvendor Problem* and the *Beer Distribution Game* settings. For this, adequate statistical models have been fitted to each participant's dataset of recorded decisions. The exact fitting procedures that have been followed, as well as the exact decision models that correspond to the participants in the

Newsvendor Problem and the *Beer Distribution Game* settings, are described in *Sub-sections 4.3.3* and *7.3.3*, respectively. These decision models are subsequently input into the corresponding ABS model and combined in a way that ensures that the strategies of all participants are combined with each other. This constitutes the object of *Stage 4*.

In *Stage 4* all possible combinations of decision models, or else inferred human decision making strategies, are simulated, so that their respective outcomes can be compared. So, the key outcomes that serve to investigate the research hypotheses of the two settings originate from appropriate runs of the ABS models. The research hypotheses that are relevant to the *Newsvendor Problem* setting are presented in *Section 4.2*, while the research hypotheses that are related to the *Beer Distribution Game* are provided in *Section 7.2*.

These four stages along with their associated outcomes are described in some detail in the paragraphs that follow.

3.3.1 Stage 1: The Decision Making Process

The purpose of this first stage is two-fold: *i.* identify the decision task(s) that each participant is entrusted with or else the *decision variable(s)* of each *agent*, *ii.* recognise the factors or else *decision attributes* that most human participants seem to take into account in order to make these decisions, respectively. The *decision variable(s)* derive from the specification of the setting, namely the *Newsvendor Problem* or the *Beer Distribution Game*. In order to recognise the most significant *decision attributes* for any role's *decision variable*, the reported results from relevant experimental research are referred to, as outlined in *Chapter 2*. Informal pilot sessions with student volunteers have been conducted to confirm the applicability of these reported results on the settings under study. These sessions have been followed by interviews, during which all subjects were given the opportunity to describe and explain the underlying reasoning behind their decisions. All relevant details for the *Newsvendor Problem* and the *Beer Distribution Game* are provided in *Sub-sections 4.3.1* and *7.3.1*, respectively.

The final concrete outcome that derives from *Stage 1* is equation (3.1) that represents the one-to-one association between each role's (*i) k-th decision variable* (k = 1,..,K) dv_i^k and the corresponding *decision attributes* da_j, where j is the index of a specific *decision attribute* that can take up to the value of J. J represents the total number of *decision attribute*s that have been identified as significant for the role's (*i*) *k*-th *decision variable*, namely dv_i^k.

$$dv_i^k = f_i^{dv_i^k}\left[\, da_1, da_2, \dots, da_j, \dots, da_J\right] \tag{3.1}$$

In any setting there are i=1,...,I different possible roles. In the *Newsvendor Problem i* takes the values of the manufacturer and the retailer (*i.e. MAN* and *RET*, respectively); while in the *Beer Distribution Game i* can take the values of the manufacturer, the wholesaler and the retailer (*i.e. MAN*, *WHL* and *RET*, respectively).

The detailed specification of the *Newsvendor Problem* and the *Beer Distribution Game* settings that are provided in *Sub-sections 2.1.1* and *2.2.*1, respectively, combined with the decision functions of type (3.1), lead to the development of the corresponding ABS models. For reasons of speed of model build, ease of use and familiarity with the data presentation, these have been developed in Excel-VBA, following Robinson's (2004) and North and Macal's

(2007) suggestions. These models are described in some detail in *Sub-sections 4.3.1* and *7.3.1*, respectively.

3.3.2 Stage 2: The Gaming Sessions

The objective of the second stage is to collect data for each human decision maker. To this end, volunteers were recruited from a pool of 2007, 2008 and 2009 intakes of graduate students at the University of Warwick (PhD in Management, MSc in Engineering Business Management, MSc in Management, MSc in Management Science and Operational Research, MSc in Business Analytics and Consulting) and asked to play different supply chain roles, depending on the setting that was used as the computational framework, namely the *Newsvendor Problem* or the *Beer Distribution Game*. The only requirement set for participation was that all participants had received formal classroom training in the principles of inventory management, prior to the experiment, as part of their curriculum. This requirement, in line with recent empirical studies that confirmed the overall analogous performance of well trained students when compared with experienced supply chain managers (Croson and Donohue, 2006; Bolton *et al*, 2008), intended to control and, thus, ensure a standard and common level of knowledge across all participants[7].

[7]The author of this PhD thesis is aware of the stream of research that casts doubt about the validity and reliability of the use of students as surrogates of real life decision makers in behavioural experiments in fields such as human relations in business (*i.e*. justify a manager's decision to fire with no apparent reasons a subordinate: Alpert, 1967), financial reporting and accounting (*e.g*. Birnberg and Nath, 1968; Copeland, Francia and Strawser, 1973) and banking (*i.e*. make a decision about granting a loan to a firm: Abdel-Khalik, 1974). Nevertheless, the author of this PhD thesis adopts the view of Dickhaut,

In the case of the *Newsvendor Problem* all participants were asked to interact via a computer interface with a set of representative response sets or else *scenarios*. This computer interface has been adapted from the ABS model of the *Newsvendor Problem*. The exact way that these scenarios have been generated is discussed in *Sub-section 4.3.2*. In the case of the *Beer Distribution Game* some participants were asked to interact over the specially designed board of the game, while some others were asked to interact via a computer interface with a set of pre-selected partners' responses. The computer interface has been adapted from the ABS model of the *Beer Distribution Game*. Whether a participant would be asked to play over the board or via the computer interface, and the exact set of responses or else *scenarios* that were provided to him/her have been rigorously

---

Livingstone and Watson (1972) according to which the appropriateness of students as subjects depends on the setting and nature of the decision task at hand. For this reason, the recent empirical finding of Croson and Donohue (2006) and Bolton *et al*. (2008) in the area of inventory management, that is relevant to this thesis, is instead accounted for. [Sources:

Abdel-Khalik, A. 1974. On the efficiency of subject surrogation in accounting research. *The Accounting Review* 49(4), 743-750.

Alpert, B. 1967. Non-Businessmen as surrogates for businessmen in behavioral experiments. *The Journal of Business* 40(2), 203-207.

Birnberg, J., Nath, R. 1968. Laboratory experimentation in accounting research. *The Accounting Review* 43(1), 38-45.

Copeland, R., Francia, A., Strawser, R. 1973. Students as subjects in behavioral business research. *The Accounting Review* 48(2), 365-372.]

selected via a specially developed methodology. This methodology is described in *Sub-section 7.3.2.*

In both the *Newsvendor Problem* and the *Beer Distribution Game* settings, in total *S* different subjects were assigned to each of the available roles i (i = 1,...,*I*). The available roles i = 1,...,*I* were the factors of analysis, while the different subjects s = 1,...,*S* were the different levels for each factor. In this regard, i_s reflects the *s*-th participant that was assigned to the role *i*. Since each role *i* was assigned in total S_i different subjects or else levels, there were in total $S_1 \times S_2 \times \ldots \times S_I$ possible combinations.

The decisions of all participants over time were recorded and constituted the associated datasets of decisions that can be seen in Figure 3.2.

3.3.3 Stage 3: The Decision Making Strategies

The object of the third stage is to determine the decision model that corresponds to each participant, namely identify the relations of type (3.1) that associate all *k* = 1,...*K* *decision variable*s of a participant i_s with the corresponding *decision attribute*s:

$$dv_{i_s}^{k} = f_{i_s}^{dv_{i_s}^{k}}\left[\, da_1, da_2, \ldots, da_j, \ldots, da_J\right] \tag{3.2}$$

Since Bowman's managerial coefficient theory (Bowman, 1963) has already been widely used to model decision making in experimental work (*e.g.* Remus, 1978; Croson and Donohue, 2006; Kunc and Morecroft, 2007, Benzion *et al*, 2008), appropriate modifications of it have been applied in this PhD thesis. According to this, the importance that each participant i_s assigns to his/her *j*-th *decision attribute* for his/her *k*-th decision (*i.e.* $dv_{i_s}^{k}$) is portrayed by the value of each coefficient $a_j^{dv_{i_s}^k}$ in appropriate linear models. In respect to this, each participant's decision making strategies (3.2) are portrayed by simple linear models, that is:

$$\langle dv_{i_s}^k \rangle_{i_s} = a_0^{dv_{i_s}^k} + a_1^{dv_{i_s}^k} \cdot da_1 + \cdots + a_2^{dv_{i_s}^k} \cdot da_2 + \cdots + a_J^{dv_{i_s}^k} \cdot da_J \qquad (3.3)$$

These linear models are built on the assumptions of *independence*, *linearity*, *normality,* and *homo-skedasticity* (Weisberg, 2005; Hair *et al*, 2006; Fox, 2008). In order, thus, to assess the compliance of all dependent and independent variables with these assumptions, elaborate tests have been performed; the scatterplot matrix is only used as a first indicator to this end. All details of the exact fitting procedures that have been followed in the cases of the *Newsvendor Problem* and the *Beer Distribution Game* settings are provided in *Sub-sections 4.3.3* and *7.3.3*, respectively. These sub-sections also discuss the remedies that have been pursued to overcome the departures from *linearity*, *normality* and *homo-skedasticity* that have been observed in the two settings under study. In addition, they present the different decision models that have been fitted to the different participants' datasets of recorded decisions.

3.3.4 Stage 4: The Agent-Based Simulation Model Runs

The object of the fourth stage is to explore the overall performance of the *wholesale price contract* under all possible interactions of inferred decision making strategies. To this end, the ABS models that correspond to the *Newsvendor Problem* and the *Beer Distribution Game* are run for all possible combinations of decision models or else treatment factors [i_s]. Since the total number of all possible combinations (*i.e.* $S_1 \times S_2 \times \ldots \times S_I$) is not prohibitively high, the corresponding full factorial experimental design is followed, according to which each factor level is combined with all possible levels of all other factors (Robinson, 2000; Toutenburg, 2002; Mukerjee and Wu, 2006). The results that are obtained from the corresponding ABS models are subsequently used to infer statistically accurate conclusions about the research hypotheses that are of relevance to the *Newsvendor Problem* and the *Beer Distribution Game* settings. These research hypotheses are formulated in *Sections 4.2* and *7.2*, respectively.

The key results that are generated from the ABS model of the *Newsvendor Problem* concern: *i.* the prices that are charged by the simulated human manufacturers, *ii.* the quantities that are ordered by the simulated human retailers, *iii.* the *efficiency scores* that are attained by the simulated interactions of all inferred decision models. The key results that are obtained from the ABS model of the *Beer Distribution Game* reflect: *i.* the prices that are charged by the simulated human participants, *ii.* the quantities that are ordered by the simulated human participants, *iii.* the *competition penalties* that are attained by the simulated interactions of inferred decision models, *iv.* the degree to which the *bullwhip effect* prevails in different simulated interactions of decision making strategies. The key outcomes that correspond to the *Newsvendor Problem* and the *Beer Distribution Game* are reported in *Sub-sections 4.3.4* and *7.3.4*, respectively.

3.4 Verification and Validation

Before using the results that are obtained from the appropriate ABS models, the models' internal consistency and external validity are tested (Pidd, 2004; Robinson, 2004; Law, 2007; North and Macal, 2007). Although verification and validation are performed in parallel with all other activities of this PhD thesis

(North and Macal, 2007; Robinson, 2008), for reasons of simplicity and clarity the steps that have been undertaken to verify and validate the ABS models that correspond to the *Newsvendor Problem* and the *Beer Distribution Game* are discussed in *Sections 4.4* and *7.4*, respectively.

3.5 Summary

This chapter describes the approach that this PhD thesis has followed to investigate the effect that the different possible interactions between dynamic, autonomous and heterogeneous decisions of supply chain managers can have on the *wholesale price contract*'s overall performance.

By basing the research on the interaction of human subjects in supply chain settings, this approach makes provision for: *i.* human *intentions* that might be different from profit maximisation or cost minimisation, *ii.* human *actions* that might differ from their corresponding *intention*s in *heterogeneous* ways (*i.e*. heterogeneous *boundedly rational actions), iii*. human *reactions* that might depend on their surrounding environments and any occurring changes to it , *iv*. human *decisions* that might be *independent* and *autonomous.* In this way, this approach aims at addressing the literature gaps about human *intentions* (*i.e*. G.1), *actions* (*i.e*. G.2), *reactions* (*i.e*. G.3) and *decisions* (*i.e*. G.4) that are identified in Table 2.5 of *Section 2.4*. The approach manages to address these existing literature gaps by complementing laboratory experiments with simulation experiments (*i.e*. experiments *in silico*). In greater detail, the simulation models are calibrated via the results that have been obtained from the experiments run in the laboratory with human subjects. In this way, statistically accurate conclusions about the effect that different prolonged interactions between dynamic, heterogeneous and autonomous decisions can have on the *wholesale price* *contract's* overall performance are drawn. The reason that these conclusions are statistically accurate is that they can simultaneously address the requirements of multiple interactions, prolonged interaction lengths and multiple replications, which would not have been possible if only experiments with human subjects were run.

In greater detail, this approach builds on Robinson *et al.*'s (2005) *Knowledge Based Improvement* methodology, but appropriately adopts it to the needs of Agent Based Simulation (ABS). The reason that ABS is chosen to study the *Newsvendor Problem* and the *Beer Distribution Game* settings is that by modelling different supply chain managers as *agents*, their aptitude to have various differing *intentions*, make heterogeneous *actions*, learn and react to changes (*i.e*. *reactions*), make independent and autonomous *decisions* is captured. In addition, in ABS models, any human decision making strategy could be input as a factor of analysis and combined with any other existing decision making strategy over extended periods of time and for many independent replications. Furthermore, via ABS models one has the potential to shed light on the possible existence of *emergent phenomena*. Some indicative examples of expected *emergent phenomena* are the *emergence* of 'globally good' performances from 'locally poor' decisions.

This approach comprises five distinct stages: The purpose of the first stage is to identify the *decision variable(s)* of each *agent* and the most popular *decision attributes* that relate to each *decision variable*. The objective of the second stage is to collect data for each human decision maker. To this end, volunteers have been randomly assigned to the available supply chain roles; their respective decisions over time have been recorded in simulation games. The object of the third stage is to determine the exact decision model that associates each participant's *decision attributes* to the *decision variables*. The fourth stage aims at exploring the overall performance of the *wholesale price contract* under all different interactions of inferred decision making strategies. Adequate runs of the ABS models that correspond to the *Newsvendor Problem* and the *Beer Distribution Game* are to this end used. This approach is adapted in *Section 4.3* to the exact needs of the *Newsvendor Problem* setting. *Section 7.3* adapts this approach to the needs of the *Beer Distribution Game* setting.

The reader should at this point be reminded that the remaining two literature gaps that are identified in Table 2.5 (*s. Section 2.4*) and concern the *Contract Beer Distribution Game* (*i.e.* G.5) and its corresponding standard normative models (*i.e.* G.6) require as a pre-requisite the development of a new version of the *Beer Distribution Game*, where the *wholesale price contract* constitutes the basis of any interaction between adjacent supply chain partners. This is the reason why these two literature gaps are specifically addressed in *Chapter 6*, where the mechanics of the game and the standard normative models that correspond to it are explored.

Chapter 4

The Newsvendor Problem Approach

The purpose of this chapter is to describe the approach that this PhD thesis has undertaken to investigate the effect that different prolonged interactions between manufacturers' and retailers' dynamic, heterogeneous and autonomous decisions can have on the *wholesale price contract's efficiency*, when applied to the *Newsvendor Problem* setting. In other words, this chapter formulates the research hypotheses that are of interest to the *Newsvendor Problem* setting and, in addition, explains how the approach of this PhD thesis, as outlined in *Chapter 3*, has been applied to this setting. In respect to this, *Chapter 3* describes how this approach successfully addresses the literature gaps that concern human *intentions* (*i.e.* G.1), *actions* (*i.e.* G.2), *reactions* (*i.e.* G.3) and *decisions* (*i.e.* G.4), as have been identified in Table 2.5 (*s. Section 2.4*), in the case that the *wholesale price contract* is put in force in the *Newsvendor Problem* setting.

The chapter starts by a brief description of the *Newsvendor Problem* and its existing analytical and experimental results. It subsequently uses these extant results to build the research hypotheses that are of interest to this study. It then discusses in some detail all steps of the approach that have been followed to address these research hypotheses. Last but not least, the chapter concludes with a brief summary.

4.1 The Newsvendor Problem

The typical *integrated newsvendor* setting is illustrated in Figure 4.1. In this case, the only decision that needs to be made is the order quantity q. The reader is at this point reminded that customer demand is assumed to follow the truncated at zero normal distribution (with μ=140 and σ = 80), because it more closely reflects real cases, where limited information about the distribution of customer demand is available (Gallego and Moon, 1993; Son and Sheu, 2008; Ho *et al*, 2009). Because of this truncation at zero, demand mean and variance need to be modified according to Barr and Sherrill (1999)'s recommendations to μ'≈147 and σ' ≈ 65. It is also assumed that: p=250 *m.u.*(*i.e.* monetary units); c=50 *m.u.*; g=1 *m.u.*

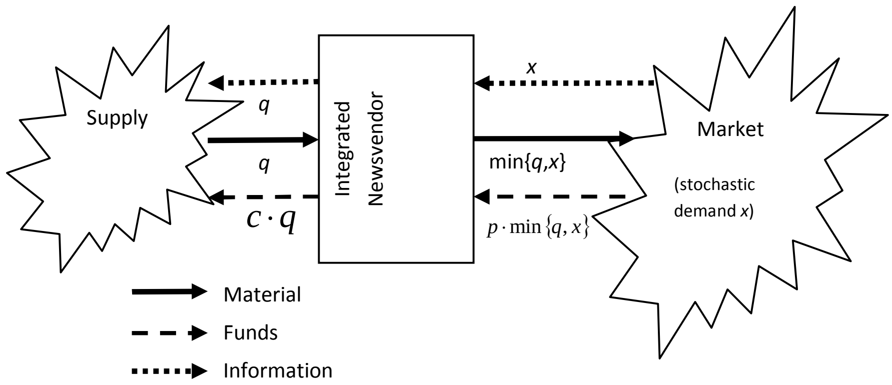


Figure 4.1: The *integrated newsvendor* problem

If this *integrated newsvendor* is exclusively interested in maximising the overall profit $\prod_c$, then he/she would order as much as q^*_{int}, as given by equation (2.2), and would consequently generate the *first-best case maximum* profit of the entire channel $\prod^*_{\text{int}}$ that is given by relation (2.1). Relations (2.1) and (2.2) are provided in *Sub-section 2.1.1.* In *Sub-section 2.1.1* can also be found the notation that is used here.

Nevertheless, in the case that there are two distinct decision makers in the *Newsvendor Problem* setting that interact via the *wholesale price contract*, the setting differs in the way that Figure 4.2 demonstrates. In greater detail, each decision maker needs to make exactly one decision: the manufacturer needs to determine the price w that is charged to the retailer in each time period t, while the retailer needs to specify the chosen order quantity q. If the manufacturer is exclusively interested in maximising his/her individual profit, he/she charges $w*$, as given by equation (2.8) (*s. Sub-section 2.1.1*), where q_m^* represents the order quantity that the rationally optimizing retailer would place in response to this price $w*$, or else $q_m^* = \arg\left[\max \prod_{\mathrm{m}}(w^*, \mathrm{q})\right] = F^{-1}(\frac{p+g-w^*}{p+g})$. The result is that the manufacturer would expect to produce a profit of $\prod_m^*$, that is given by equation (2.7). If the retailer is in turn exclusively interested in maximising his/her individual profit, he/she orders exactly q_r^* units as calculated by relation (2.4) and subsequently expects to attain a profit of Π_r, according to equation (2.3). When these decisions are combined, they generate an aggregate channel profit of $\prod_{\mathrm{c}} = \prod_m^* + \prod_r^*$, that is significantly lower than the aggregate *first-best case maximum* profit of $\prod_{int}^*$ (Lariviere and Porteus, 2001; Cachon, 2003). Relations (2.3), (2.4), (2.7) and (2.8) are provided in *Sub-section 2.1.1*.

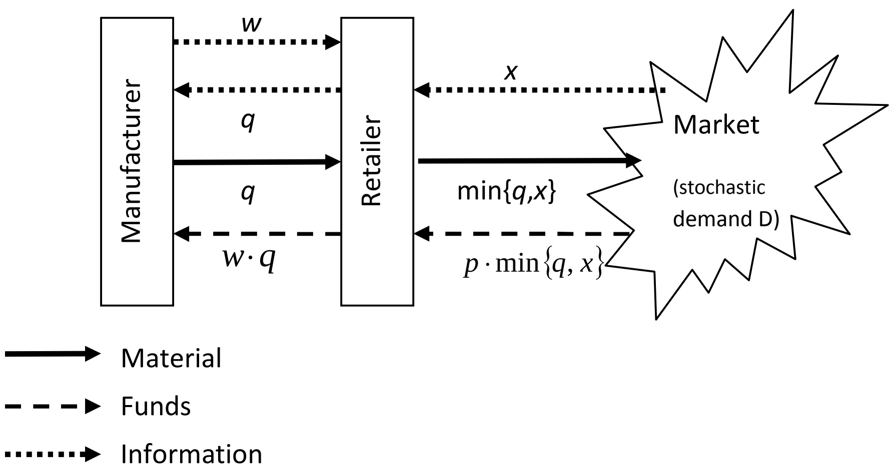


Figure 4.2: The *de-centralised operation newsvendor* problem

The results is that the *efficiency score* that is attained by this interaction of $w*$ with q_r^* (which in this case happens to coincide with q_s^*) is $Eff = \frac{\Pi_{\mathrm{c}}}{\Pi_{\mathrm{int}}^*} < 1$, which signifies the *wholesale price contract's inefficiency*. The reason is that neither the manufacturer, who is the first to make any decisions and, therefore the *Stackelberg leader* (Stackelberg, 1934 in: Cachon and Netessine, 2004), nor the retailer, take into account the effect of their decisions on the overall channel's profit. This phenomenon is known as the *double marginalization problem* (Spengler, 1950).

Nevertheless, it has already been established that very rarely would human manufacturers and retailers make price and quantity decisions, respectively, that follow the above decision rules. Thus, whether the *double marginalization problem* perseveres, or else whether the *efficiency score* attained would remain strictly lower than one, is still open to further exploration. In a number of laboratory experiments that have been conducted with human subjects, it is confirmed that there persists a systematic divergence of both human manufacturers' prices and human retailers' order quantities from the corresponding prices and quantities that are predicted by the standard normative models. *First*, human manufacturers are found to charge prices (w) that are significantly different from the prices that would maximise their individual profits w^* (Keser and Paleologo, 2004; Katok and Wu, 2009). *Second*, human retailers are found to systematically order quantities (q) that are significantly different from the quantities that their rationally profit maximising counterparts would order (q_r^*), that is, in response to the prices w that are charged to them (Schweitzer and Cachon, 2000; Schultz and McClain, 2007; Benzion *et al,* 2008; Bolton and Katok, 2008; Bostian *et al*, 2008; Kremer *et al*, 2008; Su, 2008; Lurie and Swaminathan, 2009).

In greater detail, human retailers are found to: *i. under-order*, namely order less than q_{int}^{*}, if the product being exchanged is of the high profit type and *ii. over-order*, namely order more than q_{int}^{*}, if the product being exchanged is of the low profit type (Schweitzer and Cachon, 2000; Benzion *et al*, 2008; Bolton and Katok, 2008; Bostian *et al*, 2008). Schweitzer and Cachon (2000) make the distinction that a product is characterized as being of the high profit type if its "critical fractile" is greater than 0.5, while a product is characterized as being of the low profit type, if its *critical fractile* is less than 0.5. A *critical fractile* is defined according to relation (4.1) that follows:

Critical Fractile under Centralised Operation

$$Cr.Fr. = \frac{p+g-c}{p+g} \tag{4.1}$$

Given the aforementioned product specification (*i.e. p*=250 *m.u*, *c*=50 *m.u.*, *g*=1 *m.u.*), the critical fractile becomes according to relation (4.1): $Cr.Fr. = \frac{p+g-c}{p+g}$ =0.8>0.5, which signifies that the product under study here is of the high profit type.

This *too low/too high* systematic pattern of human retailers' order quantities is known as the *pull-to-centre effect* (Bostian *et al*, 2008). A number of different individual behavioural biases are used by different researchers to justify these systematically erroneous decisions of human retailers, such as for example *risk-seeking*, *risk-aversion*, *reference-dependence*, *loss-aversion*, *waste-aversion*, *stock-out aversion*, *opportunity costs under-estimation*, *ex-post inventory error minimisation*, *mean anchor*, *demand chasing*, or collectively *bounded rationality* (Schweitzer and Cachon, 2000; Benzion *et al*, 2008; Bolton and Katok, 2008;

Bostian *et al*, 2008; Kremer *et al*, 2008; Su, 2008; Lurie and Swaminathan, 2009).

The result of the combination of the previous human decisions (*i.e*. *w* and *q*) is that the *wholesale price contract* is unable to give rise to the *first-best case maximum* profit $\prod_{\text{int}}^{*}$; its *inefficiency*, thus, predominates and the *double marginalization problem* remains. Nevertheless, the *efficiency score* that it attains is significantly higher than theoretically predicted. For this reason, it is established that the *wholesale price contract*'s overall performance is much better than theoretically expected (Keser and Paleologo, 2004; Katok and Wu, 2009). But it still remains open to further exploration whether it would be possible for the *wholesale price contract* to *coordinate* the *Newsvendor Problem*, namely attain an *efficiency score* that may not statistically differ from 1.

Building on the aforementioned existing results, the section that follows formulates the research hypotheses that this PhD thesis seeks to address for the *Newsvendor Problem* setting.

4.2 Research Hypotheses

This study addresses three distinct sets of research hypotheses: *First*, there is a research hypothesis that tests how human manufacturers' prices compare with perfectly rational, profit maximising prices *w**. *Second*, there are research hypotheses that test how human retailers' order quantities compare with overall profit maximising quantities q_{int}^{*} and individual profit maximising quantities *q**. *Last*, there are research hypotheses that concern the *efficiency score* that is attained by the overall channel; these test how the overall *efficiency score* compares to its corresponding theoretical prediction and whether the *double* *marginalization problem* dominates, namely, whether the *efficiency score* remains strictly lower than one. The paragraphs that follow outline and justify these research hypotheses.

4.2.1 Manufacturers' w-prices

In line with Keser and Paleologo's (2004) and Katok and Wu's (2009) earlier experimental results, human manufacturers would be expected to charge prices that are not consistent with the profit maximising price w^*. This is exactly what the first research hypothesis suggests. Although Keser and Paleologo (2004) provide evidence in favour of human manufacturers charging significantly lower prices than the rationally optimizing manufacturer w^*, the prices of Katok and Wu's (2009) subjects differ and depend on the magnitude of customer demand. Therefore, it is safer to leave the first research hypothesis about human manufacturers' *w*-prices as two-tailed.

Hypothesis NP.1 Human manufacturers charge *w*-prices that are significantly different from the rationally optimizing manufacturer's price w^* ($w \neq w^*$)

Since the price that the rationally optimizing manufacturer would charge (w^*) would maximise the manufacturer's profit, this price w^* could be considered as a 'locally good' price. So, this first research hypothesis implies that human manufacturers would not be expected to make 'locally good' decisions.

4.2.2 Retailers' q-quantities

Human retailers would be expected to order significantly different quantities than the ones that are predicted by the relevant standard normative models. In this regard, human retailers would be expected to reproduce the *pull-to-centre* effect that is experimentally verified for high profit products (*e.g.* Schweitzer and Cachon, 2000; Benzion *et al*, 2008; Bolton and Katok, 2008; Bostian *et al*, 2008), since the product that is here under study is of the high profit type (*i.e.* $Cr.Fr. = \frac{p+g-c}{p+g}$ =0.8>0.5). For this reason, human retailers would be anticipated to *under-order*, namely order significantly lower quantities than the rationally profit maximising *integrated newsvendor* q^*_{int}. Hence, research hypothesis 2.1 is as follows:

Hypothesis NP.2.1 Human retailers place orders of *q*-quantities that are significantly lower than the rationally profit maximising *integrated newsvendor's quantities* q^*_{int} $(q < q^*_{int})$

Moreover, human retailers would not be expected to order in accordance with the corresponding quantities q^* that would represent their *best possible replies* to manufacturers' prices (Keser and Paleologo, 2004; Katok and Wu, 2009). So, human retailers would be expected to order significantly different quantities than their rationally optimizing counterparts.

The different prices w that manufacturers charge to human retailers transform the *critical fractiles* defined by Schweitzer and Cachon (2000) as implied by relation (4.2).

<u>Critical Fractile under De-centralised Operation</u>

$$Cr.Fr. = \frac{p+g-w}{p+g} \tag{4.2}$$

The result is that a retailer may perceive a product of the high profit type as of the low profit type and may, additionally, interpret a product of the low profit type as a high profit product, depending on the price *w* that the interacting manufacturer charges.

Hence, the different manufacturer prices *w* have a significant effect on a retailer's individual interpretation of the *pull-to-centre effect*. This could be one of the reasons explaining why Keser and Paleologo (2004) and Katok and Wu (2009) obtain conflicting results for the *pull-to-centre effect*. Although Keser and Paleologo obtain no evidence of the *pull-to-centre effect*, Katok and Wu establish its prevalence. Since Keser and Paleologo's and Katok and Wu's human manufacturers charge significantly different prices, they also perceive critical fractiles in completely different ways and, thus, place orders of significantly different quantities. Nevertheless, both papers confirm human retailers' natural tendency to order significantly lower quantities than their *best possible replies* to manufacturers' prices q^*, that is irrespectively of these prices *w*. This is exactly why research hypothesis NP. 2.2 seeks to address whether human retailers' order quantities are significantly lower than their rationally optimizing counterparts, instead of testing human retailers' compliance with their individual interpretations of the *pull-to-centre* effect.

Hypothesis NP.2.2 Human retailers place orders of *q*-quantities that are significantly lower than the rationally optimizing retailer's quantities q^* ($q<q^*$).

Since the quantity that the rationally optimizing retailer would order (q^*) would maximise the retailer's profit, this quantity q^* could be considered as a 'locally good' order quantity. So, the research hypothesis NP.2.2 implies that human retailers would not be expected to make 'locally good' decisions.

4.2.3 Efficiency Scores

In line with Keser and Paleologo's (2004) earlier experimental result, the overall *efficiency scores* that would be attained by human manufacturer-retailer interactions are expected to closely follow their corresponding theoretical prediction of 0.85, which is the *efficiency score* that *Sub-section 2.1.1* estimates for the interaction of the price $w*$ that maximises the manufacturer's profit $\prod_s^*$ with the order quantity $q*$ that maximises the retailer's profit $\prod_r^*$. This is exactly what research hypothesis 3.1 seeks to address.

Hypothesis NP.3.1 The attained *efficiency scores* do not differ from 0.85 (*Eff*=0.85)

Yet, even in the instances that the overall attained *efficiency scores* do not coincide with 0.85 (Katok and Wu, 2009), provided that these instances exist, the overall *efficiency scores* are anticipated to remain significantly lower than 1 (Katok and Wu, 2009). In respect to this, it is expected that the *double marginalization* problem would persevere. The research hypothesis 3.2 serves to test exactly this phenomenon.

Hypothesis NP.3.2 The attained efficiency scores are significantly lower than 1 (*Eff*<1).

Since an *efficiency score* equal to one signifies that the *first-best case maximum* profit is attained, the research hypothesis NP.3.2 implies that the interaction of human manufacturers and retailers would not be expected to give rise to 'globally *efficient*' interactions, or else eliminate the *double marginalization problem*.

Now that the research hypotheses of this study have been formulated, how the approach of this PhD thesis, as outlined in *Chapter 3*, is applied to the *Newsvendor Problem* setting is described. In this way, the aforementioned research hypotheses can be tested.

4.3 The Approach

In order to elicit knowledge on how human subjects make their price and order quantity decisions and assess the overall performance of all their possible interactions, the approach that is presented in Figure 3.2 (*i.e Section 3.3*) has been adapted to the needs of the *Newsvendor Problem*. In this regard, in *Stage 1* the *decision variables* of each *agent* are recognised, namely the price for the manufacturer and the order quantity for the retailer. Following informal pilot sessions, the *decision attributes* that correspond to each *decision variable* are also identified. In *Stage 2* volunteers are randomly assigned to play the *manufacturer* and the *retailer* roles in simulation games and their consecutive decisions over time are recorded. To this end, all participants interact with a representative set of scenarios that are generated in accordance with the specification of the *Newsvendor Problem*. More specific details about the exact response sets that the different participants were provided follow in *Sub-section 4.3.2*. In *Stage 3* multiple regression models of the *first* order auto-regressive time-series type are fitted to each participant's data set of recorded decisions. In *Stage 4* the ABS model that corresponds to the *Newsvendor Problem* is run for all possible combinations of all human manufacturers' decision models with all human retailers' decision models. In this way, the respective outcomes can be compared and, thus, the research hypotheses about manufacturers' prices (*i.e*. NP.1), retailers' order quantities (*i.e*. NP2.1 - NP.2.2) and deriving *efficiency scores* (*i.e*.

NP.3.1 – NP.3.2) are investigated. Each of these stages is now described in some detail.

4.3.1 Stage 1: The Decision Making Process

The objective of the informal pilot sessions is to identify the *decision attributes* that correspond to the two *decision variables* of this study: that is, the price for manufacturers and the order quantity for retailers. These pilot sessions were conducted via simulation games, but differed from *Stage 2* gaming sessions in two ways. *First*, the subjects were provided all information that was relevant to their respective role over the course of the entire game; no previous round's data were hidden from them. *Next,* these simulation games were shorter in duration, yet, they were followed by interviews, during the course of which the subjects were encouraged to discuss which information they had found of relevance to their required decision task. They were also asked to explain the underlying reasoning for the decisions that they had made. In this way, the *decision attributes* that they had considered as significant for their respective decisions were identified.

From these informal sessions evidence is found that most participants almost ignore all history information, except for the last round. They also choose to take into account information about the present round, because this seems to have an immediate effect on their realised profits; this is why human retailers consider the prices that they are currently charged in their order quantity decisions. This selective behaviour of human subjects relates well to the individual bias that Camerer (1995) and Loch and Wu (2007) define as *immediacy.* The result of this selective behaviour of human subjects is the prominence, or else *salience,* of a sub-set of the available information over all history information, that is the past and present round's. Camerer (1995) and Loch and Wu (2007) also recognise *salience* as another significant behavioural bias that affects individual decision making.

In addition, in the informal interviews most human manufacturers admitted that they had relied heavily on the retailers' previous order quantities for their price decisions, while human retailers stated that they had based their order quantity decision on the previous demand realizations. The reason was that manufacturers could not predict with certainty the incoming order quantities; in the same way retailers could not predict with certainty the customer demand. Camerer (1995) and Loch and Wu (2007) perceive this tendency of individual decision makers to use relevant information that is available as a substitute for the underlying *uncertainty*. Last but not least, after the end of the game most volunteers revealed that they had difficulty in understanding how their current decisions would affect their profits and the system overall performance in the next round of the game. In order, thus, to make simpler and faster decisions, they preferred to use their own previously realised profit, as given to them by the computer interface. This simplification is viewed as the result of the *complexity* that is inherent with the *Newsvendor Problem*; Camerer (1995) and Loch and Wu (2007) consider *complexity* as another behavioural bias that seems to have a significant effect on individual decision making.

In accordance with the aforementioned behavioural biases and with Axelrod's (1997) KISS principle (*i.e*. Keep It Simple Stupid), human manufacturers (i = MAN) are considered to base each period's wholesale price decision $w(t)$ on the following three factors:

i. the previously charged wholesale price *w*(*t*-1) [*i.e. immediacy* and *salience*],

ii. the previously placed order quantity *q*(*t*-1) [*i.e. immediacy, salience* and *ambiguity*], and

iii. the previously realized profit $P_M(t-1)$ [*i.e. immediacy, salience* and *complexity*]

These are the manufacturers'*decision attributes* that have been used in the subsequent gaming sessions. Therefore, the relation (3.1) that presents the one-to-one association of the manufacturer's (*i* = *MAN*) *decision variable* *w*(*t*) with all corresponding *decision attributes* (*i.e.* *w*(*t*-1); *q*(*t*-1); $P_M(t-1)$) becomes:

The Price's Decision Function

$$< w(t) >_{MAN} = f_{MAN}^{w(t)}[\, w(t-1), q(t-1), P_M(t-1)] \tag{4.3}$$

For the same reasons, human retailers (*i* = *RET*) are considered to base each period's order quantity decision *q*(*t*) on the following four factors:

i. the currently charged wholesale price *w*(*t*) [*i.e. immediacy*],

ii. the last period's order quantity *q*(*t*-1) [*i.e. immediacy* and *salience*],

iii. the previously observed demand *d*(*t*-1) [*i.e. immediacy, salience* and *ambiguity*] and

iv. the previously realized profit $P_r(t-1)$ [*i.e. immediacy*, *salience* and *complexity*].

These are the retailers'*decision attributes* that have been used in the subsequent gaming sessions. Therefore, the relation (3.1) that presents the one-to-one association of the retailer's (i = R) *decision variable* $q(t)$ with all corresponding *decision attributes* (*i.e*. $w(t)$; $q(t\text{-}1)$; $d(t\text{-}1)$; $P_R(t-1)$) becomes:

<u>*The Order Quantity's Decision Function*</u>

$$< q(t) >_{RET} = f_{RET}^{q(t)}[\, w(t), q(t-1), d(t-1), P_R(t-1)] \tag{4.4}$$

The description of the *Newsvendor Problem* that is provided in *Sub-section 2.1.1* along with the decision functions (4.3) and (4.4) fully specify the ABS *Newsvendor* model, which is described in greater detail in the sub-section that follows.

Outcome 1: The Agent-Based Simulation Newsvendor Model

According to the exact specification of the *Newsvendor Problem* that is provided in *Sub-section 2.1.1*, there are two different types of agents: the *manufacturer-agent* and the *retailer-agent*. In accordance with the definition of an agent that is provided in *Section 3.2*, the bulleted list that follows briefly summarises how both the *manufacturer-agent* and the *retailer-agent* satisfy all requirements and are, thus, eligible to be considered as agents:

- *Social Ability*: both the *manufacturer-agent* and the *retailer-agent* have the social ability to communicate with each other and their surrounding environment. The *wholesale price contract* specifies all terms of trade and any exchange that occurs between them.

- *Capability to learn*: both the *manufacturer-agent* and the *retailer-agent* use the feedback information that is provided to them to better understand their partners' *reaction*s and any changes that are occurring to their environment. In this way, they can modify and, thus, adapt their behaviours accordingly. The reader should at this point be reminded that the decision functions of both the *manufacturer-agent* (*i.e*. relation 4.3) and the *retailer-agent* (*i.e*. relation 4.4) may remain fixed, but the *agents'* exact decisions do vary with time, depending on the previous period's results. This dynamic behaviour encapsulates their capability to learn.

- *Autonomy:* both the *manufacturer-agent* and the *retailer-agent* have separate and well determined goals to achieve and clearly defined internal logic rules that govern their actions.

- *Heterogeneity:* both the *manufacturer-agent* and the *retailer-agent* follow their own *intention*s and make different decisions.

In this regard, Table 4.1 outlines the basic structure (*i.e*. attributes and behavioural characteristics) of the *manufacturer-agent*; while Table 4.2 does so for the *retailer-agent*.

It is evident from Table 4.1 that the different *manufacturer-agent*s only differ in the exact values of their corresponding attributes; these are in turn given by the specific decision models of type (4.3) that have been fitted to the associated human manufacturer's respective decisions. Their exact values are reported in *Sub-section 4.3.3*, where the decision models that have been fitted to all participants' datasets of recorded decisions are presented. Nevertheless, the association of the manufacturer's (i = *MAN*) *decision variable* $w(t)$ with any *decision attribute*, that is the corresponding decision model coefficient, constitutes exactly what specifies the ABS model attribute (*e.g*. the association of $w(t)$ with $w(t\text{-}1)$ provides the ABS model attribute $a_{w(t-1)}^{w(t) \cdot M_i}$, that differs accross different *manufacturer-agent*s).

Following the same rationale, Table 4.2 shows that the different *retailer-agents* only differ in the exact values of their corresponding attributes. These ABS model attributes are in turn given by the decision models of type (4.4) that have been fitted to the human retailers' respective decisions. Although their exact values are reported in *Sub-section 4.3.3*, their specification is provided by the decision model of type (4.4) that associates the retailers' *decision variable* $q(t)$ with all corresponding *decision attributes*.

Table 4.1: The basic structure of the *manufacturer-agent*

The Manufacturer-Agent	
Attributes: Decision Model Coefficients • $a_0^{w(t)\cdot M_i}$ • $a_{w(t-1)}^{w(t)\cdot M_i}$ • $a_{q(t-1)}^{w(t)\cdot M_i}$ • $a_{P_M(t-1)}^{w(t)\cdot M_i}$	Behaviours: • Deciding a price *w* • Accepting an order (of quantity *q)* • Producing • Delivering a shipment • Incurring production cost • Earning profits

Table 4.2: The basic structure of the *retailer-agent*

The Retailer-Agent	
Attributes: Regression Coefficients • $\beta_0^{q(t)\cdot R_j}$ • $\beta_{w(t)}^{q(t)\cdot R_j}$ • $\beta_{q(t-1)}^{q(t)\cdot R_j}$ • $\beta_{d(t-1)}^{q(t)\cdot R_j}$ • $\beta_{P_R(t-1)}^{q(t)\cdot R_j}$	Behaviours: • Accepting a price *w* • Deciding an order quantity (of quantity *q)* • Receiving a shipment • Paying the total shipment cost • Satisfying customer demand • Incurring remaining inventory cost • Earning profits

The behaviour of the *manufacturer-agent* is presented in the statechart of Figure 4.3; while the behaviour of the *retailer-agent* is illustrated in Figure 4.4.

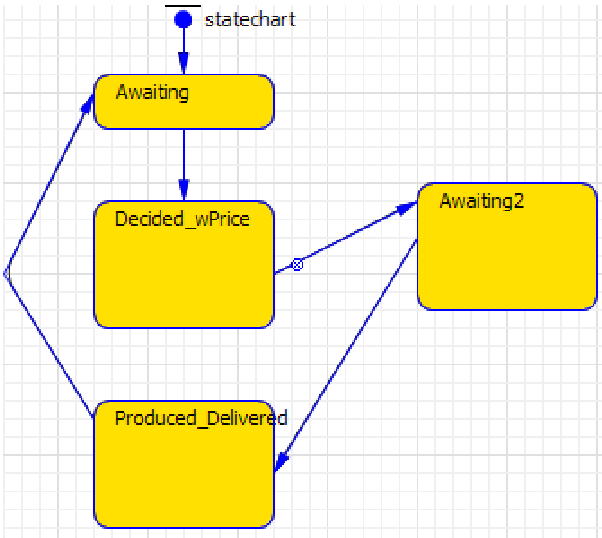


Figure 4.3: The statechart of the *manufacturer-agent*

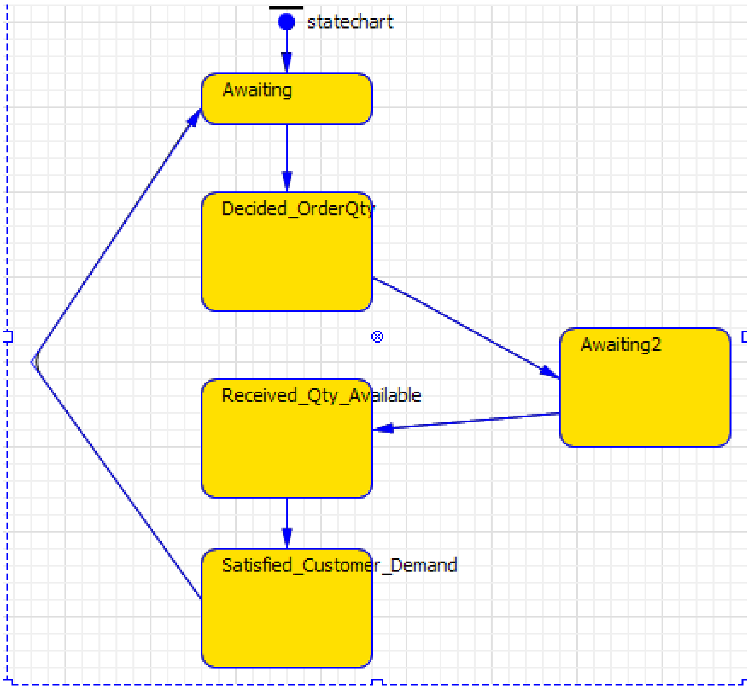


Figure 4.4: The statechart of the *retailer-agent*

From Figure 4.3 it is evident that the *manufacturer-agent* is considered to be in idle (*i.e.* awaiting) state while waiting for his/her partner's response to his/her initial decision. From Figure 4.4 it is evident that the *retailer-agent* is in an awaiting state in two different instances: *first*, while waiting for his/her partner's initiating price decision and *second*, while waiting to receive the manufacturer's shipment.

The underlying *environment* of the ABS model symbolizes the market, that is, the environment reflects the customer demand that is uncertain in nature. The element of *combined evolution* is of most relevance to the research hypotheses NP.3.1and NP.3.2 that concern, respectively, whether the *emerging efficiency scores* differ statistically from their corresponding theoretical prediction of 0.85 or are significantly lower than 1. In this way, it can be established whether 'globally *efficient*' interactions can *emerge* from the interactions of 'locally poor' decisions. 'Globally *efficient*' interactions would attain overall *efficiency scores* that would not differ significantly from 1. As for 'locally poor' decisions, they would be decisions that would differ substantially from the corresponding rationally optimizing counterparts'.

Based on the above specifications, given the problem's small size and mostly for reasons of speed of model build, ease of use and familiarity with the data presentation, a spreadsheet version of the model (in Excel-VBA) has initially been developed (Robinson, 2004; North and Macal, 2007). Nevertheless, North and Macal's (2007) suggestion to incrementally move up to a special purpose agent modelling facility has subsequently been followed. For this reason, a version of the model in AnyLogic® Version 6.2.2 (XJ Technologies, 2007) has then been developed. Figure 4.5 presents an example from an interface from the AnyLogic® version of the model.

In both of these two versions of the ABS *Newsvendor Problem* model true customer demand instances are obtained via integer values of normal distribution variates truncated at zero, according to Barr and Sherrill's (1999) recommendations. In order to ensure the efficacy and repeatability of results, these variates are produced by using the Mersenne-Twister pseudo-random number generator (Matsumoto and Nishimura, 1998). This AnyLogic© version of the model produces exactly the same results as the spreadsheet version of the model. The results that are obtained from the two different models have complete numerical identity, hence, successful "alignment" or "docking" of the two models is guaranteed (Axelrod, 1997: pp. 183).

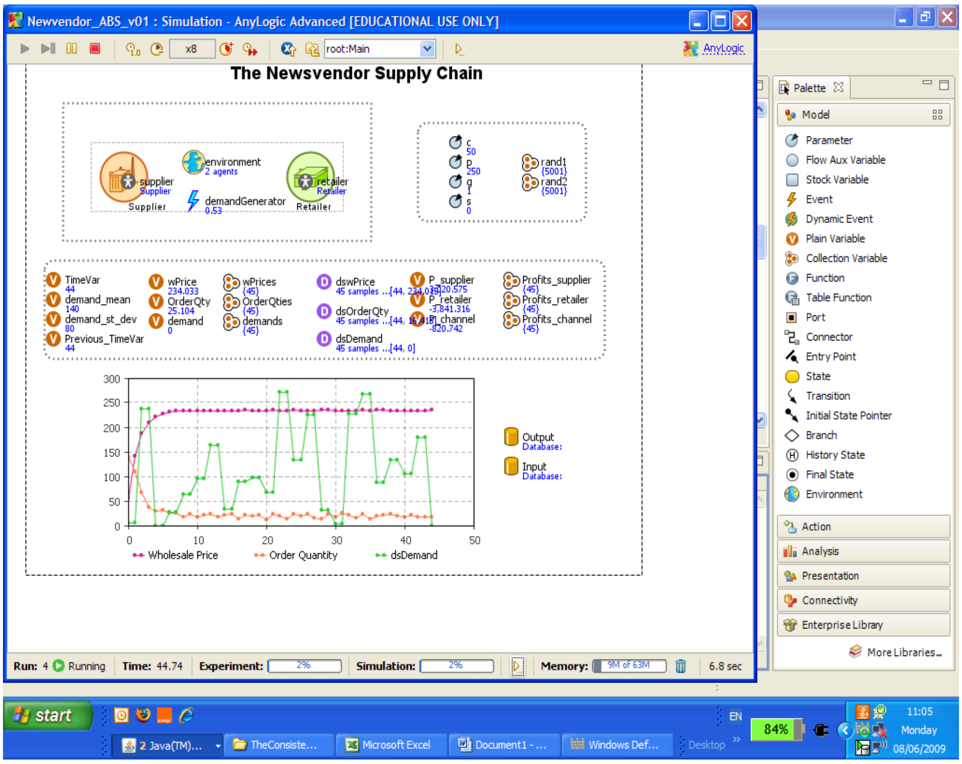


Figure 4.5: The AnyLogic© interface of the *ABS Newsvendor* model

4.3.2 Stage 2: The Gaming Sessions

The objective of the second stage is to collect data for each human decision maker. To this end, volunteers were recruited from a pool of 2007 graduate students at the University of Warwick. Three were asked to act as manufacturers (*i.e.* S_{MAN} = 3), denoted as MAN_1 to MAN_3 and four as retailers (*i.e.* S_{RET} = 4), denoted in turn as RET_1 to RET_4. Table 4.3 summarizes the main demographic characteristics of the human subjects that played the role of the manufacturer, while Table 4.4 does so for those who played the role of the retailer. The only requirement set was that all participants had received formal classroom training in the *Newsvendor Problem* prior to the experiment as part of their curriculum. The reason is that an earlier empirical study confirms the superior performance of well trained students acting as newsvendors compared to experienced supply chain managers (Bolton *et al*, 2008).

Participants were randomly assigned to play either the role of the manufacturer or the retailer against an automated retailer or manufacturer, respectively. They worked with a computer interface that simulated the interacting partner's responses. This computer interface has been adapted from the ABS model of the *Newsvendor Problem* that is developed at the end of *Stage 1* (*i.e. Outcome 1*). An illustrative screen shot of this computer interface, as shown to the human manufacturers, is given in Figure 4.6; while the corresponding screenshot of the computer interface that was presented to the human retailers is shown in Figure 4.7.

Table 4.3: The human manufacturers - subjects

Factor level	Course	Age
MAN_1	PhD in Management Subject Area: Information Systems and Management	29
MAN_2	MSc in Management	25
MAN_3	MSc in Management Science and Operational Research	23

Table 4.4: The human retailers - subjects

Factor level	**Course**	**Age**
RET_1	MSc in Management Science and Operational Research	24
RET_2	PhD in Management Subject Area: Industrial Relations / Organizational Behaviour	27
RET_3	MSc in Engineering Business Management	25
RET_4	PhD in Management Subject Area: Employment Research	27

At this point it is admitted that provision of automated players may not be as realistic as direct interaction of human manufacturers and retailers would, but it controls for social preferences and reputational effects, such as, for example, players' possible concern regarding fairness, reciprocity, status seeking and group identity (Loch and Wu, 2008; Katok and Wu, 2009) that remains outside the interests of this study.

Written instructions on the required task were distributed to all participants well in advance of their allocated session, so they could get familiar with the task and the available software as quickly as possible. The instructions informed the participants that the product under study is a perishable widget of general nature facing random customer demand. They were also made aware that each round's demand is independent of any previous round's, but they were not informed about the exact type of distribution that customer demand follows. The main reason is to protect the experimental design from the additional behavioural biases that are associated with the participants' potential inability to fully understand the nature of the demand distribution (Bearden and Rapoport, 2005).

The instructions that were distributed to the subjects who played the role of the manufacturer are presented in Appendix A.1, while the instructions that were distributed to the subjects who were asked to play the role of the retailer are outlined in Appendix A.2.

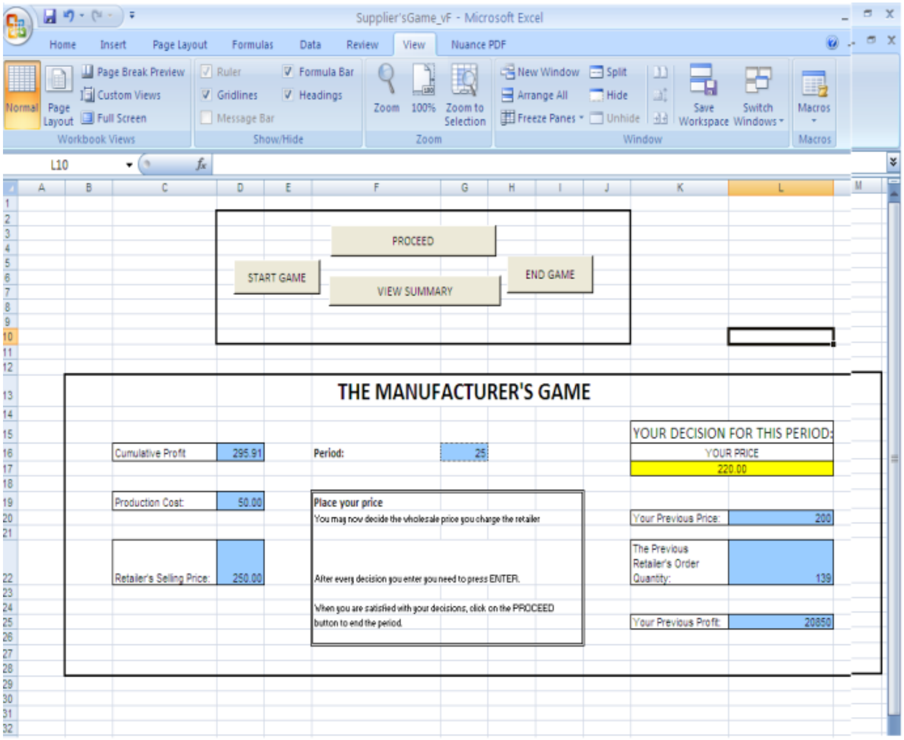


Figure 4.6: The computer interface of the simulation game that is faced by the human manufacturers

The participants were also instructed to make decisions that, to their best knowledge, would make the entire aggregate channel as highly profitable as possible. But in order to reflect real manufacturer-retailer interactions as accurately as possible, participants were not provided information about the aggregate channel profit that was realised at the end of each round. Finally, the participants were not offered any financial incentives, because there was no budget available to this end. Nevertheless, it remains unclear whether providing financial incentives would have a significant impact on the inferred decision making strategies (Smith and Walker, 1993; Camerer and Hogarth, 1999; Croson, 2002).

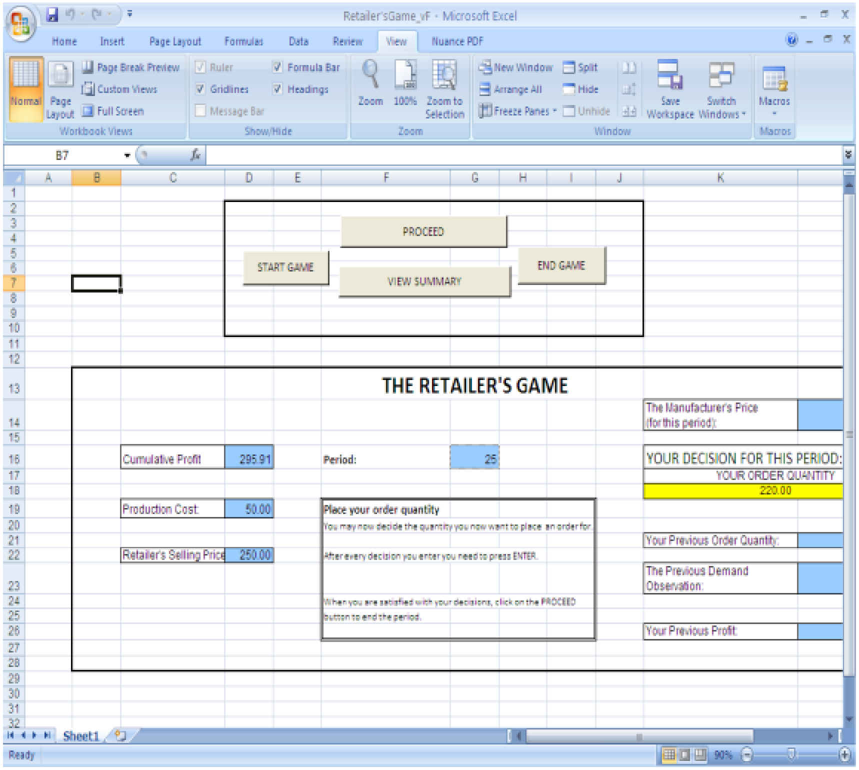


Figure 4.7: The computer interface of the simulation game that is faced by the human retailers

Apart from written instructions, the participants could address questions both before the start of the session and during its course. Nevertheless, the game could not be re-started once it had begun. Participants were asked to make their respective decisions consecutively, that is over a number of periods. In order to give participants some time to get used to their new roles, the first 10 rounds were used as trial periods; the participants were informed in advance about the fact that these rounds were only meant for their practice and would not count towards the final outcome (*i.e.* 'dry-run' periods: Friedman and Sunder, 1994, pg. 78). In total, the game was run for 50 consecutive rounds for each participant (including the trial periods). After every period participants received feedback on their previous decisions and their realized profit. The retailer also received feedback on the previous round's demand.

The reasons that manufacturers did not have access to this customer demand information were two-fold. *First*, customer demand did not have any impact on the manufacturer's profit, according to relation (2.5) (*s. Sub-section 2.1.1*). S*econd*, according to the existing tradition of "business flight simulators" (Sterman, 1989; 1992), sharing customer demand information would not represent reality accurately. The participants were not aware of the exact session's duration, so that end-of-game effects could be eliminated (Steckel *et al*, 2004). In order to comply with the minimum sample size requirements and ensure sufficient statistical power, more than 10 samples for each *decision attribute* were collected (Weisberg, 2005; Hair *et al*, 2006), namely 3x10 for the manufacturers' and 4x10 for the retailers' decision models, as given by relations (4.3) and (4.4), respectively.

All participants acting as the manufacturer were asked to play against the same automated retailer that exhibits all possible ordering strategies ranging from 0 to $q^* + 3 \cdot \sigma$ (σ = 80). In order to ensure consistency across different subjects' gaming sessions, all human manufacturers were presented with the same series of scenarios in exactly the same order. Figure 4.8 illustrates an indicative example of one of the participants' *w*-decisions over time (*i.e.* MAN_2). It is evident that MAN_2 systematically orders lower prices than would the rationally optimizing manufacturer w^* (*i.e.* $w<w^*$), which is in accordance with the research hypothesis NP.1 that postulates that human manufacturers charge *w*-prices that are significantly different from the rationally optimizing manufacturer's price w^* ($w \neq w^*$).

All participants acting as the retailer were asked to play against the same automated manufacturer that exhibits the same pricing strategy, charging all possible prices between c=50 and p=250, according to the uniform distribution. Figure 4.9 presents RET_1 q-decisions over time in purple colour.

Figure 4.8: MAN_2 w-prices, as observed in the laboratory

It seems that RET_1 systematically 'under-orders', or else places lower orders than would the rationally optimizing *integrated newsvendor* (*i.e.* $q < q^*_{int}$), which is in turn illustrated in blue colour. This visual observation for RET_1 is in support of the *pull-to-centre* effect, as perceived on the aggregated channel level and expressed by the research hypothesis N.P.2.1. From Figure 4.9, it is also evident that although RET_1 seems to closely follow the rationally optimizing retailer's order quantity q^*, he tends to order on average lower quantities than would the rationally optimizing retailer (*i.e.* $q<q^*$). The rationally optimizing retailer's order quantity q^* is presented in yellow colour. This observation lends support to the research hypothesis N.P.2.2, which postulates exactly that human retailers place orders of q-quantities that are significantly lower than the rationally optimizing retailer's quantities q^* ($q<q^*$). . Last but not least, RET_1's

attempt to closely follow customer demand (*i.e. demand chasing*) is obvious. In Figure 4.9 demand realisations are coloured in green.

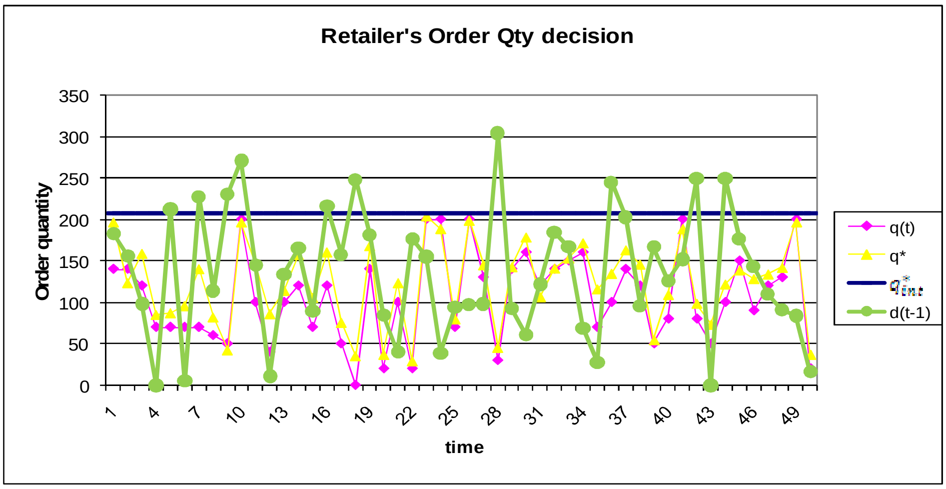


Figure 4.9: RET_1 *q*- quantities, as observed in the laboratory

Outcome 2: The Datasets of Participants' recorded Decisions

All participants' recorded decisions are collectively gathered with the associated *decision attributes* in appropriate datasets. The dataset of recorded decisions of RET_1 is indicatively attached to Appendix A.3.

4.3.3 Stage 3: The Decision Making Strategies

The objective of the third stage is to determine the decision model that corresponds to each participant, namely specify the relations of type (4.3) that correspond to each human manufacturer *i* (MAN_i with $i = 1,...,3$) and the relations of type (4.4) that correspond to each human retailer *j* (RET_j with $j = 1,...,4$).

Since all participants' recorded *w*- and *q*- decisions satisfy the *linearity*, *normality* and *hetero-skedasticity* requirements of linear regression (Weisberg, 2005; Hair *et al*, 2006), each human manufacturer's (MAN_i) pricing strategy is portrayed as the first order auto-regressive time-series models *AR*(1) of type (4.5) and each human retailer's (RET_j) ordering strategy is reflected by the corresponding first order auto-regressive time-series models *AR*(1) of type (4.6) (Mills, 1990; Box *et al*, 1994; Hamilton, 1994; Greene, 2002). The exact testing procedure that has been followed to ensure that the *linearity*, *normality* and *hetero-skedasticity* requirements of linear regression are satisfied is attached to Appendix A.4 (Weisberg, 2005; Hair *et al*, 2006).

<u>*Types of Decision Models in the Newsvendor Problem*</u>

$$\langle w(t)\rangle_{MAN_i} = a_0^{w(t)\cdot_{MAN_i}} + a_{w(t-1)}^{w(t)\cdot_{MAN_i}} \cdot w(t-1) + a_{q(t-1)}^{w(t)\cdot_{MAN_i}} \cdot q(t-1) + a_{P_M(t-1)}^{w(t)\cdot_{MAN_i}} \cdot P_M(t-1) \tag{4.5}$$

$$\langle q(t)\rangle_{REt_j} = \beta_0^{q(t)\cdot_{RET_j}} + \beta_{w(t)}^{q(t)\cdot_{RET_j}} \cdot w(t) + \beta_{q(t-1)}^{q(t)\cdot_{RET_j}} \cdot q(t-1) + \beta_{d(t-1)}^{q(t)\cdot_{RET_j}} \cdot d(t-1) + \beta_{P_R(t-1)}^{q(t)\cdot_{R_{ETj}}} \cdot P_R(t-1) \tag{4.6}$$

In these simple linear models, the value of each coefficient $a_k^{w(t)\cdot_{MAN_i}}$(where $k = w(t-1);\ q(t-1);\ P_M(t-1)$) and $\beta_k^{q(t)\cdot_{RET_j}}$ (where $k = w(t);\ q(t-1);\ d(t-1); P_R(t-1)$) reflects the importance that each manufacturer MAN_i and retailer RET_j, respectively, assign to each of the *decision attribute*s that they consider for their respective *decision variables* $\langle w(t)\rangle_{MAN_i}$ and $\langle q(t)\rangle_{RET_j}$.

The reason that no interaction terms are included in the above decision models (4.5) and (4.6) is that the high *adjusted coefficients of determination* that have been attained by all decision models fitted (*i.e.* R^2>70%) are interpreted as an indication that there is no reason to include any additional terms (Weisberg, 2005; Hair *et al*, 2006; Fox, 2008). Although the *adjusted coefficient of* *determination* and the *coefficient of determination* indicate the degree of the dependent variable's variability that is explained by the list of independent variables, the reason that the *adjusted coefficient of determination* is preferred over the *coefficient of determination* to assess a decision model's goodness-of-fit is that it additionally incorporates the possible effect of the sample size (Hair *et al*, 2006; Fox, 2008). More details about the decision models' goodness-of-fit are provided later on.

At this point the reader should be informed that for some of the human manufacturers' MAN_i and retailers' RET_j decision models the corresponding profits $P_M(t-1)$ and $P_R(t-1)$ are removed from the list of independent variables. This is due to the high multi-collinearity that is existent between the profits $P_M(t-1)$ and $P_R(t-1)$ and the remaining independent variables (*i.e.* $w(t-1)$, $q(t-1)$ and $w(t)$, $q(t-1)$, $d(t-1)$, respectively). High *multi-collinearity* is exhibited by tolerance levels that are lower than 0.10. *Tolerance levels* are defined as the amount of variability of $P_M(t-1)$ and $P_R(t-1)$, that cannot be explained by the remaining independent variables, that is $w(t-1)$, $q(t-1)$ and $w(t)$, $q(t-1)$, $d(t-1)$, respectively (Hair *et al*, 2006).

Since in the decision models (4.5) and (4.6) the lagged dependent variable (*i.e.* $w(t-1)$ and $q(t-1)$) is included in the list of explanatory variables, auto-correlation is existent within all the collected data-sets, which is also confirmed by the Breusch-Godfrey test (Breusch, 1978; Godfrey, 1978). For this reason, the appropriate quasi-differences data transformations are applied. Nevertheless, because of the relatively small sample sizes (*i.e.* $N_{M|AN}$=30, N_{RET}=40) and the low values of correlation ρ, the ordinary least squares estimators are used instead of the feasible generalised least squares that are tailored to time-series processes (Rao and Griliches, 1969).

Outcome 3: The Participants' Decision Models

The linear regression models that have been fitted to the human manufacturers MAN_i datasets of recorded decisions, along with their corresponding *t*-values and *p*-values are presented in Table 4.5, while the respective models that have been fitted to the human retailers RET_j sets of decisions are provided in Table 4.6. The *p*-values demonstrate the lowest significance level for which the corresponding *decision attribute*s are taken into account by subjects MAN_i and RET_j in their respective *decisions variables* $\langle w(t) \rangle_{SUP_i}$ and $\langle q(t) \rangle_{RET_j}$.

It is evident from Table 4.5 that all human manufacturers (MAN_i with i=1,..,3*)* assign significant importance to the wholesale price that they charged during last period $w(t$-1) (significant at levels lower than 0.1%). Nevertheless, no human manufacturer takes into account the profit that he/she previously realized ($|t\text{-values}|<2.763$, which is the critical value at the 0.1% significance level).

Although human manufacturers do assign some marginal consideration to the retailer's response quantity ($q(t$-1)), the corresponding *t*-values indicate that this effect might not differ statistically from zero (corresponding *p*-values>0.45). Most probably it is because the manufacturers lack the knowledge and control over the way that retailers order that they tend to only base their *w*-decisions on their own previous *w*-prices. Overall the decision models that have been fitted to human manufacturers are statistically significant at the 1% level and explain more than 85% of the total variation that exists in their recorded decisions ($adj.R^2$).

Table 4.5: Human manufacturers' linear regression decision models

	MAN₁			*MAN₂*			*MAN₃*		
	Coef.	*t*-value	*p*-value	*Coef.*	*t*-value	*p*-value	*Coef.*	*t*-value	*p*-value
$a_0^{w(t)_{MAN_i}}$	115.851	14.710	<0.001	43.929	4.919	<0.001	11.733	2.596	0.015
$a_{w(t-1)}^{w(t)_{MAN_i}}$	0.506	15.941	<0.001	0.769	19.098	<0.001	0.921	32.955	<0.001
$a_{q(t-1)}^{w(t)_{MAN_i}}$	-0.014	-0.708	0.485	0.011	0.404	0.689	-0.002	-0.097	0.923
$a_{P_M(t-1)}^{w(t)_{MAN_i}}$	0	-0.002	0.998	0	0.003	0.998	0	0.005	0.996
Adj. R^2	0.852			0.889			0.958		

Table 4.6 demonstrates that RET_1, RET_2 and RET_3 concentrate on the wholesale price *w*(*t*) that their manufacturer charges to them (significant at levels lower than 0.1%). On the contrary, RET_4 seems to ignore this exogenously set price for which he has neither understanding nor control (│t-values│<2.712, which is the critical value at the 1% significance level). Instead he prefers to concentrate on his own earlier order quantity decision *q*(*t*-1) and previously realised profit $P_R(t-1)$ (significant at levels lower than 0.1%). Finally, RET_2 is the only human retailer who does take into account the previous demand realization *d*(*t*-1) for his order quantity decision *q*(*t*) (significant at the 0.5% level).

Overall the decision models that have been fitted to human retailers' decisions are statistically significant at the 1% level and explain more than 70% of the total variation that is inherent in their recorded decisions (*adj.*R^2).

Table 4.6: Human retailers' linear regression decision models

	RET_1			*RET_2*		
	Coef.	*t*-value	*p*-value	*Coef.*	*t*-value	*p*-value
$\beta_0^{q(t)_{RET_j}}$	246.807	18.564	<0.001	258.416	12.294	<0.001
$\beta_{w(t)}^{q(t)_{RET_j}}$	-0.945	-17.686	<0.001	-1.030	-13.110	<0.001
$\beta_{q(t-1)}^{q(t)_{RET_j}}$	-0.033	-0.449	0.656	0.180	2.311	0.027
$\beta_{d(t-1)}^{q(t)_{RET_j}}$	-0.045	-0.852	0.400	0.262	3.018	0.005
$+\beta_{P_R(t-1)}^{q(t)_{RET_j}}$	0	0.813	0.421	-0.001	-3.146	0.003
Adj. R^2	0.867			0.778		
	RET_3			*RET_4*		
	Coef.	*t*-value	*p*-value	*Coef.*	*t*-value	*p*-value
$\beta_0^{q(t)_{RET_j}}$	246.067	14.492	<0.001	32.589	2.938	0.006
$\beta_{w(t)}^{q(t)_{RET_j}}$	-0.952	-18.690	<0.001	-0.048	-1.048	0.301
$\beta_{q(t-1)}^{q(t)_{RET_j}}$	0.035	0.469	0.642	0.455	5.797	<0.001
$\beta_{d(t-1)}^{q(t)_{RET_j}}$	0.173	2.285	0.028	0.029	0.794	0.432
$\beta_{P_R(t-1)}^{q(t)_{RET_j}}$	-0.001	-1.591	0.120	0.002	6.785	<0.001
Adj. R^2	0.881			0.724		

4.3.4 Stage 4: The Agent-Based Simulation Model Runs

The object of the fourth stage is to explore under all possible interactions of inferred decision making strategies the overall performance of the *wholesale price contract* in the *Newsvendor Problem setting*. To this end, the ABS model of the *Newsvendor Problem* is run for all possible combinations of decision models. In greater detail, the interacting manufacturers' and retailers' respective decision models are treated as the two treatment factors of analysis (TF_1: manufacturer, TF_2: retailer), with TF_1 appearing at s_1=4 levels (SUP_i, i=1, 2, 3, *OPT*) and TF_2 at s_2=5 levels (RET_j, j=1, 2, 3, 4, *OPT*). The reason that the rationally optimizing manufacturer and retailer (with the index *OPT*) are kept in the experimental design is that in this way it would be much easier to directly compare the human manufacturers' and retailers' decisions to their rationally optimizing counterparts'. Since the total number of all possible $TF_1 – TF_2$ combinations (TF_1 x TF_2 =20) is not prohibitively high, *Chapter 5* reports the simulation results of the resulting asymmetrical, full factorial 'two way layout' experimental design (Robinson, 2000; Toutenburg, 2002; Mukerjee and Wu, 2006).

But in order to draw statistically accurate conclusions and, thus, test the research hypotheses that concern the simulated human manufacturers' *w*- prices (*i.e*. NP.1), the simulated human retailers' *q*-quantities (*i.e*. NP. 2.1 and NP. 2.2) and the attained *efficiency scores* (*i.e*. NP. 3.1 and N.P. 3.2), a number of conventions need to be applied to all ABS model runs. The run strategy that is followed (*i.e*. warm-up, run length and number of replications) is summarized in the paragraph that follows.

Figures 4.10 and 4.11 demonstrate how manufacturers' and retailers' decision rules require some time to converge to their steady state mean values, since they start from an initial state that is far removed from the corresponding steady state mean values. To this end, the examples of the manufacturer MAN_1, when interacting with RET_1 and the retailer RET_1, when in turn interacting with MAN_1, are illustrated in purple colour. Similar conclusions can also be drawn for all decisions of all participants in all studied treatment combinations.

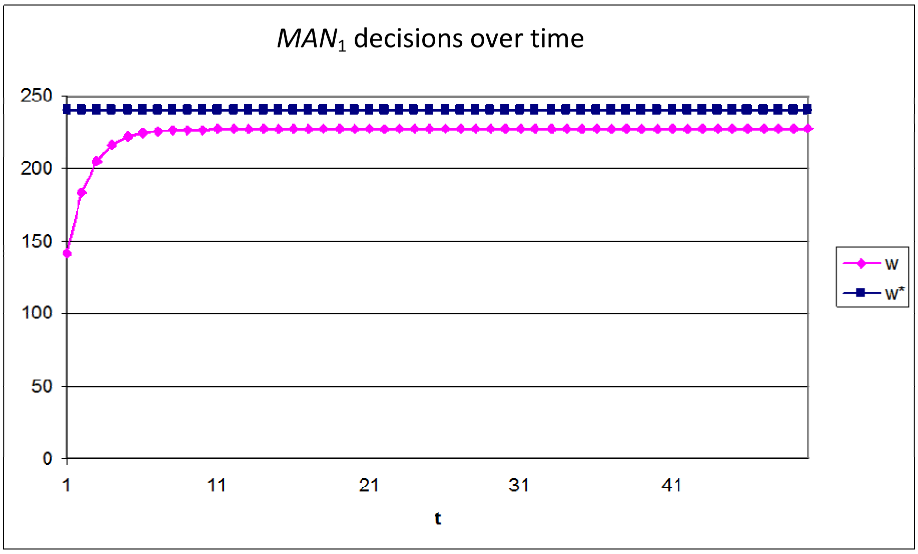


Figure 4.10: MAN_1 *w*-decisions over time, according to the simulation model (when in interaction with RET_1)

In order, thus, to ensure that inferences are not made while the "initialization bias" phenomenon (Pidd, 2004; Robinson, 2004; Law, 2007; Hoad *et al*, 2009a) is still present and, in addition, to obtain accurate estimates of mean performances, the following run strategy is implemented: *i.* An estimate of the warm-up length is established, according to the MSER-5 method (White, 1997; White and Spratt, 2000). The warm-up length is found from the longest warm-up (*i.e.* of the efficiency score) for all the output values to amount to 160 time periods. *ii.* The model is run for 1,800 time periods (including the warm-up), according to Banks *et al*.'s (2005) recommendation to run for at least ten times the length of the warm-up period. *iii.* In order to obtain accurate estimates of mean performances each simulation ran is replicated for *n*=100 times, following Hoad *et al*.'s (2009b) replications algorithm.

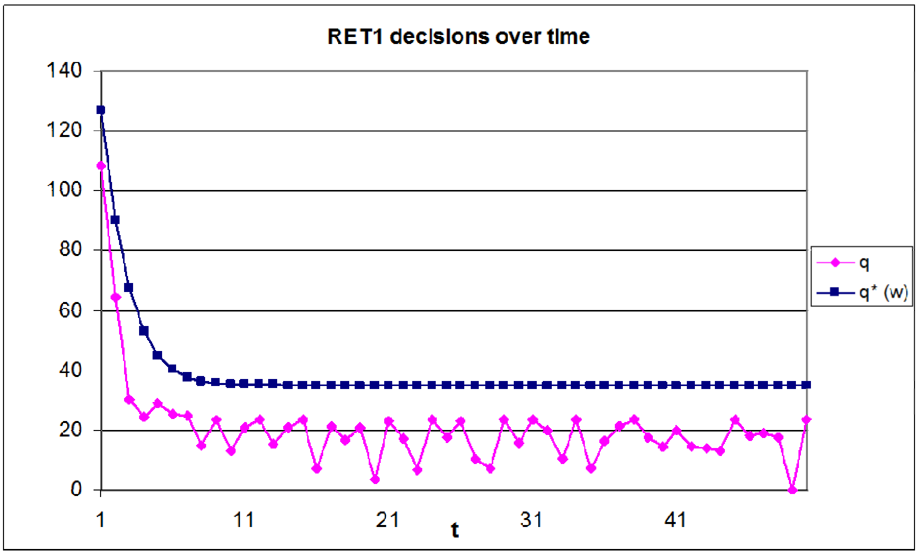


Figure 4.11: RET_1 *q*-decisions over time, according to the simulation model (when in interaction with MAN_1)

Outcome 4: The Key Outcomes

The key outcomes that are obtained from the *ABS Newsvendor* model (*i.e.* manufacturers' *w*-prices, retailers' *q*-quantities and *emergent* interactions' *efficiency scores*) are presented in *Chapter* 5.

4.4 Verification and Validation

Although verification and validation are performed in parallel with developing any version of the ABS *Newsvendor* model (North and Macal, 2007; Robinson, 2008), some steps that have been undertaken to verify and validate the ABS model are summarised in the paragraphs that follow.

Since the objective of all verification activities is to ensure that the ABS model performs according to its *intend*ed use and specification from an operational perspective (Law, 2007; North and Macal, 2007), source code analysis and 'unit testing' have been performed (Pidd, 2004; North and Macal, 2007).

As the objective of validation is to check whether the ABS model under study successfully represents and correctly reproduces the behaviours that are observed in its real-world equivalent, both the agents' distinct behavioural rules and the overall ABS model behaviour have been validated (Robinson, 2004; Law, 2007; North and Macal, 2007). In respect to validating the agents' decision rules, a *reliable correspondence* (of at least 80%) between the agents' simulated decisions and the corresponding participants' true decisions, as observed in the laboratory, has been ensured (Sterman, 1989). In view of validating the overall ABS model behaviour, 'black box validation' (Pidd, 2004; Robinson, 2004) has been performed, according to which the results that are obtained from the ABS model seen as a whole are compared with extant, confirmed, results (Swaminathan *et al*, 1998; North and Macal, 2007). The exact reasoning under which 'black box' validation has been performed is highlighted in *Section 5.3*. Last but not least, the successful "alignment" or "docking" (Axelrod, 1997: pp. 183) of the spreadsheet and Anylogic versions of the model are viewed as a further successful validation exercise of this study (North and Macal, 2007).

4.5 Summary

This chapter reminds the reader of the *Newsvendor Problem*'s specification and the existing analytical and experimental results. It then uses these known results to build the research hypotheses about human manufacturers' *w*-prices being significantly different from the rationally optimizing manufacturer's price w^* (*i.e.* NP.1), human retailers' q-quantities being significantly lower than the rationally profit maximising *integrated newsvendor's quantities* q_{int}^* (*i.e.* NP.2.1) and the rationally optimizing retailer's quantities q^* (*i.e.* NP.2.2), the *emerging efficiency scores* being not significantly different from 0.85 (*i.e.* N.P.3.1) and significantly lower than 1 (*i.e.* NP.3.2).

The chapter subsequently describes the approach that this PhD thesis has followed to address the aforementioned research hypotheses. In greater detail, this research uses adequate ABS models, which have been calibrated via human experiments. In this way, it builds statistically accurate conclusions about the effect that different prolonged interactions between dynamic, heterogeneous and autonomous decisions of human manufacturers and retailers can have on the *wholesale price contract*'s *efficiency*. Therefore, it manages to accommodate: *i.* human *intentions* that might be different from profit maximisation, *ii.* human *actions* that might differ from their corresponding *intentions* in heterogeneous ways (*i.e.* heterogeneous *bounded rationality*), *iii.* human *reactions* that might depend on their surrounding environment and changes that occur, if any and *iv.* human *decisions* that are *independent* and *autonomous*. In this way, it successfully addresses the literature gaps G.1-G.4 that are identified in Table 2.5 (*s. Section 2.4*) for the *Newsvendor Problem*.

Chapter 5 presents the results that are obtained from the ABS *Newsvendor* model, so that statistically accurate conclusions about the research hypotheses NP.1, NP.2.1-NP.2.2 and NP.3.1-NP.3.2 can be drawn.

Chapter 5

The Newsvendor Problem Results

The purpose of this chapter is to draw statistically accurate conclusions about the effect that different prolonged interactions between manufacturers' and retailers' dynamic, heterogeneous and autonomous decisions can have on the *wholesale price contract's efficiency*, when applied to the *Newsvendor Problem* setting. To this end, this chapter presents and discusses the results that are obtained from the ABS model that is described in the previous chapter (*i.e. sub-section 4.3.4*). In this way, *Chapter 5* addresses the research hypotheses that concern human manufacturers' *w*-prices ($w \neq w^*$: *i.e.* NP1), human retailers' *q*-quantities ($q < q^*_{int}$: *i.e.* NP.2.1 and $q < q^*$: *i.e.* NP.2.2) and the *emerging efficiency scores* (*Eff*=0.85: *i.e.* N.P.3.1; *Eff*<1: *i.e.* NP.3.2) that are formulated in *Section 4.2*.

This chapter presents the results that are acquired from the ABS model in the same order that the research hypotheses are also provided. It starts by discussing the simulated human manufacturers' *w*-prices, proceeds to the simulated human retailers' *q*-quantities and finishes with exposing the *emergent* interactions' *efficiency scores*. The chapter concludes with a brief discussion and a reflection on the managerial implications and practical significance of the results that are obtained.

The steady-state mean results of *n*=100 simulated replications for all possible treatment combinations are presented in corresponding tables. These tables also report between parentheses *()* in *italics font* the standard deviation of all the replications' results, while they also provide between brackets **[] in bold font** the half widths of the corresponding 99% confidence intervals. The reason all inferences are based on the low significance level of α = 0.01 is on the side of caution in rejecting a null hypothesis and, so, reducing the probability of committing a *Type I* error.

5.1 Manufacturers' *w*-prices

The object of this section is to test the research hypothesis about human manufacturers' *w*-prices being significantly different from the rationally optimizing manufacturer's price w^* (*i.e.* NP1). In this regard, Table 5.1 presents all simulated human manufacturers' steady- state mean $\overline{w}$-prices over n = 100 simulated replications for all 20 treatment combinations studied.

It is evident from Table 5.1 that the human manufacturers' simulated $\overline{w}$-prices have standard deviations that are equal to or very close to 0, that is, they do not vary much, when asked to interact with different retailers. The reason is that for every new decision they make they do not take into account their retailers' response quantities to a statistically significant degree, as the non-differing than 0 coefficients for $q(t\text{-}1)$ (*i.e.* $a_{q(t-1)}^{w(t)\cdot M_i}$) can demonstrate (*s.* Table 4.3). Meanwhile, MAN_{OPT} consistently charges w^*=184 monetary units (according to expression (2.7)), which is independent of the retailer's response and, thus, the underlying random demand observations. This is why the standard deviations in the last row of Table 5.1 are exactly equal to 0, turning all corresponding half-width 99% confidence intervals for all $\overline{w}$-decisions reported to 0. The same is also true for all standard deviations and half-width 99% confidence intervals in the last column of Table 5.1, as RET_{OPT} consistently orders quantities that would maximise his/her respective expected profit. So, there is no fluctuation in the mean $\overline{w}$–prices for the different replications.

From Table 5.1 there seem to be two different strategies that the simulated human manufacturers i=1,...,3 employ to ensure their profitability. *First*, they might attempt to maximise their individual profits by reserving strictly positive profit margins; in this regard, charging high prices would guarantee strictly positive profit margins. For this reason, this pricing strategy can be characterised as 'profit margin - driven'. *Alternatively*, they might prefer to attract a demand that is sufficiently high to maximise their individual profit; in order to achieve this, they might insist on charging low prices. In this regard, this pricing strategy could be viewed as 'demand – driven'. In respect to these pricing strategies, MAN_1 appears to adopt the first strategy (*i.e*. 'profit margin – driven'), initially charging the highest price and subsequently adjusting his initial decision only to a moderate degree. In contrast, MAN_3 appears to adopt the completely opposite strategy (*i.e*. 'demand – driven') by initially charging lower prices to stimulate demand and then adjusting her prices to further improve the interacting retailers' response quantities. As for MAN_2, he prefers some mixture of the above two strategies (*i.e*. 'demand and profit margin – driven'), because he initially charges low prices, while he subsequently increases his prices to such a degree that become on average higher than the rationally optimizing manufacturer's (*i.e*. w^*=184 *m.u.*).

MAN_1, in all the interactions in which he participates, charges the highest mean $\overline{w}$-prices. Thus, MAN_1 systematically 'over-charges', namely charges prices that are even higher than the rationally optimizing manufacturer's MAN_{OPT} (at a significance level that is lower than 0.1%). MAN_1's prices are followed in order of decreasing magnitude by MAN_2's, whose $\overline{w}$-prices are still significantly higher than w^* (at a significance level that is lower than 1%). As for MAN_3, in all the interactions in which he participates, MAN_3 'under-charges', namely charges prices that are significantly lower than the rationally optimizing manufacturer's MAN_{OPT} (at a significance level that is lower than 0.1%).

Since all simulated human manufacturers charge significantly different prices than the rationally optimizing manufacturer MAN_{OPT}, the research hypothesis NP.1 could not be rejected (*i.e.* $w \neq w^*$: at $p<0.01$). It is very interesting that some of the simulated human manufacturers' *bounded rationality* leads them to charge prices that are even higher than required to maximise their expected profit. That is why it becomes even more interesting to understand the *emergent efficiency scores* that these high prices would generate.

5.2 Retailers' *q*-quantities

Attention is now turned to how *boundedly rational* human retailers respond to the above manufacturer $\overline{w}$-prices. The reason that the simulated retailers' $\bar{q}$-quantities are interesting is because the simulated human manufacturers' $\overline{w}$-prices are high and, thus, generate low profit margins for the retailers. That is why, in contrast to the research hypothesis NP.2.2, the simulated human retailers would normally be anticipated to 'over-order', that is on average order higher quantities than their rationally optimizing counterpart ($q^*(\overline{w})$). This is due to their individual interpretations of the *pull-to-centre* effect, as results from the high $\overline{w}$-prices that they are charged by the simulated human manufacturers. In other words, their respective, individual versions of the *pull-to-centre* effect differs from the aggregate channel's, because each human retailer individually perceives the product under study as of the low profit type, given that the $\overline{w}$-prices that they are charged produce critical fractiles $\frac{p+g-\overline{w}}{p+g}$ that are well below 0.5 for all studied treatment combinations.

In this regard, the purpose of this section is two-fold: *i*. test the research hypotheses that concern human retailers' q-quantities being significantly lower than the rationally profit maximising *integrated newsvendor's quantities* q_{int}^{*} (*i.e*. NP.2.1) and the rationally optimizing retailer's quantities $q*$ (*i.e*. NP.2.2) and *ii*. test whether the simulated human retailers comply with their individual interpretations of the *pull-to-centre effect*. In respect to this, Table 5.2 presents all simulated human retailers' steady-state mean $\bar{q}$-quantities over n = 100 simulated replications for all 20 treatment combinations studied.

From the last column of Table 5.2 it is detected that the standard deviations of all observations and resulting half width 99% confidence intervals of all combinations, in which the rationally optimizing retailer participates, amount to 0. The reason is again that the rationally optimizing retailer orders quantities that would maximise his/her expected profit and, thus, do not depend at all on the demand observations that vary from one period to the next.

Table 5.2 demonstrates that all human retailers order significantly lower quantities than the rationally optimizing *integrated newsvendor* would ($q_{int}^{*} = 202$). Therefore, the research hypothesis NP.2.1 cannot be rejected (q<q_{int}^{*}: at p<0.001). This conclusion provides further favourable evidence for the *pull-to-centre* effect as perceived on the aggregate channel's level, that is, in addition to the already existing evidence (*e.g*. Schweitzer and Cachon, 2000; Benzion *et al*, 2008; Bolton and Katok, 2008; Bostian *et al*, 2008).

Moreover, RET_1 is the only simulated human retailer who orders quantities that are significantly lower than the rationally optimizing retailer's ($q^{*}(\bar{w})$). Thus, the research hypothesis NP.2.2 cannot be rejected for RET_1 (q<q*: at p=0.01) and it can also be concluded that RET_1 does not order according to his individual interpretation of the *pull-to-centre* effect. In other words, the 'under-ordering' behaviour that RET_1 employs seems to be driven by his strong preference to 'minimise left - overs' that at the end of the period need to be dismissed. The result is that RET_1 quantity decisions are kept further away from the rationally optimizing *integrated newsvendor*'s (q^*_{int}).

RET_2 and RET_4 order significantly higher quantities than the rationally optimizing retailer ($q^*(\overline{w})$). Therefore, the research hypothesis NP.2.2. needs to be rejected for RET_2 and RET_4 (at the 1% significance level). But RET_2 and RET_4 are the only simulated human retailers who satisfy their individual interpretations of the *pull-to-centre* effect. This ordering behaviour that is exhibited by both RET_2 and RET_4 seems to be driven by their strong preference to 'maximise sales'. In greater detail, neither RET_2 nor RET_4 would like to lose sales because of inventory unavailability. The result is that, in their attempt not to disappoint any potential customers, RET_2 and RET_4, order quantities that tend to more closely approximate the rationally optimizing *integrated newsvendor*'s (q^*_{int}).

Finally, RET_3 is the only simulated human retailer whose order quantities do not substantially differ from the rationally optimizing retailer's ($q^*(\overline{w})$). Hence, the research hypothesis NP.2.2. needs to be rejected for RET_3 (at the 1% significance level). It is also evident that since RET_3 's $\overline{q}$-quantities closely follow the rationally optimizing retailer's ($q^*(\overline{w})$), RET_3 almost ignores his individual interpretation of the *pull-to-centre* effect. In greater detail, RET_3 appears to order slightly more than $q^*(\overline{w})$ in the case where he interacts with the most expensively charging manufacturer, namely SUP_1, and significantly less than $q^*(\overline{w})$, in the case where he interacts with the remaining manufacturers SUP_2, SUP_3 and SUP_{OPT}. For this reason, RET_3 appears to employ in his ordering decisions a combination of preferences, that is, 'left - overs minimisation and sales maximisation'.

In summary, it is surprising that although RET_1, RET_2, RET_3 follow rather similar ordering strategies in that they mostly rely on the prices that are currently charged by their manufacturer *w(t)*, they place order quantities that are so considerably different. It is also very interesting that the simulated human retailers who are driven by 'sales maximisation' would tend to comply with their own individual interpretation of the *pull-to-centre* effect, while the simulated human retailers who are driven by 'left – overs minimisation' would almost ignore their own individual interpretation of the *pull-to-centre* effect. Last but not least, most of the simulated human retailers prove to be consistent in their preferred ordering strategies, namely they do not vary noticeably their order quantities in response to the prices that are charged to them. Attention is now turned to how these ordering strategies affect the *emergent efficiency scores* that are attained by all the interactions studied.

5.3 Emergent *Efficiency Scores*

The objective of this section is to test the research hypotheses that concern the *emergent efficiency scores*, namely test whether these are not different to the corresponding theoretical prediction of 0.85 (*i.e*. NP.3.1) and significantly lower than 1 (*i.e*. NP.3.2). In this regard, Table 5.3 presents the mean *efficiency score* ($\overline{Eff}$) over n=100 replications achieved by all 20 treatment combinations studied.

From Table 5.3 it becomes evident that the *efficiency score* achieved, when the rationally optimizing manufacturer (MAN_{OPT}) and the rationally optimizing retailer (RET_{OPT}) interact with each other (*i.e*. last cell of Table 5.3), is exactly as theoretically predicted (*i.e*. 0.85). As this concurs with the analytical result, it provides further confidence in the validity of the model (*i.e*. a "black-box validation" test: Robinson, 2004). Hence, the research hypothesis NP.3.1 for the interaction of the rationally optimizing manufacturer and the rationally optimizing retailer cannot be rejected (Eff*<1: at p<0.01).

It is also very interesting that there are another 3/20 simulated interactions that attain *efficiency scores* that are not significantly different from 0.85 (*i.e*. MAN_1-RET_2, MAN_3-RET_1, MAN_3-RET_4). Therefore, in total, the research hypothesis NP.3.1 could not be rejected for 20% of the interactions studied (*Eff*=0.85: at p<0.01).

Nevertheless, the research hypothesis NP.3.1 needs to be rejected for the remaining 80% of the interactions studied. Obviously, the research hypothesis NP.3.2 also has to be accepted for the 4 interactions studied, for which the research hypothesis NP.3.1 is accepted (*i.e*. *Eff*<1 at p<0.01 for MAN_1-RET_2, MAN_3-RET_1, MAN_3-RET_4, MAN_{OPT}-RET_{OPT}).

From the remaining interactions studied 9/20 attain *efficiency scores* that are significantly lower than 0.85 (*i.e*. MAN_1-RET_1, MAN_1-RET_3, MAN_1-RET_{OPT}, MAN_2-RET_1, MAN_2-RET_3, MAN_2-RET_{OPT}, MAN_{OPT}-RET_1, MAN_{OPT}-RET_2, MAN_{OPT}-RET_3). Therefore, the research hypothesis NP.3.2 is also accepted for these 9 interactions studied (*Eff*<1 at p<0.01). Since these interactions give rise to lower *efficiency scores* than the interaction of their *rationally optimizing* counterparts, these interactions could be characterised as 'under-performing'. It is interesting that RET_1 and RET_3 often come into play in these 'under-performing' interactions. The reason is that both RET_1 and RET_3, concerned about 'minimisation of left – overs' as they are, systematically place orders of low quantities, namely they order, respectively, either less than or approximately as much as the rationally optimizing retailer would $q^*(\overline{w})$. This is problematic, because the rationally optimizing retailer, exclusively interested in his/her expected profit as he/she is, systematically orders significantly lower quantities than the rationally optimizing *integrated newsvendor* and, therefore, causes the aggregate total channel profit to be far-off from the *first-best case maximum* profit.

The remaining 7/20 simulated human manufacturer-retailer interactions attain *efficiency scores* that are significantly higher than 0.85 (*i.e*. MAN_1-RET_4, MAN_2-RET_2, MAN_2-RET_4, MAN_3-RET_2, MAN_3-RET_3, MAN_3-RET_{OPT}, MAN_{OPT}-RET_4). As these 7 interactions *emerge* as 'nearly efficient', they could be characterised as 'well performing'. Therefore, testing research hypothesis NP.3.2 for these *nearly efficient* interactions would shed some light on whether true *efficiency* is achieved by any of these simulated human manufacturer-retailer interactions.

One of these interactions generates an efficiency score with a 99% confidence interval that includes the value of one: the interaction of MAN_3 with RET_2 (*i.e*. the shaded cell in Table 5.3). This implies that this particular interaction gives rise to an *efficiency score* that does not differ statistically from 1. Therefore, the research hypothesis NP.3.2 needs to be rejected for the interaction of MAN_3 with RET_2 (at the 1% significance level). Thus, in stark contrast to analytical predictions, it cannot be rejected that human decision makers' *bounded rationality* can lead the aggregate channel to the *first-best case maximum* profit. Even though MAN_3 and RET_2 both make 'locally poor' decisions, namely charge prices and order quantities, respectively, that systematically deviate from the rationally optimizing *integrated newsvendor*'s, when combined, they may give rise to an overall *efficient* interaction. Therefore, it is from the interaction between MAN_3 and RET_2, namely the interplay between their differing preferences and cognitive limitations, and not the performance of their distinct decision making strategies that the *wholesale price contract*'s *efficiency* may *emerge*. This result is considered as a valuable addition to the existing experimental research on *supply chain contracts*.

It is also very interesting that both MAN_3 and RET_2 are better aligned with the rationally optimizing *integrated newsvendor*'s corresponding decisions in that MAN_3, 'demand – driven' as she is, she systematically 'under-charges' and RET_2, 'sales maximising' as he is, he consistently 'over-orders'. That is why it also becomes important to understand why it is the interaction of RET_2 and not RET_4 with MAN_3 that generate *efficiency*. RET_4 is 'sales maximising' as well and, indeed, exhibits an even greater degree of 'sales maximisation' by on average ordering quantities than are higher than RET_2's. Still, RET_4 's interaction with MAN_3 fails to attain the *first-best case maximum* profit. The reason is that RET_4, in order to determine his quantity decisions, mostly relies on his own earlier order quantity decision q_{t-1} and previously realised profit $P_r(t-1)$. Since he almost ignores the prices that are charged to him in each round, he ends up ordering higher quantities than would give rise to the *first-best case maximum* profit. Hence, RET_4 demonstrates an unnecessary 'too-high' degree of 'sales maximisation preference'. What mainly differentiates RET_2 from exhibiting a similar 'too-high' 'sales maximisation preference' is the high priority that he assigns to the wholesale prices that are charged to him.

For the remaining 6/20 *nearly efficient* simulated human manufacturer-retailer interactions (*i.e.* MAN_1-RET_4, MAN_2-RET_2, MAN_2-RET_4, MAN_3-RET_3,

MAN_3-RET_{OPT}, MAN_{OPT}-RET_4) the research hypothesis NP.3.2 could not be rejected, in spite of the higher than 0.85 efficiency scores that are attained. It does not come as a surprise that the 'demand – driven' MAN_3 or the 'sales maximising' decision makers RET_2 or RET_4 participate in these *nearly efficient* interactions. The reasons are two-fold: MAN_3 is the only simulated human manufacturer who on average charges lower prices than his rationally optimizing counterpart. RET_2 and RET_4 comply with their individual interpretations of the *pull-to-centre* effect and, thus, order on average higher quantities than their rationally optimizing counterparts would. So, even though the decisions of MAN_3, RET_2 and RET_4 are significantly different from their rationally optimizing counterparts', they follow them more closely than most other simulated human manufacturers and retailers. This is exactly what explains why their participation plays such an important role in the high *efficiency scores* that are attained by them.

This is also what helps draw some general prescriptions about how supply chain *efficiency* could be achieved in practice when the *wholesale price contract* is in force. Generally, decision makers would be advised to follow the example of the 'demand – driven' MAN_3 and the 'sales maximising' RET_2, in that they deviate from their isolated views of individual profit and keep the aggregate channel profit in mind when making their respective decisions. In this way, they are better aligned with the rationally optimizing counterparts' decisions. But since they do not have access to perfect symmetric information, they can simply resort to the relevant information that is available to them, namely, follow the example of MAN_3, who determines her prices by prioritizing the previously received order quantity and the example of RET_2, who places his order quantities by prioritizing the currently charged wholesale prices. In addition, considering the previous order quantities and manufacturer prices may protect them from unnecessarily compromising their prices and order quantities, respectively.

5.4 Concluding Discussion

This chapter presents the results that are obtained from the ABS model that is described in S*ub-section 4.3.4* and, therefore, addresses the research hypotheses that concern human manufacturers' *w*-prices ($w \neq w^*$: *i.e.* NP1), human retailers' *q*-quantities ($q < q_{int}^*$: *i.e.* NP.2.1 and $q<q^*$: *i.e.* NP.2.2) and the *emerging efficiency scores* (*Eff*=0.85: *i.e.* N.P.3.1; *Eff*<1: *i.e.* NP.3.2), as are formulated in *Section 4.2*. In this way, *Chapter 5* reports on the first study that explores the effect that different prolonged interactions between manufacturers' and retailers' dynamic, heterogeneous and autonomous decisions can have on the *wholesale price contract*'s *efficiency*, that is when applied to the *Newsvendor Problem* setting.

The simulated human manufacturers charge prices that are significantly different from the prices that their rationally optimizing counterparts would charge, irrespective of whether they prefer to adopt a pricing strategy that is 'profit margin – driven' or 'demand - driven'. As for the simulated human retailers, they order significantly lower quantities than the rationally optimizing *integrated newsvendor* would. For this reason, they reproduce the *pull-to-centre* effect, as perceived on the aggregate channel's level. Nevertheless, only 50% of the simulated human retailers satisfy their corresponding individual interpretations of the *pull-to-centre* effect. The result is that the majority of the simulated human retailers don't take into account the small profit margins that are left to them by their respective manufacturers' high prices. In addition, the simulated human retailers' order quantities greatly vary, when compared to the corresponding order quantities of their rationally optimizing counterparts. A number of them order significantly lower quantities, while others order significantly higher quantities; yet there still is one simulated human retailer whose order quantities closely follow the *rationally optimizing* retailer's. Overall the different simulated human retailers exhibit different preferences, depending on their individual preferences and cognitive abilities; these individual preferences vary from 'left - overs minimisation' to 'sales maximisation'.

This range of simulated human retailers' ordering behaviours generates varying *efficiency scores*. These results, as obtained from the ABS model, are surprising: In stark contrast to previous theoretical results, the results indicate that the exact *efficiency scores* fluctuate greatly. Although the majority of interactions studied (*i*.*e*. 65%) attain *efficiency scores* that are not significantly higher than the standard normative model's theoretical prediction (*i*.*e*. 0.85), there is a significant portion of interactions studied (*i*.*e*. 35%) that attain *near efficiency*, that is *efficiency scores* that are significantly higher than 0.85. More importantly, there is also one interaction for which it could not be rejected that overall *efficiency* is achieved (*i*.*e*. an *efficiency score* that may not differ significantly from 0).

It is also very interesting that the exact *efficiency score* that is attained by each interaction under study is largely dependent on the interplay between the preferences that the interacting partners demonstrate. In greater detail, there is evidence that the interests of human retailers who comply with their individual interpretations of the *pull-to-centre* effect are better aligned with the aggregate channel's *efficiency score*. Overall, the existence of a 'left – overs minimising' decision maker in an interaction aggravates the *efficiency scores*, while the presence of at least one 'demand – driven' or 'sales maximising' decision maker has the potential to generate a *nearly efficient* interaction. Indeed, the participation of only 'demand – driven' and 'sales maximising' decision makers in an interaction may generate the *first-best case maximum* profit. Among these decision making strategies, the most *efficient* are the ones that exhibit a high responsiveness to the interacting partners' decisions, such as, for example, order quantities for the case of manufacturers and incurred wholesale prices for the case of retailers.

The results that are obtained from this study are of equal significance to both academics and practitioners. Academics will find an interest in the methodological differences of this experimental study from prior relevant work on the *Newsvendor Problem*. This is as yet the first study that explores the effect that different prolonged interactions between manufacturers' and retailers' dynamic, heterogeneous and autonomous decisions can have on the *wholesale price contract's efficiency* in the *Newsvendor Problem* setting. It clearly differs from prior existing experimental research in that it accommodates for: *i*. human manufacturers' and retailers' distinct *intentions* that might be different from profit maximisation, *ii*. human manufacturers' and retailers' distinct *actions* that might differ from their corresponding *intentions* (*i.e. boundedly rational* decisions) in heterogeneous ways, *iii*. human manufacturers' and retailers' distinct *reactions* to their surrounding environments and changes to it, if any, *iv*. human manufacturers' and retailers' independent and autonomous *decisions*. In this way, this PhD thesis successfully addresses the literature gaps G.1 - G.4 of Table 2.5 (*s. Section 2.4*). Furthermore, in stark contrast to existing research, this study establishes that it cannot be rejected that the overall *efficiency* of the *wholesale price contract* in the *Newsvendor Problem* setting may *emerge*, depending on the interplay between the different strategies that the interacting partners adopt. In this regard, the exact conditions under which the *wholesale price contract*'s *efficiency* can be achieved will also be of interest to academics.

In addition, this study introduces some innovative ideas that are useful for practitioners. In this regard, the managerial implication of this research is that it can help supply chain managers understand that instead of solely investing in implementing and administering complex, yet efficient, contract types, they could alternatively consider effective management training that focuses on overall *efficiency*. The reason is that in spite of a partner' s 'locally poor' individual decisions, global *efficiencies* can be achieved. So, it is important to train decision makers to focus on overall aggregate channel profits instead of their own individual profits, in order to reach the decisions that would give rise to 'overall efficient' interactions. With respect to this, it also becomes very important that decision makers take into account and flexibly respond to their partners' decisions, instead of exclusively focusing on their own decisions. This is exactly where the simulation games that are developed in this study could help as training tools along the lines of 'business flight simulators' (Sterman, 1992; 2000; van der Zee and Slomp, 2009). The ABS model could also serve as a 'routine decision support' tool in that it can reduce the complexity that is faced by supply chain managers and thus, support the required thinking and analysis (Pidd, 2010). Moreover, since many pricing and purchasing decisions are in reality made in group settings and conform to well-established company policies and accepted conventions (*i.e*. "group-think": Janis, 1972; 1982) the simulation games and ABS models that are developed in this study can also serve to enhance group decision making by demonstrating the potential benefits of competing decision making strategies. The modifications and extensions required for this objective (*e.g*. provision of additional *decision attribute*s and modification of deriving decision models) can be easily applied to the models of this study.

Nevertheless, this study is not without limitations. One potential limitation is that human manufacturers and retailers were asked to play against computer pre-automated scenarios. Although this approach was followed to eliminate potential biases stemming from social preferences and reputational effects (Loch and Wu, 2008; Katok and Wu, 2009), asking individuals to play interactively against each other, as is usually done in participatory simulation (North and Macal, 2007), could add some useful insights to the analysis and potentially reduce some of the approach's inherent bias. An indicative example is whether individuals learn from and adapt to their partners' actions and decisions.

Future research in this area may examine the robustness of the results that are obtained in this study in different supply chain settings. It would also be interesting to apply a similar approach and explore the effect of interactions between varying individual preferences and cognitive abilities on the overall *efficiency* of different contractual forms, such as for example the *buyback contract* (Pasternack, 1985; Lau *et al*, 2007), the *quantity discount contract* (Moorthy, 1987; Kolay *et al*, 2004), the *quantity-flexibility contract* (Tsay, 1999), the *sales rebate contract* (Taylor, 2002; Arcelus *et al*, 2007; Burer *et al*, 2008), the *revenue sharing contract* (Cachon and Lariviere, 2005). It would be very interesting to explore how different, if any, the *efficiency scores* attained by these contracts would be from their theoretical predictions, as given by the corresponding standard normative models. The standard normative models of the *buyback* and the *revenue sharing contracts* are provided in *Sub-section 2.3.1*. Finally, additional empirical work is undoubtedly required to identify more fully the range of situations over which the experimental results obtained from the ABS model of the *Newsvendor Problem* hold.

Table 5.1: Simulated human manufacturers' steady- state $\bar{w}$-prices

F_1 / F_2	**RET$_1$**	**RET$_2$**	**RET$_3$**	**RET$_4$**	**RET$_{OPT}$**
MAN$_1$	233.98 (*0.002*) [±**0.001**]	232.56 (*0.011*) [±**0.005**]	233.08 (*0.006*) [±**0.003**]	233.17 (*0.006*) [±**0.003**]	233.07 (*0*) [±**0**]
MAN$_2$	192.85 *(0.003)* [±**0.001**]	195.55 *(0.014)* [±**0.007**]	194.29 *(0.008)* [±**0.004**]	192.28 *(0.008)* [±**0.004**]	194.77 *(0)* [±**0**]
MAN$_3$	146.53 (*0.002*) [±**0.001**]	144.68 (*0.006*) [±**0.003**]	145.75 (*0.004*) [±**0.002**]	147.97 (*0.004*) [±**0.002**]	145.57 (*0*) [±**0**]
MAN$_{OPT}$ (w*)	184 (*0*) [±**0**]	184 (*0*) [±**0**]	184 (*0*) [±**0**]	184 (*0*) [±**0**]	184 (*0*) [±**0**]

Table 5.2: Simulated human retailers' steady- state $\bar{\boldsymbol{q}}$-quantities

F_1 / F_2	**RET$_1$**	**RET$_2$**	**RET$_3$**	**RET$_4$**	**RET$_{OPT}$**
MAN$_1$	17.58 (*0.06*) [±**0.028**]	97.74 (*0.29*) [±**0.133**]	59.97 (*0.21*) [±**0.09**]	124.71 (*0.38*) [±**0.15**]	58.96 (*0*) [±**0**]
MAN$_2$	44.98 (*0.06*) [±**0.03**]	125.87 (*0.25*) [±**0.11**]	85.82 (*0.18*) [±**0.08**]	118.13 (*0.32*) [±**0.71**]	92.68 (*0*) [±**0**]
MAN$_3$	97.84 (*0.06*) [±**0.03**]	178.12 (*0.18*) [±**0.08**]	133.40 (*0.13*) [±**0.06**]	107.82 (*0.24*) [±**0.11**]	135.07 (*0*) [±**0**]
MAN$_{OPT}$ (*w)**	1.19 (*0.03*) [±**0.01**]	78.78 (*0.31*) [±**0.14**]	102.41 (*0.22*) [±**0.10**]	129.66 (*0.43*) [±**0.20**]	106 (*0*) [±**0**]

Table 5.3: The *emergent* steady-state *efficiency scores*

F_1 \ F_2	**RET$_1$**	**RET$_2$**	**RET$_3$**	**RET$_4$**	**RET$_{OPT}$**
MAN$_1$	0.132 (*0.055*) [±**0.026**]	0.812 (*0.081*) [±**0.037**]	0.572 (*0.110*) [±**0.050**]	0.911 (*0.059*) [±**0.027**]	0.572 (*0.110*) [±**0.051**]
MAN$_2$	0.428 (*0.120*) [±**0.055**]	0.918 (*0.060*) [±**0.027**]	0.756 (*0.089*) [±**0.041**]	0.892 (*0.064*) [±**0.029**]	0.798 (*0.084*) [±**0.039**]
MAN$_3$	0.822 (*0.080*) [±**0.037**]	0.998 (*0.020*) [±**0.009**]	0.941 (*0.053*) [±**0.024**]	0.857 (*0.072*) [±**0.033**]	0.946 (*0.051*) [±**0.024**]
MAN$_{OPT}$ (*w)**	0.004 (*0.007*) [±**0.003**]	0.705 (*0.100*) [±**0.044**]	0.387 (*0.106*) [±**0.049**]	0.923 (*0.055*) [±**0.025**]	0.85 (*0*) [±**0**]

Chapter 6

The *Contract Beer Distribution Game*

*Chapters 4*and *5* limit attention to the *Newsvendor Problem*, that is the simplest supply chain setting that can exist, where there is only one supplier and one retailer that interact with each other. Although this setting constitutes the fundamental building block of any supply chain configuration and, thus, serves to obtain an in depth understanding of the impact that *bounded rationality* can have on supply chain decision making, it can only to a very limited degree be used to draw accurate generalizations. The reasons are three-fold: *First*, in real supply chains more than two partners interact with each other; *second*, inventories are carried over from one period to the next; and *last*, unsatisfied demand is backlogged and needs to be satisfied in subsequent periods. Therefore, decision making becomes notoriously more complicated. Since the *Beer Distribution Game* represents a *de-centralised operation*, periodic review production-distribution supply chain with serial echelons, it manages to more realistically represent real life supply chains. As for the combination of the *Newsvendor Problem* and the *Beer Distribution Game* setting, it provides some general lessons about the way that the *wholesale price contract* operates in serial multi-echelon supply chains of general type. That is why in *Chapters 6-8* attention is turned to the *Beer Distribution Game*.

In respect to this, the purpose of this chapter is to modify the *Beer Distribution Game* in a way that ensures that the basis of any interaction between adjacent supply chain partners is the *wholesale price contract*. To this end, both the board and the mechanics of the *Beer Distribution Game* are adapted. In this regard, this chapter introduces this new version of the *Beer Distribution Game*, which is for this reason thereafter named the “Contract Beer Distribution Game”.

After the *Contract Beer Distribution Game* is designed, the corresponding standard normative models, as described in *Section 2.2.1* for the traditional *Beer Distribution Game*, are modified. These standard normative models serve to predict the perfectly rational price and order quantity decisions that participants in the *Contract Beer Distribution Game* would make, under both scenarios of *centralised* and *de-centralised operation*. These standard normative models are built under the assumption of echelon managers, who are characterised by: *i.* an exclusive interest in maximising the overall supply chain profit, under *centralised operation* (*i.e. team optimal solution*) and their individual aggregate profit, under *de-centralised operation*, *ii.* perfect rationality with no effect of individual, behavioural biases and *iii*. no account of environmental changes and, thus, no effect of learning. In this way, the *team optimal solution* can be identified and, therefore, the resulting *first-best case optimum* supply chain performance can be compared to the aggregate supply chain performance that would be generated, if the distinct echelon managers made separate decisions (*i.e. de-centralised operation*). Hence, the gap between the *first-best case optimum* supply chain performance and the aggregate supply chain performance can be evaluated. Given the *team optimizing* and individual performance optimizing decision rules, occurrence of the *bullwhip effect* can also be assessed. The *bullwhip effect* or else *Forrester effect* has been defined in *Section 2.2* as the tendency of orders to increase in magnitude and variance from the customer to the manufacturer (Forrester, 1958; 1961). The reason it is separately considered is because it further increases inventory holding and backlog costs and, thus, further amplifies overall supply chain *inefficiencies* (Chen *et al*, 1999; Dejonckheere *et al*, 2003; Sucky, 2009).

In summary, this chapter addresses the literature gap G.5 outlined in Table 2.5 (*s. Section 2.4*), because it develops the *Contract Beer Distribution Game*, that is the new version of the *Beer Distribution Game*, where all terms of trade between interacting supply chain partners are determined by the *wholesale price contract*. Moreover, since *Chapter 6* also develops the standard normative models that make provision for inclusion of prices, namely are associated with the *Contract Beer Distribution Game*, it also addresses the literature gap G.6 of Table 2.5.

The chapter is structured as follows. *First*, the main differences between Sterman's (1989) traditional version of the *Beer Distribution Game* and the *Contract Beer Distribution Game* are outlined (*Section 6.1)*. Later on the game set-up and the mechanics are described in some detail (*Section 6.2*). The basic notation and underlying dynamic transactions that take place in the setting are subsequently provided (*Section 6.*3). Last but not least, the standard normative models that correspond to the setting's distinct scenarios of *centralised* and *de-centralised operation* are presented in *Section 6.4*.

6.1 Key Differences between the *Contract Beer Distribution Game* and Sterman's Beer Distribution Game

The need for the development of the *Contract Beer Distribution Game* originates from the requirement to force the *wholesale price contract* to constitute the basis of any interaction that takes place in the *Beer Distribution Game*. In this way, the impact of prices on the ordering behaviour of participants can be fully explored.

The underlying reasoning behind the pricing decisions of participants in the *Contract Beer Distribution Game* is that they need to charge prices that would appropriately control the incoming order quantities. The result is that price decisions are distinctively hard to make. Participants need to identify the trade-off between prices that would ensure, on the one hand, satisfactory profit margins, in respect to the prices that they are themselves charged and, on the other hand, target sales; target sales are in great part determined by the participants' current inventory availability. In greater detail, as is also the case in the traditional version of the *Beer Distribution Game*, sales or demand that is too high would provoke high arising backlog costs, while demand that is too low would, in turn, generate high arising inventory holding costs.

Hence, the inclusion of prices in the *Contract Beer Distribution Game* causes two major differences between this new version of the game and the traditional *Beer Distribution Game*. *First*, echelon managers are not entrusted with exactly one decision task, but instead they have two distinct decisions to make in each time period, namely they need to determine, in addition to the order quantities, the prices that they wish to charge to their respective downstream customers. To be consistent with the *Newsvendor Problem*, the supplier of each interaction pair is the *Stackelberg leader* (Stackelberg, 1934 in: Cachon and Netessine, 2004) and, thus, the first to make the price decision. In this regard, each order is only placed in response to the associated price that is charged in each time period *t*.

The *second* major difference between the *Contract Beer Distribution Game* and the *Beer Distribution Game* is that since specific prices are charged in each time period, participants' objective is not to minimise overall inventory holding and backlog costs, but to maximise profits instead. The net profits derive from the revenues that are earned in each time period minus the total costs. The total costs consist of inventory holding and backlog costs and, in addition, production or acquisition costs, depending on the participant's role. Inventory holding and backlog costs are calculated in exactly the same way as in Sterman's (1989) original game set-up. The production costs in each time period *t* are calculated by the product of the received quantity and the fixed manufacturing cost. As for the acquisition costs in each time period *t*, they are calculated in a slightly more complicated way: by the product of the quantity received and the corresponding price. The revenues are calculated in each time period *t* by the product of the quantity delivered and the agreed price. The revenues that are received in a time period *t* from the customer of an interaction pair are exactly equal to the acquisition cost that is received from the supplier of the interaction pair. But the agreed price for different shipments might differ, depending on the decision maker's preferred pricing strategy. That is why a detailed account of the price that is charged in each time period *t* also needs to be kept.

As a result of the above two major differences between the *Contract Beer Distribution Game* and the traditional version of the *Beer Distribution Game*, the operation of the game has to be adjusted as follows:

i. All adjacent partners of any interaction pair complete the same order slip. The upstream supplier of the interaction pair completes the selected price on the left hand side column of the order slip. This semi-completed order slip is subsequently passed on to the downstream customer of the interaction pair, so that he/she can complete his/her chosen order quantity on this same order slip's right hand side column. In this way, all customers place order quantities that are strictly in response to the prices that are charged in each time period *t*. In addition, all interacting pairs in the game make both of their decisions at the same time, yet on different order slips.

ii. All shipments in transit to a partner's site have their corresponding order slips attached to them. Hence, all cases of beer that exist in the system have order slips attached to them; the only exceptions are the cases of beer that exist inside a partner's warehouse. The reason is that, in line with Sterman's (1989) original game set-up, all inventories incur the same unitary inventory holding costs. By making provision for order slips travelling with cases of beer between partners' warehouses, the customer of any exchange pair remembers, at the time of a shipment's receipt, the exact price that has been agreed at the time of order placement. In this way, the acquisition cost that is incurred by the interaction's customer can be correctly calculated, while the revenues that are earned from the interaction's supplier at the same time can also be correctly calculated. The supplier's revenues are exactly equal to the customer's acquisition cost.

iii. An account of all backlogged orders is kept separately, depending on the associated price that is agreed between the interaction's supplier and customer, at the time of order placement. Namely, all slips of backlogged orders are placed at an appropriately designed section of the *Contract Beer Distribution Game* board. These slips of backlogged orders contain the corresponding prices on their left hand side columns and the unsatisfied order quantities on their right hand side columns. These prices serve to correctly calculate the acquisition costs that are incurred at the time of the shipment's receipt by the interaction's customer, as well as the revenues that are earned by the interaction's customer (which are exactly equal to the customer's acquisition costs). To this end, whenever the interaction's supplier acquires inventory at his/her warehouse, he/she ships any quantity of cases of beer that he/she has available to his/her respective customer with the corresponding backorder slip attached.

In order to implement the *Contract Beer Distribution* the board and mechanics of the game have to be appropriately modified. *Section 6.2* now describes the board, mechanics and the sequence of steps that participants in the *Contract Beer Distribution Game* undertake.

6.2 The *Contract Beer Distribution Game*

The purpose of this section is to describe the set-up and the mechanics of the *Contract Beer Distribution Game*. Building on the aforementioned key differences between the *Contract Beer Distribution Game* and Sterman's (1989) traditional version of the *Beer Distribution Game*, this section starts in *Sub-section 6.2.1* by describing the board of the game and then proceeds in *Sub-section 6.2.2* to discussing the mechanics of the game, namely the sequence of steps that the participants in the game need to undertake.

6.2.1 The Contract Beer Distribution Game Board

The game is played on a board which portrays the production and distribution of cases of beer (Sterman, 1989; 1992). Figure 6.1 illustrates the board of the *Contract Beer Distribution* Game. As already explained, orders for cases of beer are represented by slips that move around the board, according to the game instructions. Cases of beer are represented by pennies, which are in turn manipulated by the players. Each supply chain consists of three serial echelons:

the retailer (*RET*), the wholesaler (*WHL*) and the manufacturer (*MAN*) (Steckel *et al*, 2004).

Figure 6.1 also delineates the differences between the boards of the *Contract Beer Distribution Game* and Sterman's (1989; 1992) traditional version of the *Beer Distribution* Game. In greater detail, these differences are:

i. All order slips, as they are moving around the board and being exchanged between suppliers/ customers interaction pairs, they consist of two separate columns; these columns are designed specifically to include the supplier's price and the customer's order quantity that is placed. In each time period *t* the suppliers of each interaction pair are the first to complete the left hand side column of the order slip with their chosen price, while the customers of each interaction pair subsequently complete the right hand side column of the order slip with their selected order quantity (*s. Section 6.1*). When a supplier receives an order, he/she can see not only the ordered quantity, but also the price that he/she has charged at the time of order placement. Once the order is filled and the corresponding cases of beer are shipped from the supplier, these order slips travel with the shipment to the customer's site. In this way, when the customer receives the shipment, he/she can remember correctly what he/she was charged at the time of order placement and, therefore, can calculate correctly the resultant acquisition cost. In this way, the interaction's supplier can also be correctly informed about the revenues that he/she earns at that same time.

ii. There is a section of the board that is specifically designed to accommodate all players' backorders, along with their associated respective quantities and prices. The reason is that not all ordered quantities are agreed on the basis of the same prices; that is why once a supplier of an interaction pair obtains some inventory to satisfy a backorder, he/she needs to have a memory of the agreed price, so that he/she can calculate his/her expected revenues correctly. Hence, the backorder slips serve exactly the same purpose as the order slips that are associated with shipments. The exact way that the backorder slips are created and managed is described in the paragraphs that follow, which present the sequence of steps that the participants in the game undertake.

As in Sterman's (1989; 1992) original *Beer Distribution Game* setup, a deck of cards represents customer demand. In each time period *t* customers demand beer from the retailer, who ships the requested beer out of inventory. Customer demand is assumed to follow the truncated at zero normal distribution with μ=5 and σ = 2, because it reflects reality when limited information about the distribution of customer demand is available (Gallego and Moon, 1993; Son and Sheu, 2008; Ho *et al*, 2009) and also closely approximates Sterman's (1989; 1992) step-up function that is often used in laboratory investigations (e.g. Kaminsky and Simchi-Levi, 1998; Kimbrough *et al*, 2002; Hieber and Hartel, 2003; Steckel *et al*, 2004; Nienhaus *et al*, 2006). The retailer, in turn, orders beer from the wholesaler, in response to the price that the wholesaler is currently charging. The wholesaler subsequently ships the requested beer out of inventory. Likewise the wholesaler orders and receives beer from the manufacturer, depending on the price that the manufacturer is currently charging. The manufacturer produces the beer facing no capacity restrictions.

***i. Price*- and *order quantity*- columns of order slips**

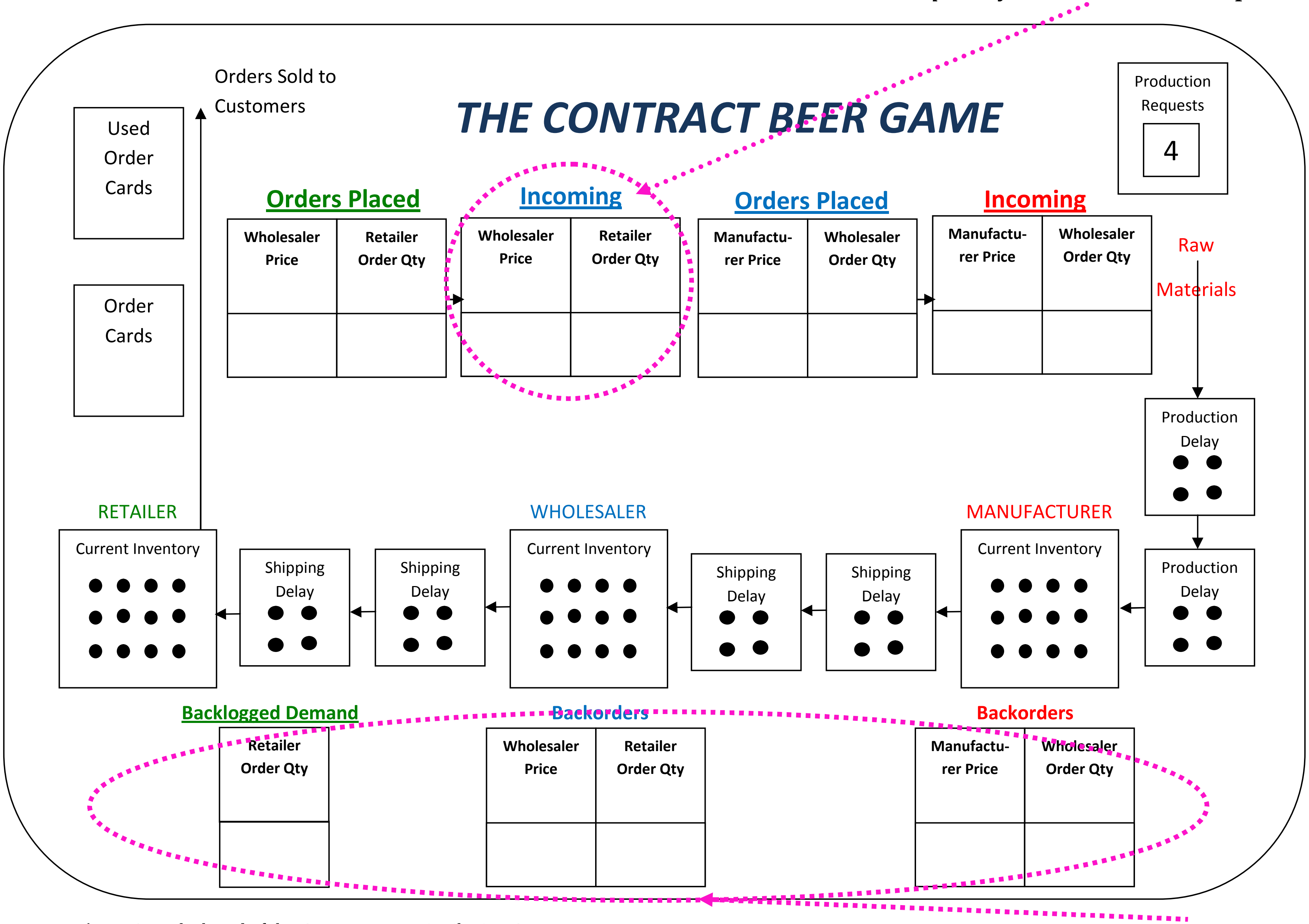


Figure 6.1: The board of the *Contract Beer Distribution Game*

***ii*. Section of the board designed for positioning the *backorders*.**

Each echelon is managed by a different player i, i = $1,..,K$ (=3), that is reflected by a different colour scheme: i = 1 with a green colour corresponds to the retailer (*RET*); i = 2 with a blue colour corresponds to the wholesaler (*WHL*); i = 3 with a red colour corresponds to the manufacturer (*MAN*). Each participant is responsible over a series of time periods t=1,...,T for: *a)*. placing orders to the corresponding upstream supplier; *b)*. charging a price to his/her downstream customer; *c)*. filling orders received (*i.e*. placed by the corresponding downstream customer); *d*). keeping track of all backlogged orders, in order of receipt and *e*). recording the payments that need to be made upon receipt of a shipment from the corresponding upstream supplier.

Figure 6.1 that presents the board of the *Contract Beer Distribution Game* also provides the initial conditions of the game. It is evident that each site initially holds an inventory of 12 cases; each shipping and production delay contains 4 cases of beer. Each order slip requests an order quantity of 4. The manufacturer initially charges the wholesaler the price of 2.5 *m.u.* (*i.e*. monetary units), while the wholesaler initially charges the retailer the price of 4.5 *m.u.* At the start of the game, the order cards are turned upside down, so that they can only be seen as dictated by the rules of the game.

The game is additionally complicated by order processing and production/shipment delays that occur between each supplier/customer pair. As Figure 6.2 demonstrates, these order processing and production/shipment delays represent, respectively, the time required to receive, process and produce/ship and deliver orders. In greater detail, once an order is placed from site i, a constant information lead time (l_i = 2) of two time periods occurs before the order actually arrives to the supply site i+1, while when an order is filled by the supply site i+1 a fixed transportation lead time (L_i= 2) of two time periods passes before the shipment gets delivered to site *i*. The total lead-time is $M_i=l_i + L_i$. At the highest echelon level (*i*=3) production requests represent production quantities. Therefore, a total of M_N = 3 periods are required to process and manufacture an order. This is why the manufacturer, who does not face any supply uncertainty, is illustrated in Figure 6.2 to receive all placed production requests after exactly M_3 = 3 time periods.

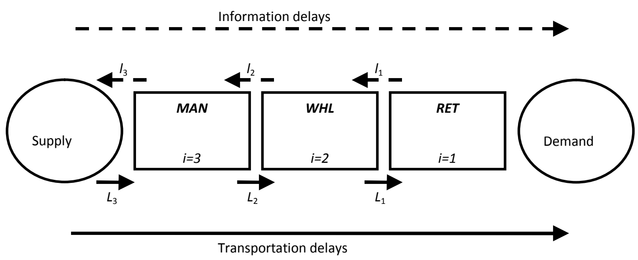


Figure 6.2: Lead times in the *Contract Beer Distribution Game*

6.2.2 Playing the Contract Beer Distribution Game

The participants' objective is to maximise the total profits during the game. The net profits derive from the revenues that are earned in each time period minus the total costs. The revenues are calculated in each time period *t* by the product of the quantity delivered and the agreed price.

The total costs consist of the inventory holding and backlog costs and, in addition, the shipment or the production costs. The inventory holding cost amount to h_i =0.50 *m.u.* for every unit of product that is kept in inventory at player's *i* warehouse for one period. The backlog costs amount to b_i =1 *m.u.* for every unit of unsatisfied beer demand. Finally, the retailer sells each case of beer at the fixed selling price of p = 3 *m.u.* and the manufacturer produces each case of beer at the fixed manufacturing cost of c = 0.50 *m.u.*

All participants in the game are required in each simulated time period *t* to perform the following sequence of nine steps:

a) *Receive inventory and pay supplier*: The contents of the shipping delay immediately to the right of the inventory ("DELAY 2") are added to the inventory. The retailers and the wholesalers use the attached order slip to calculate the acquisition cost that they need to pay to their corresponding upstream supplier[8]. The wholesalers and the manufacturers also earn revenues from their respective downstream customer (*i.e*. the retailer and the wholesaler, respectively). These revenues are exactly equal to the customer's acquisition cost that the respective downstream customers need to incur.

b) *Advance shipping delays:* The contents of the shipping delay on the far right ("DELAY 1") are moved into the delay on the near right ("DELAY 2").

c) *Fill backorders:* In case there are any backlogged orders, for as long as there is inventory left, the backlogged quantity written on the first slip from the top is shipped to the downstream customer with the backorder slip attached to it. In case there is no sufficient inventory to fully satisfy a backorder, as much inventory as there is available, is shipped to the customer. The backorder slip that is attached to it is modified to reflect the true shipped quantity. In this case, a new backorder slip is

---

[8] The formulae that the participants use to calculate the corresponding shipment costs are provided in their instructions sheet (For more details the interested reader is referred to Appendices B.1 – B.3).

additionally created with the unsatisfied order quantity; this new backorder slip is positioned at the top of the pile of backorder slips, if any.

d) *Fill incoming orders:* Retailers lift the top card in the “Customer Orders” position, while all other players inspect the contents of the “Incoming Order” that is positioned at their respective section of the board. They ship as much of this ordered quantity as their available inventory permits, out of their warehouse with the associated order slip attached. In case there is not sufficient inventory to fully satisfy an order, the order slip that is attached to the partial shipment is modified to reflect the true shipped quantity. A new backorder slip is also created to reflect the unsatisfied order quantity. This new backorder slip is positioned at the bottom of their pile of backorder slips, if any. Retailers also earn revenues from their customers, according to the quantity that is sold. As already discussed, it is assumed that the retailers sell at a fixed selling price p=3 *m.u.* that is set by competition, as is usually the case for commodity products (Hirschey *et al*, 1993; Chopra and Meindl, 2007).

e) *Record inventory or backlog*.

f) *Calculate and record profits:* The net profits derive from the revenues that are earned in each time period t minus the total costs.

g) *Advance incoming order slips:* The retailers and the wholesalers move the order slips from the “Orders Placed” position to the “Incoming Orders” position to the immediate right. The manufacturers introduce the contents of the “Production Requests” to the top “Production Delay” (“DELAY 1”).

h) *Determine prices:* The wholesalers and the manufacturers decide how much they desire to charge their respective customers, record these prices and complete the left hand side column of a new order slip with these. They subsequently pass these semi-completed order slips on to the retailers and the wholesalers, respectively.

i) *Place orders:* All players decide how much they wish to order and record these quantities. The retailers and the wholesalers complete these quantities on the right hand side column of the semi-completed order slip that they just received. They subsequently place these completed order slips face down in the "Orders Placed" position of the board that corresponds to them, respectively. The manufacturers complete these quantities on a new production request slip and place it on the "Production Request" position of the board.

It is evident from the above sequence of steps *a*-*i* that only steps *h* and *i* involve decision tasks on the part of participants in the *Contract Beer Distribution Game*. All remaining activities include book-keeping and routine tasks. The exact sequence of steps that the subjects who play the role of the retailer need to perform are detailed in Appendix B.1, while appendices B.2 and B.3, respectively, present the exact sequence of steps that the subjects playing the role of the wholesaler and the manufacturer need to undertake.

6.3 The Dynamic Transactions of the *Contract Beer Distribution Game*

This section builds on the dynamic transactions that take place in the *Contract Beer Distribution Game* to define the basic notation that is used in the remainder of this chapter. In respect to this, Figure 6.3 illustrates the material and information transactions that take place in the *Contract Beer Distribution Game* setting. It is evident from Figure 6.3 that in this setting, material flows from upstream to downstream (*i.e*. from *i* to *i*-1) and information flows from downstream to upstream (*i.e*. from *i* to *i*+1), in the form of replenishment orders, and from upstream to downstream (*i.e*. from *i* to *i*-1), in the form of charged prices.

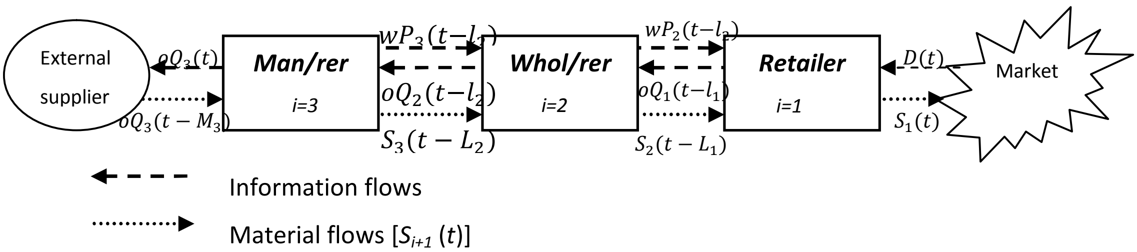


Figure 6.3: An overview of the *Contract Beer Distribution Game* setting

Therefore, the Contract *Beer Distribution Game's* setting is more complicated than Sterman's (1989; 1992) original *Beer Distribution Game* setting in that information flows in two directions. But Figure 6.3 does not present, for reasons of clarity, the financial transactions that take place in the *Contract Beer Distribution Game*. In this setting, funds flow from downstream to upstream (*i.e*. from *i* to *i*+1), that is opposite to material. From Figure 6.3 the two distinct decision tasks that each echelon manager *i* faces in each time period *t* are also missing:

a) the price desired to be charged to the downstream customer i-1 [$wP_i(t)$] and

b) the order quantity placed with the upstream supplier $i+1$ [$oQ_i(t)$].

Last but not least, Figure 6.3 omits to further highlight that material flows are simultaneously accompanied by information exchanges, given that all shipments are received with their corresponding order slips attached. The last point that should be raised about Figure 6.3 is that for simplicity it adapts the convention that *N*=3, according to Steckel *et al*.'s (2004) 3-player implementation that is followed in this game 's set-up. But the logic can be easily extended to the general case that *N*>3. As already specified in *Sub-section 6.2.1*, the customer demand *D*(*t*) in each time period *t*, namely the random variable *x*, is assumed to follow the truncated at zero normal distribution with μ=5 and σ = 2.

In order, thus, to address the aforementioned omissions of Figure 6.3, Figure 6.4 more fully explores the complicated game dynamics that each echelon manager *i* faces in each time period *t*. In this figure, physical cases of beer are not displayed to keep the graphic as simple as possible. Furthermore, lined arrows (with lining of the form:___) represent material flows; single spaced arrows (with lining of the form:_ _ _) reflect information exchanges; dotted arrows (with lining of the form:...) indicate decisions; large arrows (⇒) signify financial transactions.

The notation that is used for every site i=1,...,*N* is as follows:

x customer demand, a random variable

$f(x)$ probability density function of *x*

$F(x)$	cumulative distribution function of *x*
p	selling price per unit
c	manufacturing cost per unit
b_i	lost sales (goodwill) penalty cost per unit
h_i	inventory holding cost per unit and time period
$OQ_i(t)$	order quantity of site *i* in time period *t*
$WP_i(t)$	price charged by site *i* in time period *t* (per unit)
$S_i(t)$	shipment sent from site *i* to site site *i*-1 in time period *t* (*i.e.* site *i*-1 will receive this shipment in period t+L_{i-1})
$WS_i(t)$	price associated with shipment sent from site *i* to site site *i*-1 in time period *t* (*i.e.* site *i*-1 will receive this shipment in period t+L_{i-1})
$IN_i(t)$	net inventory position of site *i* in time period *t* (a site's net inventory position is given by its on-hand inventory position minus the backlogged orders from the downstream customer, or backlogged customer demand for the case of the retailer)
$AC_i(t)$	acquisition cost that site *i* needs to pay to upstream supplier *i+1* (the manufacturer *i*=3 needs to incur the manufacturing cost accordingly)
$R_i(t)$	revenues earned by site *i* in time period *t*

$IC_i(t)$	inventory holding and backlog cost incurred by site *i* in time period *t*
$P_i(t)$	net profit of site *i* in time period *t*
L_i	production/transportation lead-time from site *i*+1 to site *i*
l_i	information lead-time from site *i* to site *i*+1
M_i	total lead-time $M_i=l_i + L_i$
$\mathcal{L}_i$	downstream information lead-time $= \sum_{j=1}^{i-1} l_j$ with $\mathcal{L}_1 = 0$
Z_i^*	optimal inventory target level of site *i* under *centralised operation*
z_i^*	optimal inventory target level of site *i* under *de-centralised operation*

It is evident from Figure 6.4 that once cases of beer are transported, they are accompanied by their associated order slips, which in turn signify information exchange. The direction of arrows suggests the exact way by which the movement or exchange or transaction takes place: for example, the arrow indicating *i*'s revenues $R_i(t)$ points into *i*'s own site to signify that these are funds that enter into *i*'s site; while the arrow indicating *i*'s acquisition cost $AC_i(t)$ points out of *i*'s own site to indicate that these are funds that leave *i*'s site. The numbers in circles denote the specific sequence by which any transportation/exchange/transaction occurs.

In accordance to the sequence that is shown in Figure 6.4, the significant events that unfold for each echelon manager *i* in each time period *t* are the following. At this point the reader is reminded that the following numbered list presents the significant events for each echelon manager *i* and not the steps that *i* needs to undertake.

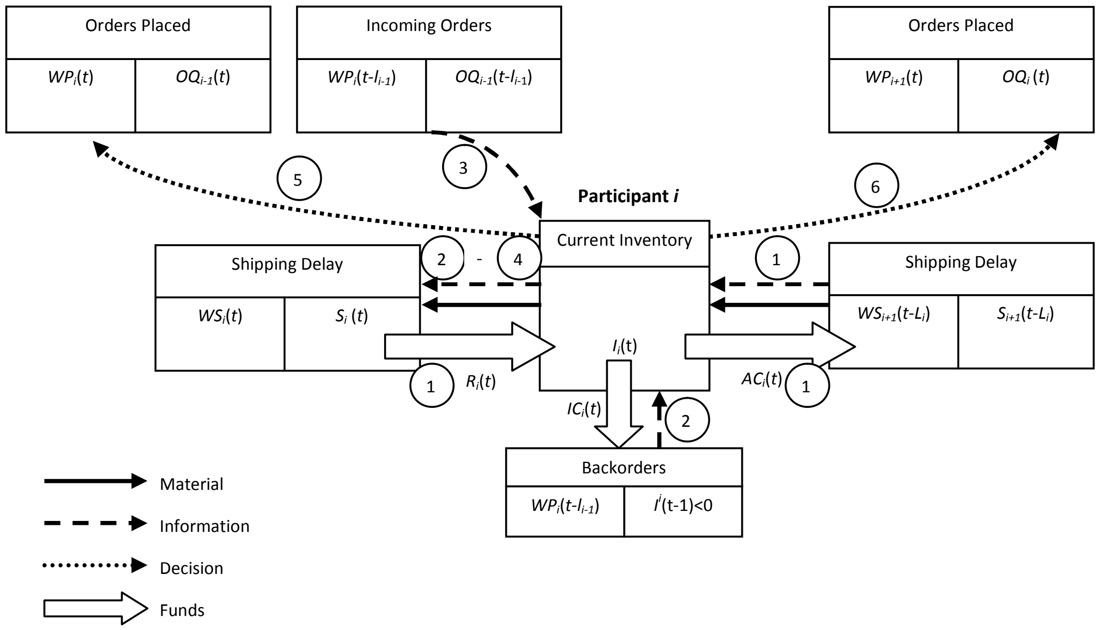


Figure 6.4: The detailed dynamics of the *Contract Beer Distribution Game* (shown for one echelon)

1. *Shipments arrive from the upstream supplier i+1. The relevant financial transactions take place.*

The first significant event for echelon manager *i* is to receive the incoming shipment from the upstream supplier, which is a material transaction. This shipment is accompanied by its attached order slip that denotes its size $S_{i+1}(t-L_i)$ and the corresponding price $wWS_{i+1}(t-L_i)$ $(1 \leq i < N)$, which is an information transaction. Because of this shipment, echelon manager *i* needs to pay the upstream supplier the corresponding acquisition cost $SC_i(t)$. For this reason, echelon managers $1 < i \leq N$ also receive payments from their downstream customers *i*-1 $R_{i-1}(t)$, respectively. The retailer (*i*=1) receives payment, when customer demand is satisfied. Payments and revenues constitute the financial transactions that occur at the same time with the first significant event of each time period t.

Since echelon manager i receives the incoming shipment of size $S_{i+1}(t-L_i)$ and corresponding price $WS_{i+1}(t-L_i)$ $(1 < i \leq N)$ i needs to pay the acquisition cost that is given by relation (6.1a). Since the unitary manufacturing cost is fixed, the manufacturer's corresponding production cost is given by relation (6.1b).

Echelon Managers' Acquisition costs in time period t

$$AC_i(t) = WS_{i+1}(t-L_i) \cdot S_{i+1}(t-L_i) \text{ for } 1 \leq i < N \tag{6.1a}$$

$$AC_N(t) = c \cdot OQ_N(t-M_N) \tag{6.1b}$$

The revenues that echelon manager i $(1 < i \leq N)$ receives originate from the shipment that the downstream customer i-1 just received. Therefore, these revenues are exactly equal to the downstream customer's respective acquisition costs at the same time, according to relation (6.2a):

Echelon Managers' Revenues in time period t

$$R_i(t) = AC_{i-1}(t) = WS_i(t-L_{i-1}) \cdot S_i(t-L_{i-1}) \text{ for } 1 < i \leq N \tag{6.2a}$$

The revenues that are received by the retailer (i=1) are calculated by equation (6.2b). The retailers' revenues depend on customer demand and since customer demand arises as a subsequent significant event for retailers, equation (6.2b) is presented later on, when customer demand actually appears at the retailer's site.

A point worthy of further attention is that in equations (6.1a) and (6.2a) no distinction is made as to whether a price that is assigned to a shipment originates from a newly received order or a backorder. It is, therefore, assumed for clarity of notation and simplicity of illustration that the shipment has in its entirety exactly the same price assigned to it, that is $WS_{i+1}(t-L_i)$, although this is not necessarily the case. Namely, in case i fills previously backlogged orders (*i.e.* $IN_i(t-1)\ <0$) prices might differ across orders that are backlogged from different periods. But this simplification does not alter calculations of profits, because all backlogged orders are satisfied in a strict First-Come First-Served (*i.e.* FCFS) discipline, which does not affect participants' choices in any way. This is further explained in *Section 6.4*, where the standard normative models that correspond to the *Contract Beer Distribution Game*'s *centralised operation* and *de-centralised operation* are provided.

2. *Backlog is filled.*

If there is any backlog (*i.e.* $IN_i(t-1)\ <0$), as much as the currently available inventory permits of this is filled. The backorder is lifted (*i.e.* information transaction), the appropriate quantity is shipped to the downstream customer (*i.e.* material transaction) with its associated order slip attached to it (*i.e.* information transaction).

3. *New orders arrive from downstream customers.*

The retailer (i=1) lifts the top demand card, while echelon manager i ($1<i\leq N$) lifts the incoming order card (*i.e.* information transaction). The result of this information transaction is that the retailer (i=1) receives customer demand $D(t)$ and echelon manager i (i>1) receives orders of quantity $OQ_{i-1}(t-l_{i-1})$ and agreed price $WP_i(t-l_{i-1})$ from the respective downstream customer i-1.

4. *Newly received orders are satisfied.*

Each echelon manager *i* satisfies as much of the ordered quantity as the currently available inventory permits. The appropriate quantity is shipped to the downstream customer i-1 (*i.e*. material transaction) with its associated order slip attached to it (*i.e*. information transaction). This is also the time that the retailer (*i*=1) receives revenues from the customer demand that he/she just satisified. So, there also is a financial transaction for retailers. For reasons of simplicity this financial transaction is not reflected in Figure 6.4.

But the exact revenues that are earned by the retailer (*i*=1) at this time period can be calculated by relation (6.2b):

Retailers' Revenues in time period t

$$R_1(t) = p \cdot S_1(t) \qquad (6.2b)$$

After both the significant events 2 and 4 have taken place, a total quantity of $S_i(t)$ has been shipped by each echelon manager *i* to the respective downstream customer i-1.This shipment entails both backlogged orders, if any, and newly received orders, depending on the inventory that is available. Equation (6.3a) presents the total quantity that is shipped by echelon managers $1 < i \leq N$at time period *t*, while Equation (6.3b) presents the total quantity that is shipped by the retailer (*i*=1) at time period *t*:

Echelon Managers' Shipment Quantity in time period t

$$S_i(t) = min\{OQ_{i-1}(t - l_i)\ , max\{IN_i(t-1) + S_{i+1}(t - L_i)\ ,0\}\} \text{ for } i\text{=2, ...,}N. \qquad (6.3a)$$

$$S_1(t) = min\{D(t), max\{IN_1(t-1) + S_2(t - L_1)\ ,0\}\} \qquad (6.3b)$$

In equations (6.3a) and (6.3b) $IN_i(t-1)$ represents the net inventory position of echelon *i* in time period *t*-1.

5. Prices are charged to downstream customers.

The fifth significant event happening in time period *t* to each echelon manager *i* (*i*>1) is the first decision task. Each echelon manager *i* (*i*=2,3,...,*N*) sets a unit price $WP_i(t)$ to his/her respective downstream customer *i*-1.

6. Orders are placed with upstream suppliers.

The sixth significant event happening in time period *t* to each echelon manager *i* is the second decision task, that is, determine the order quantity $OQ_i(\mathrm{t})$.

In greater detail, each echelon manager *i* (*i*>1) receives from his/her respective upstream supplier *i*+1 a semi-completed order slip with a price $WP_{i+1}(t)$, completes it with his/her chosen order quantity $OQ_i(\mathrm{t})$ and places it with the upstream supplier *i*+1. The manufacturer (i = 3) places a production request of quantity $OQ_N(\mathrm{t})$.

It is evident from the above significant events that occur in any time period *t* that any site's inventory increases by the shipments it receives from its upstream supplier and decreases by the incoming orders it receives from its downstream customer (according to relations (6.3a) and (6.3b)). Therefore, the following inventory balance equations can be easily deduced:

Echelon Managers' Net Inventory Positions in time period t

$$IN_i(t) = IN_i(t-1) + S_{i+1}(t-L_i) - OQ_{i-1}(t-l_i) \text{ for } 1 < i \le N \quad (6.4a)$$

$$IN_1(t) = IN_1(t-1) + S_2(t-L_1) - D(t) \tag{6.4b}$$

Following this, all holding and backorder costs are also assessed at the end of the period. Hence, every echelon manager *i* has to incur a total inventory and backlog cost of $IC_i(t)$, that is based on his/her inventory level at the end of the period, according to relation (6.5):

Echelon Managers' Inventory Holding and Backlog Costs in time period t

$$IC_i(t) = h_i \cdot [IN_i(t)]^+ + b_i \cdot [IN_i(t)]^- \tag{6.5}$$

where $[x]^+ \stackrel{\text{def}}{=} max\{x, 0\}$ and $[x]^- \stackrel{\text{def}}{=} max\{-x, 0\}$.

As already mentioned, each echelon manager's (*i*) net profits are calculated from the difference between revenues $[R_i(t)]$ and total costs, where total costs consist of inventory holding and backlog costs $[IC_i(t)]$ and, in addition, production or acquisition costs $[SC_i(t)]$. Equation (6.6) calculates the net profits of any echelon manager *i*.

Echelon Managers' Net Profits in time period t

$$P_i(t) = R_i(t) - AC_i(t) \text{ -} IC_i(t) \tag{6.6}$$

The section that follows discusses the price and order decisions that perfectly rational participants in the *Contract Beer Distribution Game* would make, if exclusively interested in maximising either the aggregate supply chain profit (*i.e*. under *centralised operation*) or their individual profit (*i.e*. under *de-centralised operation*). These standard normative models also present the *first-best case* maximum profit and aggregate supply chain profit that would be attained in each case, respectively.

6.4 Standard Normative Models

This section develops standard normative models that correspond to the *Contract Beer Distribution Game*. These standard normative models serve to predict the perfectly rational price and order quantity decisions that participants in the *Contract Beer Distribution Game* would make, under both scenarios of *centralised* and *de-centralised operation*. These standard normative models are built under the assumption of echelon managers, who are characterised by: *i.* an exclusive interest in maximising the overall supply chain profit, under *centralised operation* and their individual aggregate profit, under *de-centralised operation*, *ii.* perfect rationality with no effect of individual, behavioural biases and *iii*. no account of environmental changes that may occur. In this way, the overall supply chain profits that would be attained in each of these distinct cases are assessed. A judgement as to whether the *bullwhip effect* arises is also made.

Sub-section 6.4.1 concentrates on the hypothetical scenario of *centralised operation*, while *Sub-section 6.4.2* turns attention to the scenario of *de-centralised operation*. *Sub-section 6.4.3* compares the overall performance of these two distinct cases.

6.4.1 The centralised operation

In this sub-section the *team optimal solution* of the *Contract Beer Distribution Game* that would be obtained from a system of N distinct echelons arranged in series is identified. These *team optimizing decision rules* consist of the *prices* and *order quantities* that perfectly rational echelon managers would make, if they were exclusively interested in maximising the *team overall profit*. The *team overall profit* is defined as the sum of the net profits that are realised by all interacting supply chain partners i=1,...,N over the time interval T under study.

According to this definition, the *first-best case maximum* profit can serve as the absolute upper bound of the *Contract Beer Distribution Game's* overall profit. This definition of the *first-best case maximum* profit of the *Contract Beer Distribution Game* suggests three important underlying pre-suppositions: *i*). all echelon managers share the common goal to maximise total supply chain profits through period *T* and act to this end, *ii*). all echelon managers make perfectly rational decisions, so that there is no discrepancy between their *intention*s and their *decisions* and *iii).* all echelon managers, since they are perfectly rational optimizers, do not need to resort to feedback information and previous experiences to learn and, thus, improve their decisions; for this reason, they do not take into account any environmental changes that may occur.

Since any echelon manager's total net profit in time period *t* is given by equation (6.6), the overall supply chain net profit in period *t*, $P_C(t)$, would be calculated by relation (6.7).

Total Supply Chain Net Profit in time period t

$$P_C(t) = \sum_{i=1}^{N} P_i(t) = \sum_{i=1}^{N} [R_i(t) - AC_i(t) - IC_i(t)] \tag{6.7}$$

Hence, the total supply chain profits through to period *T* become:

Total Supply Chain Net Profit through to period T

$$\sum_{t=1}^{T} P_C(t) = \sum_{t=1}^{T} \sum_{i=1}^{N} [P_i(t)] \tag{6.8}$$

Since customer demand is stationary and independently distributed across periods, given (6.8), the stochastic game reduces to a sequence of similar single period games, under the assumption of a stationary inventory policy. For this reason, it suffices to maximise overall supply chain profits in period *t*, $P_C(t)$, in order to maximise total profits through to period T, $\sum_{t=1}^{T} P_C(t)$. This is why attention is now turned to the prices $WP_i(t)$ and order quantities $oQ_i(t)$ that echelon managers i should place to maximise $P_C(t)$, as given by relation (6.7), namely attain $P_O^*(t) = \max\{P_C(t)\}$.

This *team optimal solution* is mostly relevant to two previous analytical papers that concern information *de-centralised operation* multi-echelon supply chains: Lee and Whang (1999) and Chen (1999). As already mentioned in *Sub-section 2.2.1*, Lee and Whang (1999) are concerned with developing a *transfer payment scheme* that fairly allocates overall system costs to distinct echelon managers, but takes their optimum ordering policies for granted; Chen (1999) identifies the echelon managers' ordering policies that minimise overall inventory and backlog costs. The *team optimal solution* sought in this sub-section extends these previous standard normative models in that it also includes the prices that perfectly rational echelon managers would charge to their respective customers.

While Chen (1999) is evidently more closely connected with the aims here, Chen differs from the *team optimal solution* of the *Contract Beer Distribution Game* in a number of aspects:

i. Unlike Chen (1999), it is assumed here that the ultimate objective of distinct echelon managers is to maximise total supply chain profits and not minimise total inventory and backlog costs;

ii. Dissimilarly to Chen, quantities in transit from one site to another as well as backlogged demands do not incur any inventory holding costs;

iii. All sites (that is not only the retailer, like in Chen) incur a linear backlog penalty b_i for all non-immediately satisfied demands that they receive from their respective downstream customers;

iv. In contrast to Chen, no echelon incremental holding cost rates apply. The reason is that the *Contract Beer Distribution Game* supply chain mainly serves the distribution of cases of beer and, hence, there are no value adding activities.

These differences originate from the attempt to keep the model formulation as consistent as possible with Sterman's (1989, 1992) original *Beer Distribution Game*'s set-up.

In Appendix B.4 it is demonstrated that these differences are exclusively responsible for the different formulation of objectives between the *Contract Beer Distribution Game's team optimal model* and Chen's team model. Appendix B.4 provides the formal proof that these differences areinsufficient to alter the firms' optimal decision rules. The basis of this formal proof consists of equation (6.9) that presents the *Contract Beer Distribution Game's* overall supply chain profit. The underlying reasoning is that all echelon managers' distinct net profits, as provided by relations of type (6.6), and the supply chain's aggregate net profit, as calculated by relation (6.7), demonstrate that the revenues and acquisition costs of all intermediate echelons ($1 < i < N$), namely of all firms but the retailer and the manufacturer, cancel each other out. As can be seen from equation (6.9), the result is that the prices $wP_{\mathrm{i}}(t)$ that echelon managers i charge to their downstream customers i-1 do not have any influence on overall supply chain profits $P_C(t)$.

<u>*Total Supply Chain Net Profit in time period* t</u>

$$P_C(t) = R_1(t) - AC_N(t) - \sum_{i=1}^{N} IC_i(t) \tag{6.9}$$

where $R_1(t)$ is given by (6.2b), $SC_N(t)$ by (6.1b) and $IC_i(t)$ by (6.5).

The proof that is presented in Appendix B.4 explains why if each echelon manager *i* = 1,...,N, behaved as a perfectly rational *team* and was interested in maximising the *team overall* profit, then he/she would order to keep his/her installation stock[9] at the constant level Z_i^*, *i*=1,…,*N*, where $Z_i^* = Y_i$, which is the finite maximum point of the function $G_i\ (y)$, defined following Chen's recommendation in relation (B.4.8). Hence, the precise decision rule that each echelon manager *i* needs to follow to attain this maximum total profit is easy to implement: As soon as local installation stock reaches the optimal target level Z_i^*, he/she needs to place an order of size equal to the last received order, namely follow the decision rules that are given by relations (6.10a) and (6.10b), respectively:

<u>*Echelon managers' Decision Rules that maximise the Team Overall Profit*</u>

$$OQ_1(t) = D(t-1) \tag{6.10a}$$

$$OQ_i(t) = OQ_{i-1}(t - l_{i-1}) \text{ for } 1 < i \leq N \tag{6.10b}$$

In the case that all echelon managers *i*=1,...,*N* behaved as a perfectly rational *team* and, thus, followed these optimum *order-up-to level* policies $(Z_1^*, \dots, Z_N^*)$,

[9]The term "installation stock" refers to the local inventory position of an installation (or site) of a multi-echelon inventory system [Source: Chen, F. 1998. Echelon re-order points, installation re-order points and the value of centralized demand information, *Management Science* 44(12), part 2/2, S221-S234.

then the *first-best case maximum* profit $P_O^*(t)$[10], as given by (6.9), would be attained. The *first-best case maximum* profit $P_O^*(t)$, constitutes the absolute upper bound of the *Contract Beer Distribution Game* supply chain's total profit. It only remains to explore exactly how much the *first-best case maximum* profit $P_O^*(t)$ amounts to. This question is answered in *Sub-section 6.4.3* that concerns overall supply chain performances.

6.4.2 The de-centralised operation

In this sub-section the decision rules for *prices* and *order quantities* that would be adopted by N distinct echelon managers under a *de-centralised operation* are explored. This is the case that the *wholesale price contract* constituted the basis of all interactions and, in addition, the case where all echelon managers were exclusively interested in maximising their own individual total net profit. Based on this, it is evident the standard normative model that is developed in this sub-section builds on three important simplifying assumptions: *i*). all echelon managers aim at maximising their respective net profits through to period T and act to this end, *ii*). all echelon managers make perfectly rational decisions, so there is no discrepancy between decision makers' *intention*s and *decisions* and *iii).* all echelon managers, since they are perfect optimizers, do not need to resort to feedback information and previous experiences to learn. Therefore, they do not take into account any environmental changes that may occur.

In this regard, under *de-centralised operation* each distinct echelon manager needs to determine the respective price $wWP_i(t)$ and order quantity

---

[10]The reader is at this point reminded that the subscript *o* is used to denote overall optimality.

$oOQ_i(t)$ that would maximise his/her corresponding total net profit $\sum_{t=1}^{T} P_i(t)$, where a period's net profit $P_i(t)$ is given by relation (6.6). As already explained in *Sub-section 6.4.1*, since customer demand is stationary and independently distributed across periods the stochastic game reduces to a sequence of similar single period games, under the assumption of a stationary inventory policy. Hence, it suffices for each echelon manager *i* to maximise his/her respective net profit in period *t*, $P_i(t)$, in order to maximise his/her total profits through to period T $\sum_{t=1}^{T} P_i(t)$. This is why attention is now turned to the prices $WP_i(t)$ and order quantities $OQ_i(t)$ that each echelon manager *i* should place to maximise $P_i(t)$, as given by relation (6.6).

It is obvious from (6.6) that the net profit that is realised by each echelon manager *i* depends on the shipment that he/she received from the corresponding upstream supplier i+1 in time period t (*i.e.* via $AC_i(t)$). But this shipment that is received from the supplier *i*+1 is in turn determined by the supplier's inventory availability (*i.e.* $IN_{i+1}(t - l_i)$), according to relations of type (6.3). Inventory balance equations of type (6.4) demonstrate that the supplier's (*i*+1) inventory availability is in part determined by the supplier's (*i*+1) own order quantity decision and in part by the inventory availability of the supplier's supplier (*i*+2) and so on. In any case, the status of the upstream supplier (*i*+1) is completely out of *i*'s own control. Because of this uncertainty that is inherent with (6.6), *intending* to maximise (6.6) is not considered a feasible objective for any echelon manager *i*. In order to overcome this problem, we have followed the example of existing management and accounting literature (*e.g.* Horngren and Foster, 1991; Chen, 1999) and, thus, assumed that *i*'s objective is to maximise his/her respective expected net profit, from which all supply uncertainty is eliminated.

Appendix B.5 presents the formal proof about the price and order quantity decisions that perfectly rational echelon managers would make in the *Contract Beer Distribution Game*. It is there demonstrated why under conditions of assumed perfect rationality, the retailer i=1 would make order quantity decisions $OQ_1(t)$that would satisfy the condition (6.11), while all other echelon managers i >1 would make price $WP_i(t)$ decisions and order quantity $OQ_i(t)$ decisions that would satisfy the conditions (6.12) and (6.13). In other words, all echelon managers' i=1,...,N order quantity decisions would be such that would maintain their corresponding optimal target levels z_i^*. Namely, as soon as their respective inventory availabilities reach the corresponding optimal target levels z_i^* that are defined by (6.11) and (6.13), they would follow the optimal decision rules (6.10a) and (6.10b), respectively.

Retailers' Optimal Inventory Target Level under De-centralised Operation

$$p \cdot F(z_1^*) + (h_1 + b_1) \cdot F^{M_1+1}(z_1^*) = b_1 + p \tag{6.11}$$

In relation (6.11) F reflects the cumulative distribution function of customer demand and F^{M_1} represents the cumulative distribution function of the customer demand that has occurred over the last M_1 periods.

Conditions for Echelon Managers' Optimal Price and Quantity Decisions under De-centralised Operation

$$\int_0^{z_i} u f_i(u)du + \int_{z_i}^{\infty} z_i f_i(u)du = 0 \quad \text{for } 1 < i \leq N \tag{6.12}$$

$$w_i \cdot F_i(s_i^*) + (h_i + b_i) \cdot F_i^{M_i}(s_i^*) = b_i + w_i \text{ for } 1 < i \leq N \tag{6.13}$$

In relations (6.12) and (6.13) F_i reflects the cumulative distribution function of the demand that echelon manager i faces (incoming from i-1) and $F_i^{M_i}$ the cumulative distribution function of the demand that echelon manager *i* faces over the last M_i periods.

From relations (6.11), (6.12) and (6.13) it is evident that the common underlying assumption is that the distinct echelon managers are perfectly knowledgeable of the distribution that their corresponding demand follows. The result is that the demand that each echelon manager faces follows exactly the same customer demand distribution. So, it becomes a time-shifted truncated at zero normal distribution with $\mu=5$ *and* $\sigma = 2$.

As the strategy profile of all *order-up-to level* policies $(z_1^*, \ldots, z_N^*)$ is the result of all echelon managers' perfect rationality, it prevails as an *iterated dominance* equilibrium[11] (*e.g.* Rasmusen, 1989; Camerer, 2003). Now it only remains to explore exactly to how much the aggregate channel profit would amount, in case all echelon managers were perfectly rational and, thus, followed the above decision rules (6.10a) and (6.10b). This question is answered in *Sub-section 6.4.3* that concerns overall supply chain performances.

At this point the reader should be reminded that in *Sub-section 6.4.1* is shown that the perfectly rational echelon managers under *centralised operation* follow again the same *order-up-to-level* policies $(Z_1^*, \ldots, Z_N^*)$, but with different optimal target levels (*i.e.* Z_i^* and not with z_i^*). As soon as these levels are

[11] The term "iterated dominance equilibrium" refers to the "strategy profile" (*i.e.* the specification of strategies or actions that each player of the game employs), in which every strategy or action employed constitutes the best response to every other strategy or action played. A strategy or action is assessed in regard to the corresponding payoff that it generates [source: http://en.wikipedia.org/wiki/Solution_concept last accessed: 31/08/2010].

reached, in order to attain the *first-best case maximum* profit, the perfectly rational echelon managers follow the same optimal decision rules that are given by (6.10a) and (6.10b), respectively. In this regard, it appears very interesting that the assumed perfectly rational echelon managers would follow the same policies and the same optimal decision rules for their order quantity decisions, irrespectively of whether they aim at maximising the *team overall* profit (*i.e.* under *centralised operation*) or their own individual profit (*i.e.* under *de-centralised operation*). For this reason, it also becomes very interesting to identify the discrepancy between the *first-best case maximum* profit $P_0^*$and the aggregate channel profit $\hat{P}_C$, under *de-centralised operation,* that is if any. This is usually quantified via the 'competition penalty' (Cachon and Zipkin, 1999; Cachon, 2003), which is defined according to relation (6.14). Relation (6.14) adapts the definition of the *competition penalty* that is provided in (2.17), in respect to net profits instead of total costs:

<u>*Competition Penalty*</u>

$$CP = \frac{\widehat{P_0^*} - \hat{P}_C}{\widehat{P_0^*}} \tag{6.14}$$

The closer to 0 a *competition penalty* is the better the overall performance of the multi-echelon inventory system under study and, also, the closer the aggregate channel net profit P_c to the *first-best case maximum* profit P^*_o . The relevant discussion is provided in *Section 6.4.3*.

6.4.3 Supply Chain Performance

The objective of this sub-section is to assess the overall supply chain performance in the cases of *centralised operation* and *de-centralised operation*.

To this end, it first calculates the expected value of the aggregate channel profit that would have been realised, if all echelon managers were perfectly rational and *intended* to maximise the *team overall* profit (*i.e*. *centralised operation*), while it subsequently establishes the deviation that would occur, if any, in case the distinct echelon managers *intended* to maximise their respective individual profits. In both of these settings the degree to which the *bullwhip effect* prevails is also explored.

The case of *centralised operation* is first considered. Under this hypothetical scenario, all distinct echelon managers implement *order-up-to level* policies $(Z_1^*, \ldots, Z_N^*)$. In this regard, as soon as they have reached their respective optimal target levels Z_i^*, they place orders of sizes that are exactly equal to their incoming order quantities. In this way, they can together attain the *first-best case maximum profit* $\widehat{P_O^*}$ of the *Contract Beer Distribution Game* supply chain. As already discussed in *Sub-section 6.4.1*, the prices $wP_\mathrm{i}(t)$ that they would decide to charge to their respective downstream customers would not have any impact on the supply chain's expected profit $P_O^*(t)$. Since $\widehat{P_O^*} = max\,\{\widehat{P_C}\}$, the *first-best case* maximum *profit* $\widehat{P_O^*}$ of the *Contract Beer Distribution Game* is calculated from the expected value of relation (6.9) that the perfectly rational *team optimizing* decision rules (6.10a) and (6.10b) would generate. The reason is that the steady state expected net profit of the *Contract Beer Distribution Game* supply chain is under study here, so all perfectly rational decision makers are assumed to have already reached their respective optimal target levels Z_i^*.

In order, thus, to calculate the steady state expected value of (6.9), the expected value of the retailer's revenues $\widehat{R_1} = E\{R_1\}$ needs to be first calculated. In this regard, since there is over the long run in the retailer's warehouse sufficient inventory to fully satisfy customer demand, the retailer's steady state expected net profit is given by (6.15):

Retailer's Steady State Expected Net Profit

$$\widehat{R_1} = p \cdot E\{x\} = p \cdot \mu \tag{6.15}$$

The expected value of the production cost that the manufacturer has to incur can be calculated by (6.1b): $\widehat{SC_N} = c \cdot OQ_N(t - M_N)$. By recursive application of the decision rules (6.10a) and (6.10b) the expected value of the manufacturer's production cost easily gets transformed to:

Manufacturer's Expected Production Cost

$$\widehat{SC_N} = c \cdot D(t - M_N - l_{N-1} - \cdots - l_1 - 1) \tag{6.16}$$

As for the expected value of the inventory holding and backlog cost that each echelon manager *i* has to incur, it is estimated via (6.5), taking into account that each echelon manager *i* adopts the decision rules that are given by (6.10a) and (6.10b):

Echelon Managers' Expected Inventory Holding and Backlog Costs

$$\widehat{IC_i} = h_i \cdot [Z_i^* - D(t - l_1 - l_2 - \cdots - l_{i-1})]^+ + b_i \cdot [Z_i^* - D(t - l_1 - l_2 - \cdots - l_{i-1})]^- \tag{6.17}$$

By combining (6.15), (6.16) and (6.17) according to (6.9) the expected value of the total net profit of the *Contract Beer Distribution Game* supply chain, or else the *first-best case* maximum *profit* $\widehat{P_O^*}$ becomes:

Expected Total Supply Chain Net Profit

$$P_0^* = p \cdot \mu - c \cdot D(t - M_N - l_{N-1} - \cdots - l_1 - 1) - \sum_{i=1}^{N} h_i \cdot [Z_i^* - D(t - l_1 - l_2 - \cdots l_{i-1}]^+ + b_i \cdot [Z_i^* - D(t - l_1 - l_2 - \cdots - l_{i-1}]^- \quad (6.18)$$

Since all echelon managers of the *Contract Beer Distribution Game* would follow the decision rules of type (6.10a) and (6.10b) under this hypothetical scenario of *centralised operation*, they would simply order as much as they are themselves requested to deliver to their respective customers. So, the variance of all orders across different roles would remain exactly the same (*i.e.* $Var[D(t)] = \sigma^2$) and, so, there would be no *bullwhip effect*.

Attention is now turned to the case of *de-centralised operation*. Under this hypothetical scenario, all distinct echelon managers would implement *order-up-to level* policies $(z_1^*, \dots, z_N^*)$ in order to maximise the expected value of their respective individual net profits $\hat{P}_i$. In this regard, as soon as they have reached their respective optimal target levels z_i^*, they place orders of sizes that are exactly equal to their incoming order quantities. Since the expected value of their net profits is of interest here, it can be safely assumed that their respective optimal target levels z_i^* have been reached and, therefore, their order quantity decisions would be determined by the decision rules of type (6.10a) and (6.10b). But the decision rules of type (6.10) are exactly the same as the decision rules that would dictate the perfectly rational decisions under *centralised operation*. In this regard, the aggregate channel profit $\hat{P}_C$ that would arise in the case of *de-centralised operation* is given by relation (6.9) and is exactly equal to the *first-best case maximum profit* $\widehat{P_0^*}$ of the *Contract Beer Distribution Game*, or else $\widehat{P_0^*} = \hat{P}_C$. Therefore, according to relation (6.14) the *competition penalty* of the *de-centralised operation* would become equal to 0, which denotes a perfect coordination of the *Contract Beer Distribution Game* supply chain. As already discussed, the decision rules of type (6.10a) and (6.10b) that the perfectly rational decision makers would follow also ensure that the *bullwhip effect* does not occur.

6.5 Summary

This chapter designs a new version of the *Beer Distribution Game*, named the *Contract Beer Distribution Game,* where the *wholesale price contract* constitutes the basis of any interaction that takes place between adjacent supply chain partners. In order, thus, to accommodate the extra decision task that participants are asked to perform (*i.e*. charge prices to their respective downstream customers) and the associated complications that this causes, the board, the rules and the mechanics of the traditional *Beer Distribution Game* are appropriately modified. This chapter serves to introduce this new game.

Building on this game, the chapter additionally develops the corresponding standard normative models that predict the perfectly rational price and order quantity decisions that participants in the *Contract Beer Distribution Game* would make, under both scenarios of *centralised* and *de-centralised operation*. These standard normative models are built under the assumption of echelon managers, who are characterised by: *i.* an exclusive interest in maximising the overall supply chain profit, under *centralised operation* (*i.e*. *team optimal solution*) and their individual aggregate profit, under *de-centralised operation*, *ii.* perfect rationality with no effect of individual, behavioural biases and *iii*. no account of environmental changes and, thus, no effect of learning.

The chapter follows a rigorous formal procedure to prove that although the exact optimal inventory targets under the two hypothetical scenarios of *centralised operation* (*i.e*. Z_i^*) and *de-centralised operation* (*i.e* z_i^*) substantially differ, the inventory policies remain exactly the same. Namely, in order to maximise the *team overall* profit or the individual profit, all distinct echelon managers need to follow the same *order-up-to level* policies, yet of different *order-up-to level*s. Following this, once they have reached their respective optimal inventory targets, they apply exactly the same order quantity decision rules. The result is that in steady state they attain exactly the same aggregate supply chain profit, namely the *first-best case maximum profit* $\widehat{P_O^*}$ of the *Contract Beer Distribution Game* supply chain, or else $\widehat{P_0^*} = \hat{P}_C$. In addition, after having reached their respective optimal target levels Z_i^*or z_i^*, all echelon managers, under both modes of *centralised* and *de-centralised operation* would order as much as they have been requested to deliver to their respective customers. Therefore, the size and variance of orders would stay exactly the same across the whole *Contract Beer Distribution Game* supply chain (*i.e*. equal to σ^2). Thus, there would be no *bullwhip effect*.

In summary, by introducing the *Contract Beer Distribution Game* and developing the corresponding standard normative models, *Chapter 6* starts to address the literature gaps G.5 and G.6 that are identified in Table 2.5 (*s. Sub-section 2.4*). In greater detail, this chapter demonstrates that the *wholesale price contract*, when applied to the *Beer Distribution Game* setting, offers remarkably improved performances in comparison to when applied to the simpler *Newsvendor Problem* setting. In stark contrast to the analytical results that are known about the *wholesale price contract*, as applied in the *Newsvendor Problem* setting (*s. Section 2.1.1*), the *wholesale price contract* can perfectly *coordinate the Beer Distribution Game*. It establishes that an *intention* to maximise the *team overall profit* or the individual profit does not cause any divergences of either the inventory policies, or the decision rules, or the aggregate channel profit that can be attained. This can explain why there is an absolute coincidence of the aggregate channel profit that would be attained in the cases of *centralised operation* and *de-centralised operation*. Moreover, it demonstrates that the *wholesale price contract* is able to eliminate the *bullwhip effect*, provided that all interacting echelon managers make perfectly rational decisions and possess perfect symmetric information.

Nevertheless, it still remains to further explore what would happen in the case where there was at least one decision maker whose decisions were not dictated by perfect rationality, as is highly likely. (For a detailed survey of the behavioural biases that are already recognised to prevent human decision makers from perfectly rational decisions in the Beer Distribution Game setting the reader is referred to *Sub-section 2.2.2*). In this case, the standard normative models that are presented in this chapter cannot predict human decisions. The result is that discrepancies might arise between the *first-best case maximum* profit $\widehat{P_0^*}$ that would be attained under *centralised operation* and the aggregate channel profit $\hat{P}_C$ that the separate decisions of distinct echelon managers would generate. For this reason, a *competition penalty* equal to zero might not be practically feasible and, therefore, the *wholesale price contract* might in practice be unable to perfectly *coordinate* the *Beer Distribution Game* supply chain. Since human decision makers might, in addition, make significantly different decisions than their perfectly rationally optimizing counterparts, it is likely that the *bullwhip effect* might occur.

In this regard, *Chapters 7* and *8* concentrate on investigating the true decisions that human participants in the *Contract Beer Distribution Game* make and how different they are, if any, to the decisions of their perfectly rational counterparts that are predicted by the standard normative models of *Chapter 6*. *Chapters 7* and *8* additionally explore the effect of these decisions on the resulting overall supply chain performance and how this acquired overall supply chain performance diverges from its equivalent theoretical prediction of *Chapter 6*. In greater detail, *Chapter 7* describes the approach that is undertaken to this end, while *Chapter 8* presents and discusses the results that are obtained. In this way, *Chapter 8* builds on these results to draw managerial implications and novel insights for the *Contract Beer Distribution Game*.

The Impact of Prices on Boundedly Rational Decision Makers in Supply Chains

by

Stavrianna Dimitriou

A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy

The University of Warwick, Warwick Business School

June 2010

Volume 2 / 2

Table of Contents (of volume 2 / 2)

List of Figures (of volume 2 / 2)

List of Tables (of volume 2 / 2)

Chapter 7

The *Contract Beer Distribution Game* Approach

The purpose of this chapter is to describe the approach that this PhD thesis has undertaken to investigate the effect that different prolonged interactions between dynamic, heterogeneous and autonomous decisions can have on the *wholesale price contract's performance* in the context of the *Beer Distribution Game*. This chapter explains how the approach of this PhD thesis, as outlined *in Chapter 3*, is applied to the *Beer Distribution Game* setting. By making provision for: *i.* human decision makers' distinct *intentions* that might differ from profit maximisation, *ii.* human *actions* that might differ from their corresponding *intentions* in heterogeneous ways (*i.e. boundedly rational* decisions), *iii.* human *reactions* to changes going on in the surrounding environment and *iv.* human *decisions* that may be independent and autonomous, this approach successfully addresses the literature gaps G.1-G.4 of Table 2.5 (*s. Section 2.4*) for the *Beer Distribution Game* setting.

The chapter starts by reminding the reader of the most important analytical results about the *Contract Beer Distribution Game* that are obtained in *Chapter 6* and the most relevant experimental results that are presented in *Section 2.2.2*. It subsequently uses these extant results to build the research hypotheses that are of interest to this study. It then discusses in some detail all steps of the approach that have been followed to address these research hypotheses. The chapter concludes with a brief summary.

7.1 The *Wholesale Price Contract* in the Beer Distribution Game

In Sub-Section 6.4.1 is shown that in the case where all distinct echelon managers that come into play in the *Contract Beer Distribution Game* setting share the common *intention* to maximise the *team overall profit*, then they do not need to pay any attention to the intermediate prices that they decide to charge to each other. In order to attain the *first-best case maximum profit* $\widehat{P_O^*}$, they simply need to place with their respective upstream suppliers orders of sizes that would satisfy *order-up-to level* policies; namely they would need to reach their corresponding optimal target levels Z_i^* and thereafter order as much as they have been themselves requested to deliver. The result of this policy is that not only would the *first-best case maximum profit* $\widehat{P_O^*}$ be achieved, but there would also be no increase in the size and variance of orders across different roles; hence, there would be no *bullwhip effect*. The reason that the absence of the *bullwhip effect* is considered significant is because it is a key determinant of operational *inefficiencies* in the *Beer Distribution Game*.

Sub-section 6.4.2 formally proves that in the case where the interacting distinct echelon managers are interested in maximising their respective individual profits, then they need to charge prices and, also, order quantities that satisfy certain conditions. It is very interesting that the conditions that concern order quantity decisions force the distinct echelon managers to follow similar *order-up-to level* policies. The exact optimal inventory targets z_i^* may be different from the inventory target levels Z_i^* that they would follow if they *intend*ed to maximise the *team overall* profit. Yet, once they reach their respective optimal inventory targets z_i^* they apply exactly the same order quantity decision rules in order to maximise their respective individual profits $\widehat{P_i^*}$. The result is that in steady state the aggregate supply chain profit that they would together attain is exactly equal to the *first-best case maximum* profit $\widehat{P_O^*}$ of the *Contract Beer Distribution Game* supply chain, or else $\widehat{P_0^*} = \widehat{P}_C$.

This perfect coincidence of the aggregate channel profit that the individual profit maximising decision makers would attain $\hat{P}_C$ with the *first-best case maximum* profit P_0^* signifies that the *competition penalty* would be exactly equal to 0. In accordance with this, the *wholesale price contract* is demonstrated as being in a position to perfectly *coordinate* the *Beer Distribution Game* supply chain. Last but not least, following the *order-up-to level* policies that the perfectly rational decision makers would adopt to maximise their individual profit, there would again be no increase in the size and variance of orders and, so, there would be no *bullwhip effect*. The elimination of the *bullwhip effect* serves as an additional indication of the overall good performance of the *wholesale price contract* in the *Contract Beer Distribution Game* setting.

Nevertheless, a number of previous laboratory investigations of Sterman's (1989; 1992) original *Beer Distribution Game* set-up, establish that very rarely would human decision makers' decisions, as observed in the laboratory, follow the above perfectly rational decision rules (Sterman, 1989; Kaminsky and Simchi-Levi, 1998; Croson and Donohue, 2003; Steckel *et al*, 2004; Croson and Donohue, 2005; Croson and Donohue, 2006; Wu and Katok, 2006; Croson *et al*, 2007). The reason is that in reality a human decision maker may be: *i.* concerned about a variety of different objectives, possibly other than exclusive profit maximisation, *ii.* unable, for various different reasons, to act according to his/her *intention*s and *iii.* influenced, in a variety of different ways, by occurring environmental changes and also learning. In addition, a number of individual behavioural biases are held responsible for this systematic divergence of human decisions from standard normative models' predictions, such as for example: *anchoring and insufficient adjustment heuristic* (Sterman, 1989); *supply line under-weighting* (Sterman, 1989; Kaminsky and Simchi-Levi, 1998; Croson and Donohue, 2003; Croson and Donohue, 2005; Croson and Donohue, 2006; Croson *et al*, 2007); *organizational learning* (Wu and Katok, 2006); *coordination risk* (Croson *et al*, 2007); protection against other partners' biases (Su, 2008). These might vary from subject to subject (*i.e.* heterogeneity). In this regard, the results of these erroneous human decisions that are established are *two*-fold: *i*. a persistent discrepancy between the resulting aggregate channel performance and the *first-best case optimum performance* (Sterman, 1989; Kaminsky and Simchi-Levi, 1998; Steckel *et al*, 2004) and *ii*. a prevalence of the *bullwhip effect* (Sterman, 1989; Croson and Donohue, 2003; Croson and Donohue, 2005; Croson and Donohue, 2006; Wu and Katok, 2006; Croson *et al*, 2007).

Since the inclusion of prices has as yet not been explored in the laboratory, there is still no laboratory evidence about the true price decisions that participants in the *Contract Beer Distribution Game* would make, in the case where the *wholesale price contract* constitutes the basis of all interactions. Following this, it still remains open to further exploration what would happen at the aggregate channel level when human price and order quantity decisions are combined together. In respect to this, it would be very interesting to explore whether the *wholesale price contract* is in a position to perfectly *coordinate* the *Beer Distribution Game* setting (that is, attain a *competition penalty* that would be exactly equal to 0), as has been analytically predicted (*s. Section 6.4*). Furthermore, it would be valuable to investigate whether the *bullwhip effect* persists in the *Beer Distribution Game* setting or whether the inclusion of prices in the *Contract Beer Distribution Game* setting manages to completely eliminate it, as is analytically predicted by the corresponding standard normative models (*s. Section 6.4*).

The section that follows builds on the aforementioned existing results to formulate the research hypotheses that this PhD thesis seeks to address for the *Beer Distribution Game* setting.

7.2 Research Hypotheses

This study addresses four distinct sets of research hypotheses: *First*, there is a research hypothesis that concerns the prices wP_i that human participants in the *Contract Beer Distribution Game* would decide to charge to their respective downstream customers. *Second*, there is a research hypothesis that relates to the quantity decisions oQ_i that human participants in the *Contract Beer Distribution Game* would decide to place with their respective upstream suppliers. *Third*, there is a research hypothesis that reflects the true *competition penalty CP* that the overall channel would attain. This research hypothesis serves a dual purpose. On the one hand, it directly tests how the overall *competition penalty CP* compares to 0, which is the corresponding theoretical prediction of the performance of the *wholesale price contract*, when it is assumed to be in force in the *Beer Distribution Game* setting. On the other hand, it indirectly explores, under the same assumption, the level of profits that the overall channel can secure, that is, if any. *Last*, there is a research hypothesis that tests whether the *bullwhip effect* dominates, namely, whether the variance of orders between adjacent supply chain roles strictly increases, in the case where the *wholesale price contract* is imposed as the basis of all interactions. The paragraphs that follow outline and justify these research hypotheses.

7.2.1 Participants' wP_i - prices

There is no previous laboratory evidence on the true price decisions $\overline{wP_i}$ that human participants in the *Contract Beer Distribution Game* would make, in the case where the *wholesale price contract* constitutes the basis of all interactions. For this reason, the relevant experimental results that exist for the *Newsvendor Problem* setting are adapted in an appropriate way that can reflect expectations of human participants' prices.

In this regard, in line with earlier experimental results (Keser and Paleologo, 2004; Katok and Wu, 2009; Dimitriou *et al*, 2009), human manufacturers would be expected to charge prices that are not consistent with the prices that their perfectly rational counterparts would charge. Under *centralised operation*, there is no firm condition about the prices that the perfectly rational echelon managers should follow in order to maximise the *team overall profit* and, hence, attain the *first-best case maximum profit* P_0^* (*s. Sub-section 6.4.1*). Under *de-centralised operation* the prices that the perfectly rational echelon managers should charge in order to maximise their respective individual profit P_i^* must satisfy conditions (6.12) and (6.13) (*s. Sub-section 6.4.2*). These conditions combined ensure that the selected prices are neither too high nor too low, so that desired sales can be attracted and, also, sufficient profit margins can be guaranteed. Nevertheless, these conditions appear distinctively hard for human subjects to quickly understand and, thus, implement. This is why they are found rather unrealistic. For this reason, a simplification based on common intuition is instead preferred. Human participants in the *Contract Beer Distribution Game* are anticipated to charge prices that would be strictly higher than the prices that they are themselves charged by their corresponding upstream suppliers. This charging behaviour would at least help them attain a reasonable profit margin. This is exactly what the first research hypothesis suggests.

Hypothesis CBG.1 Human participants in the *Contract Beer Distribution Game* charge wP_i -prices that are strictly higher than the prices that they are charged wP_{i+1} ($\overline{WP}_i > \overline{WP}_{i+1}$).

Since charging strictly higher prices than being charged is but a simplification of conditions (6.12) and (6.13) that the perfectly rational prices should satisfy, this pricing rule of closely following the price of the upstream supplier $\overline{WP}_{i+1}$ could be considered as a 'locally good' price. So, this first research hypothesis implies that human participants in the *Contract Beer Distribution Game* would be expected to make 'locally good' decisions.

7.2.2 Participants' oQ_i - quantities

In accordance with previous experimental research on Sterman's (1989, 1992) original *Beer Distribution Game* (Sterman, 1989; Kaminsky and Simchi-Levi, 1998; Croson and Donohue, 2003; Steckel *et al*, 2004; Croson and Donohue, 2005; Croson and Donohue, 2006; Wu and Katok, 2006; Croson *et al*, 2007), human participants in the *Contract Beer Distribution Game* would be expected to order significantly different quantities than the ones that are predicted by the relevant standard normative models. This constitutes the basis of the second research hypothesis.

The standard normative models that correspond to the *Contract Beer Distribution Game* are provided in *Section 6.4*. These demonstrate that the perfectly rational distinct echelon managers that participate in the game first need to attain the optimal target levels that are implied by their respective *intention*s to either maximise the *team overall* profit P_0^* under *centralised operation* (that is, Z_i^*) or the individual profit P_i^* under *de-centralised operation* (that is, z_i^*). Once they reach these target levels, they simply need to follow the optimal decision rules that are given by relations (6.10a) and (6.10b), depending on their respective roles. Following these optimal decision rules, perfectly rational echelon managers order ($\overline{oQ}_i$) as much as they are themselves requested to deliver ($\overline{oQ}_{i-1}$).

Kaminsky and Simchi-Levi's (1998), Croson and Donohue's (2003; 2005; 2006) and Croson *et al*.'s (2007) human participants tend to *under-weight* their supply line in their order quantity decisions, that is, for every new order quantity decision they make, they assign higher significance to their current inventory position than to their outstanding orders (*i.e.* orders they have placed but have not yet received from their upstream manufacturers). The result is that they are inclined to order higher quantities than they are requested to deliver. But this is not the case for Sterman's (1989) subjects, who *anchor* their order quantities on initial stock levels and subsequently *insufficiently adjust* towards desired stock levels. This application of Kahneman *et al*.'s (1982) *anchoring and insufficient adjustment* heuristic by Sterman's (1989) participants implies that they practically order quantities that are different from the quantities that they are themselves requested to deliver. That is why it is safer to leave the second research hypothesis about human participants' oQ_i - quantities as two-tailed.

Hypothesis CBG.2 Human participants in the *Contract Beer Distribution Game* order OQ_i - quantities that are significantly different from the quantities that they are requested to deliver OQ_{i-1} ($\overline{OQ}_i \neq \overline{OQ}_{i-1}$).

Since ordering as much as being requested to deliver would maximise both the individual profit that each distinct echelon manager could make and the *team overall* profit, this decision rule of ordering as much as the downstream customer requests $\overline{OQ}_{i-1}$ could be considered as a 'locally good' order quantity decision. In respect to this, the second research hypothesis implies that human participants in the *Contract Beer Distribution Game* would be expected to make 'locally poor' order decisions.

7.2.3 Competition Penalties

Earlier experimental research on Sterman's (1989, 1992) original *Beer Distribution Game* demonstrates that there exists a persistent discrepancy between the resulting aggregate channel cost IC_c that is incurred by human participants and the *first-best case minimum cost* IC^*_0 that would be attained by perfectly rational echelon managers (Sterman, 1989; Kaminsky and Simchi-Levi, 1998; Steckel et al, 2004). This systematic deviation implies that the *competition penalty* that is attained by interacting human decision makers is strictly different than 0. The competition penalty *CP* is defined according to relation (2.17), when supply chain overall costs come into play.

In line with this existing experimental research, the *competition penalties* that would be attained by interactions of human participants in the *Contract Beer Distribution Game* would be expected to be significantly different from 0. This is exactly what the third research hypothesis seeks to address.

Hypothesis CBG.3 The attained *competition penalties* are significantly different from zero ($CP \neq 0$).

But in the case of the *Contract Beer Distribution Game* setting, supply chain overall profits, instead of supply chain overall costs, become of interest. Because of this, the *competition penalties* that different interactions attain can be determined by relation (6.14). According to equation (6.14), the aggregate channel cost IC_c becomes the aggregate channel profit $\hat{P}_C$ and the *first-best case minimum cost* IC^*_0 becomes the *first-best case maximum* profit $\widehat{P_O^*}$. Hence, the third research hypothesis anticipates a systematic deviation between the *first-best case maximum* profit $\widehat{P_O^*}$ and the aggregate channel profit $\hat{P}_C$ that would be attained by human participants in the *Contract Beer Distribution Game*. The equivalent expectation is that human interactions could not give rise to 'globally *efficient*' interactions.

7.2.4 The Bullwhip effect

Prior experimental research on Sterman's (1989, 1992) original *Beer Distribution Game* (*e.g*. Croson and Donohue, 2006; Wu and Katok, 2006; Croson *et al*, 2007) verifies the prevalence of the *bullwhip effect*, even under simplified laboratory conditions, when all its corresponding operational causes, as recognised by Lee *et al*. (1997a; b), are systematically removed. In addition, Su (2008) offers a formal proof that explains why the existence of at least one non-perfectly rational decision maker in the *Beer Distribution Game* constitutes a necessary and sufficient condition for the occurrence of the *bullwhip effect*. Building on these extant results, the introduction of the *wholesale price contract* as the basis of any transaction in the *Beer Distribution Game* could not be considered as a sufficient condition to abolish the *bullwhip effect*. So, it is anticipated that the *bullwhip effect* will persist in the *Contract Beer Distribution Game* setting.

Since the *bullwhip effect* or else the *Forrester effect* (Forrester, 1958; 1961) is defined as the tendency of orders to increase in magnitude and variance as one moves upstream away from the customer to the manufacturer, it can be quantified by the amplification of demand variance from each level *i* to the corresponding upstream supplier's level *i*+1, namely via $\bar{\sigma}_i^2 < \bar{\sigma}_{i+1}^2$. This is exactly what the fourth research hypothesis proposes:

Hypothesis CBG.4 The *bullwhip effect* persists ($\frac{\bar{\sigma}_{i+1}^2}{\bar{\sigma}_i^2} > 1$).

The persistence of the *bullwhip effect* in the *Contract Beer Distribution Game* setting signifies that the interaction of human participants is not expected to be in a position to completely eliminate the operational *inefficiencies* that are existent in the *Contract Beer Distribution Game*. Therefore, human participants are not anticipated to generate 'globally efficient' interactions.

Now that the research hypotheses of this study are formulated, the approach of this research, as outlined in *Chapter 3*, is described in greater detail with respect to the *Contract Beer Distribution Game* setting. In this way, the research hypotheses CBG.1 - CBG.4 can be tested.

7.3 The Approach

In order to elicit knowledge on how human subjects make their price and order quantity decisions and assess the overall performance of all their possible interactions, the approach that is presented in Figure 3.2 (*s. Section 3.2*) has been adapted to the needs of the *Contract Beer Distribution Game*. In this regard, in *Stage 1* the *decision variables* of each *agent* are recognised, namely the price for the wholesaler and the manufacturer and the order quantity for the retailer, the wholesaler and the manufacturer. Following informal pilot sessions, the *decision attributes* that correspond to each *decision variable* are also identified. In *Stage 2* volunteers are randomly assigned to play the three different roles in simulation games and their consecutive decisions over time are recorded. Some participants are asked to interact over the specially designed board of the game, while some others are asked to interact via a computer interface with a set of pre-selected partners' responses. Whether a participant was asked to play over the board or via the computer interface, and the exact set of responses or else *scenarios* that were provided to him/her have been rigorously selected via a specially developed methodology that is described in *Sub-section 7.3.2.* In *Stage 3* a combination of multiple regression models of the first order auto-regressive time-series type and multiple logistic regression models is fitted to the data that are collected from each participant. In *Stage 4* the ABS model that corresponds to the *Contract Beer Distribution Game* is run for all possible combinations of the participants' decision models. In this way, the respective outcomes can be compared and, thus, the research hypotheses about simulated manufacturers' prices (*i.e*. CBG.1), order quantities (*i.e*. CBG.2), attained *competition penalties* (*i.e*. CBG.3) and prevalence of the *bullwhip effect* (*i.e*. CBG.4) can be investigated. Each of these stages is now described in some detail.

7.3.1 Stage 1: The Decision Making Process

The objective of the informal pilot sessions is to identify the *decision attributes* that correspond to the two *decision variables* of this study: that is, the price and the order quantity decisions. These pilot sessions were conducted via simulation games, but differed from *Stage 2* gaming sessions in two ways. *First*, the subjects were provided all information that was relevant to their respective role over the course of the entire game; no previous round's data were hidden from them. *Next*, these simulation games were shorter in duration, yet, they were followed by interviews, during the course of which the subjects were encouraged to discuss which information they had found of relevance to their required decision task. They were also asked to explain the underlying reasoning for the decisions that they had made. In this way, the *decision attributes* that they had considered as significant for their respective *decision variables* were identified.

From these informal sessions evidence is found that most participants assign significantly higher significance to losses, even of small magnitude, than to equally sized profits. In other words, most participants seem to be highly loss averse. Furthermore, since the game starts with an initial inventory of 12 cases for each participant and, in addition, the backlog penalties cost prices that are double as high as the inventory holding costs, most participants appear to be highly averse to backlogged demand. In other words, most participants assign greater significance to whether their inventory position falls below 0 than to exactly how much above 0 it actually is. But this aversion of most human participants to losses and backlogs seems to reproduce *Prospect theory*'s (Kahneman and Tversky, 1979) *reference dependence*. Building on this loss and backlog aversion of human participants, net profits that are exactly equal to 0 and net inventory positions that are exactly equal to 0 can be treated as references.

In addition, in the informal interviews all human participants admitted that they had based their order quantity decisions on the incoming order quantities or previous demand realizations. The reason is that they could not predict with certainty the incoming order quantities or the customer demand, respectively. Camerer (1995) and Loch and Wu (2007) perceive this tendency of individual decision makers to use relevant information that is available as the result of underlying *uncertainty*. Last but not least, after the end of the game most volunteers revealed that they had difficulty in understanding how their current decisions would affect their profits and the system overall performance in the next round of the game. In order, thus, to make simpler and faster decisions, they preferred to use their own previously realised profit, as given to them by the computer interface. This simplification is viewed as the result of the *complexity* that is inherent with the *Contract Beer Distribution Game*. Camerer (1995) and Loch and Wu (2007) consider *complexity* as another behavioural bias that seems to have a significant effect on individual decision making.

In accordance with the aforementioned behavioural biases and with Axelrod's (1997) KISS principle (*i.e.* Keep It Simple Stupid) all human participants in the *Contract Beer Distribution Game* (i = *MAN*, *WHL*) are considered to base each period's price decision $wP_i(t)$ on the following seven factors or else *decision attributes*:

i. the price that was charged by the upstream supplier i+1 in the same time period t WP_{i+1}(t) [*i.e.* *immediacy* and *salience*]. The reader is at this point reminded that this *decision attribute* is not applicable to the role of the manufacturer (i = *SUP*),

ii. the previous order quantity $O(t-1)$ [*i.e.* *immediacy* and *salience*],

iii. the shipment that is in transit to i's own warehouse $S_{i+1}(t-L_i$+1) [*i.e.* *reference dependence*, *immediacy*, *salience* and *ambiguity*],

iv. the incoming order quantity $OQ_{i-1}(t-l_{i-1})$ [*i.e.* *immediacy*, *salience* and *ambiguity*], *v.* the incoming order price $WP_{\mathrm{i}}(t-l_{i-1})$ [*i.e. immediacy, salience* and *ambiguity*],

vi. the net inventory position $IN_i(\mathrm{t})$ [*i.e. reference dependence* and *complexity*],

vii. the realized cumulative profit $\sum_{j=1}^{t} P_i(j)$ [*i.e. reference dependence* and *complexity*].

These are the *decision attributes* that have been used in the subsequent gaming sessions for all human participants. Therefore, the relation (3.1) that presents the one-to-one association of the *decision variable* price $WP_i(t)$ with all corresponding *decision attributes* (*i.e.* $WP_{i+1}(\mathrm{t}), OQ_i(t-1), S_{i+1}(t-L_i+1)$, $OQ_{i-1}(t-l_{i-1}), WP_{\mathrm{i}}(t-l_{i-1}), IN_i(\mathrm{t}), \sum_{j=1}^{t} P_i(j)$) becomes:

<u>*The Price's Decision Function*</u>

$$< WP_i(t) > = f_i^{WP(t)}\left[WP_{i+1}(t-1), OQ_i(t-1), S_{i+1}(t-L_i+1), OQ_{i-1}(t-l_{i-1}), WP_{\mathrm{i}}(t-l_{i-1}), IN_i(\mathrm{t}), \sum_{j=1}^{t} P_i(j) \right] \tag{7.1}$$

For the same reasons, all human participants in the *Contract Beer Distribution Game* (*i = MAN, WHL, RET*) are considered to base each period's order quantity decision $OQ_i(t)$ on the following eight factors or else *decision attributes*:

i. the participant's own previously charged price $WP_i(t-1)$ [*i.e. immediacy* and *salience*]. The reader is at this point reminded that this *decision attribute* is not applicable to the role of the retailer (*i* = *RET*), *ii.* the player's own currently charged price $WP_i(t)$ [*i.e. immediacy* and *salience*]. This *decision attribute* is not applicable to the role of the retailer (*i* = *RET*),

iii. the price that was charged by the upstream supplier *i*+1 in the same time period *t* WP_{i+1}(t) [*i.e. immediacy* and *salience*]. This *decision attribute* is not applicable to the role of the manufacturer (*i* = *MAN*),

iv. the previously placed order quantity $OQ_i(t-1)$ [*i.e. immediacy* and *salience*],

v. the shipment that is in transit to *i*'s own warehouse $S_{i+1}(t-L_i+1)$ [*i.e. reference dependence*, *immediacy*, *salience* and *ambiguity*],

vi. the incoming order quantity $OQ_{i-1}(t-l_{i-1})$ for *i* = *MAN*, *WHL* or customer demand $D(t)$, for *i* = *RE*T [*i.e. immediacy*, *salience* and *ambiguity*],

vii. the net inventory position IN_i(t) [*i.e. reference dependence* and *complexity*],

viii. the realized cumulative profit $\sum_{j=1}^{t} P_i(j)$ [*i.e. reference dependence* and *complexity*].

These are the *decision attributes* that have been used in the subsequent gaming sessions for all human participants. Therefore, the relation (3.1) that presents the one-to-one association of the *decision variable* order quantity $oQ_i(t)$ with all corresponding *decision attributes* (*i.e.* $WP_i(t-1)$, $WP_i(t)$, WP_{i+1}(t), $OQ_i(t-1)$, $S_{i+1}(t-L_i+1)$, $OQ_{i-1}(t-l_{i-1})$, $WP_\mathrm{i}(t-l_{i-1})$, IN_i(t), $\sum_{j=1}^{t} P_i(j)$) becomes:

The Order Quantity's Decision Function

$$< OQ_i(t) >= f_i^{OQ(t)}[\,\mathrm{W}(t-1),\, WP_i(t), wP_{i+1}(\mathrm{t}), OQ_i(t-1), S_{i+1}(t-L_i+1), OQ_{i-1}(t-l_{i-1}), WP_{\mathrm{i}}(t-l_{i-1}), IN_i(\mathrm{t}), \textstyle\sum_{j=1}^{t} P_i(j)] \quad (7.2)$$

The description of the *Contract Beer Distribution Game* that is provided in *Section 6.3* along with the decision functions (7.1) and (7.2) fully specify the ABS model of the *Contract Beer Distribution Game* model, which is described in greater detail in the sub-section that follows.

Outcome 1: The Agent-Based Simulation Model of the Contract Beer Distribution Game

According to the exact specification of the *Contract Beer Distribution* that is provided in *Section 6.3*, there are three different types of agents: the *manufacturer-agent*, the *wholesaler-agent* and the *retailer-agent*. In accordance with the definition of an agent that is provided in *Section 3.2*, the bulleted list that follows briefly summarises how the *manufacturer-agent*, the *wholesaler-agent* and the *retailer-agent* satisfy all requirements and are, thus, eligible to be considered as agents:

- *Social Ability*: the *manufacturer-agent*, the *wholesaler-agent* and the *retailer-agent* have the social ability to communicate with each other and their surrounding environment. The *wholesale price contract* specifies all terms of trade and any exchange that occurs between them.

- *Capability to learn*: the *manufacturer-agent*, the *wholesaler-agent* and the *retailer-agent* use the feedback information that is provided to them to better understand their partners' *reaction*s and any changes that occur in their environment. In this way, they can modify and, thus, adapt their behaviours accordingly. The reader should at this point be reminded that the decision functions of the *manufacturer-agent* (*i.e.* relations 7.1 and 7.2), the *wholesaler-agent* (*i.e.* relations 7.1 and 7.2) and the *retailer-agent* (*i.e.* relation 7.2) may remain fixed, but the *agents'* exact decisions do vary with time, depending on the previous period's results. This dynamic behaviour encapsulates their capability to learn.

- *Autonomy:* the *manufacturer-agent*, the *wholesaler-agent* and the *retailer-agent* have separate and well determined goals to achieve and clearly defined internal logic rules that govern their actions.

- *Heterogeneity:* the *manufacturer-agent*, the *wholesaler-agent* and the *retailer-agent* follow their own *intention*s and make different decisions.

In this regard, Table 7.1 outlines the basic structure (*i.e.* attributes and behavioural characteristics) of the *retailer-agent*; Table 7.2 does the same for the *wholesaler-agent*, while Table 7.3 does so for the *manufacturer-agent*.

It is evident from Table 7.1 that the different *retailer-agent*s only differ in the exact values of their corresponding attributes. These are in turn given by the specific decision models of type (7.2) that have been fitted to the associated human retailer's respective decisions. Their exact values along with their detailed explanations are provided in *Sub-section 7.3.3*, where the decision models that have been fitted to all participants' datasets of recorded decisions are presented. Nevertheless, the association of the retailer's ($i = RET$) *decision variable* $OQ(t)$ with any *decision attribute*, that is the corresponding decision model coefficient, constitutes exactly what specifies the ABS model attribute (*e.g.* the association of

O$Q_i(t)$ with $OQ_i(t-1)$ provides the ABS model attribute $\tilde{\gamma}^{RET_s}_{OQ_{t-1}}$, that differs accross different *retailer-agent*s).

Following the same rationale, Tables 7.2 and 7.3 show that the different *wholesaler-agents* and *manufacturer-agents* only differ in the exact values of their corresponding attributes. These ABS model attributes are in turn given by the decision models of types (7.1) and (7.2) that have been fitted to the human participants' respective decisions. Although their exact values and detailed explanations are reported in *Sub-section 7.3.3*, their specification is provided by the decision model of types (7.1) and (7.2) that associates the participants' *decision variables* $wP_i(t)$ and $oQ_i(t)$ with all corresponding *decision attributes*.

The exact behaviour of the *retailer-agent* is presented in the statechart of Figure 7.1. The exact behaviour of the *wholesaler-agent* is illustrated in Figure 7.2 and the exact behaviour of the *manufacturer-agent* is illustrated in Figure 7.3.

From Figure 7.1 it is evident that the *retailer-agent* is considered to be in idle (*i.e*. awaiting) state while waiting for the wholesaler's price decision. From Figure 7.2 it is evident that the *wholesaler-agent* is in an awaiting state in two different instances. The first instance is before he/she determines his/her own price decision (possibly because he/she might wait to receive the price that is charged by the manufacturer, before making his/her decision). The second instance is while he/she waits to receive the manufacturer's price, in response to which the *wholesaler-agent* places his/her order.

Table 7.1: The basic structure of the *retailer-agent*

The Retailer-Agent		
Attributes: Regression Coefficients		Behaviours:
• $\gamma_{0}^{RET_s}$ • $\gamma_{WP_W}^{RET_s}$ • $\tilde{\gamma}_{OQ_{t-1}}^{RET_s}$ • $\lambda_{OQ_{RET}(t-1)}^{RET_s}$ • $\tilde{\gamma}_{S_{t-L_R+1}}^{RET_s}$ • $\lambda_{S_W(t-L_{RET}+1)}^{RET_s}$ • $\tilde{\gamma}_{IN_t}^{RET_s}$ • $\lambda_{IN_i(t)}^{RET_s}$ • $\tilde{\gamma}_{CP_t}^{RET_s}$ • $\lambda_{CP_t}^{RET_s}$	• $\beta_{0}^{RET_s}$ • $\beta_{WP_W}^{RET_s}$ • $\tilde{\beta}_{OQ_{t-1}}^{RET_s}$ • $\lambda_{OQ_{RET}(t-1)}^{RET_s}$ • $\tilde{\beta}_{S_{t-L_{RET}+1}}^{RET_s}$ • $\lambda_{S_W(t-L_{RET}+1)}^{RET_s}$ • $\tilde{\beta}_{IN_t}^{RET_s}$ • $\lambda_{IN_{RET}(t)}^{RET_s}$ • $\tilde{\beta}_{CP_t}^{RET_s}$ • $\lambda_{CP_t}^{RET_s}$	• Receiving a shipment (and incurring associated acquisition cost) • (Receiving and) satisfying the incoming demand • Earning profits • (Accepting the *price* and) placing an or*der*

***Table 7.2*:** The basic structure of the *wholesaler-agent*

<table>
<tr><th colspan="5">The Wholesaler-Agent</th></tr>
<tr><th colspan="4"><u>Attributes: </u>Regression Coefficients</th><th><u>Behaviours:</u></th></tr>
<tr>
<td>• $a_{0}^{WHL_s}$
• $a_{WP_{MAn}}^{WHL_s}$
• $\widetilde{a}_{OQ_{t-1}}^{WHL_s}$
• $\lambda_{OQ_{WHL}(t-1)}^{WHL_s}$
• $\widetilde{a}_{S_{t-L_{WHl}+1}}^{WHl_s}$
• $\lambda_{S_F(t-L_{WHl}+1)}^{WHL_s}$
• $\widetilde{a}_{OQ_{t-l_R}}^{WHL_s}$
• $\lambda_{OQ_{RET}(t-l_{RET})}^{WHL_s}$
• $a_{WP_{t-l_{RET}}}^{WHL_s}$
• $\widetilde{a}_{IN_t}^{WHL_s}$
• $\lambda_{IN_{WHl}(t)}^{WHl_s}$</td>
<td>• $\widetilde{a}_{CP_t}^{WHL_s}$
• $\lambda_{CP_t}^{WHL_s}$
• $\gamma_{0}^{WHL_s}$
• $\gamma_{WP_{t-1}}^{WHL_s}$
• $\gamma_{WP_t}^{WHL_s}$
• $\gamma_{WP_{MAN}}^{WHL_s}$
• $\widetilde{\gamma}_{OQ_{t-1}}^{WHL_s}$
• $\lambda_{OQ_w(t-1)}^{WHL_s}$
• $\widetilde{\gamma}_{S_{t-L_{WHL}+1}}^{WHL_s}$
• $\lambda_{S_{MAN}(t-L_{WHL}+1)}^{WHL_s}$</td>
<td>• $\widetilde{\gamma}_{OQ_{t-l_R}}^{WHL_s}$
• $\lambda_{OQ_{RET}(t-l_{RET})}^{WHL_s}$
• $\widetilde{\gamma}_{IN_t}^{WHL_s}$
• $\lambda_{IN_{WHL}(t)}^{WHL_s}$
• $\widetilde{\gamma}_{CP_t}^{WHL_s}$
• $\lambda_{CP_t}^{WHL_s}$
• $\beta_{0}^{W_s}$
• $\beta_{0}^{W_s} + \beta_{wP_{t-1}}^{W_s}$
• $\beta_{WP_t}^{W_s}$
• $\beta_{WP_F}^{W_s}$</td>
<td>• $\widetilde{\beta}_{OQ_{t-1}}^{W_s}$
• $\lambda_{OQ_W(t-1)}^{W_s}$
• $\widetilde{\beta}_{S_{t-L_W+1}}^{W_s}$
• $\lambda_{S_F(t-L_W+1)}^{W_s}$
• $\widetilde{\beta}_{OQ_{t-l_R}}^{W_s}$
• $\lambda_{OQ_R(t-l_R)}^{W_s}$
• $\widetilde{\beta}_{IN_t}^{W_s}$
• $\lambda_{IN_W(t)}^{W_s}$
• $\widetilde{\beta}_{CP_t}^{W_s}$
• $\lambda_{CP_t}^{W_s}$</td>
<td>• Receiving a shipment (and completing outstanding financial transactions)
• (Receiving incoming order and) filling the incoming order
• Earning profits
• Charging a wholesaler price
• (Accepting the price and) placing an order</td>
</tr>
</table>

Table 7.3: The basic structure of the manufacturer-agent

The Manufacturer-Agent	
Attributes: Regression Coefficients	Behaviours:
• $a_{0}^{MAN_s}$ • $\widetilde{a}_{oQ_{t-1}}^{MAN_s}$ • $\lambda_{OQ_F(t-1)}^{MAN_s}$ • $\widetilde{a}_{OQ_{t-L_{MAN}-1}}^{MAN_s}$ • $\lambda_{OQ_{MAN}(t-L_{MAN}-1)}^{MAN_s}$ • $\widetilde{a}_{OQ_{t-l_{WHL}}}^{MAN_s}$ • $\lambda_{OQ_{WHL}(t-l_{WHL})}^{MAN_s}$ • $a_{WP_{t-l_{WHL}}}^{MAN_s}$ • $\widetilde{a}_{IN_t}^{MAN_s}$ • $\lambda_{IN_{MAN}(t)}^{MAN_s}$ • $\widetilde{a}_{CP_t}^{MAN_s}$ • $\lambda_{CP_t}^{MAN_s}$ • $\gamma_{0}^{MAN_s}$ • $\gamma_{WP_{t-1}}^{MAN_s}$ • $\gamma_{WP_t}^{MAN_s}$. • $\widetilde{\gamma}_{OQ_{t-1}}^{MAN_s}$ • $\lambda_{OQ_{MAN}(t-1)}^{MAN_s}$ • $\widetilde{\gamma}_{OQ_{t-L_{MAN}-1}}^{MAN_s}$ • $\lambda_{OQ_{MAN}(t-L_{WHL}-1)'}^{MAN_s}$ • $\widetilde{\gamma}_{OQ_{t-l_{WHL}}}^{MAN_s}$ • $\lambda_{OQ_{WHL}(t-l_{WHL})}^{MAN_s}$ • $\widetilde{\gamma}_{IN_t}^{MAN_s}$ • $\lambda_{IN_{MAN}(t)}^{MAN_s}$ • $\widetilde{\gamma}_{CP_t}^{MAN_s}$ • $\lambda_{CP_t'}^{F_s}$ • $\beta_{0}^{MAN_s}$ • $\beta_{WP_{t-1}}^{MAN_s}$ • $\beta_{WP_t}^{MAN_s}$ • $\widetilde{\beta}_{OQ_{t-1}}^{MAN_s}$ • $\lambda_{OQ_{MAN}(t-1)}^{MAN_s}$ • $\widetilde{\beta}_{OQ_{t-L_{MAN}-1}}^{MAN_s}$ • $\lambda_{OQ_{MAN}(t-L_{MAN}-1)}^{MAN_s}$ • $\widetilde{\beta}_{OQ_{t-l_{WHL}}}^{MAN_s}$ • $\lambda_{OQ_{WHL}(t-l_{WHL})}^{MAN_s}$ • $\widetilde{\beta}_{IN_t}^{MAN_s}$ • $\lambda_{IN_F(t)}^{MAN_s}$ • $\widetilde{\beta}_{CP_t}^{MAN_s}$ • $\lambda_{CP_t}^{MAN_s}$	• Receiving a production lot (and completing outstanding financial transactions) • (Receiving incoming order and filling the incoming order) • Producing past production request (and incurring production cost) • Earning profits • Charging a *manufacturer price* • Placing a production request

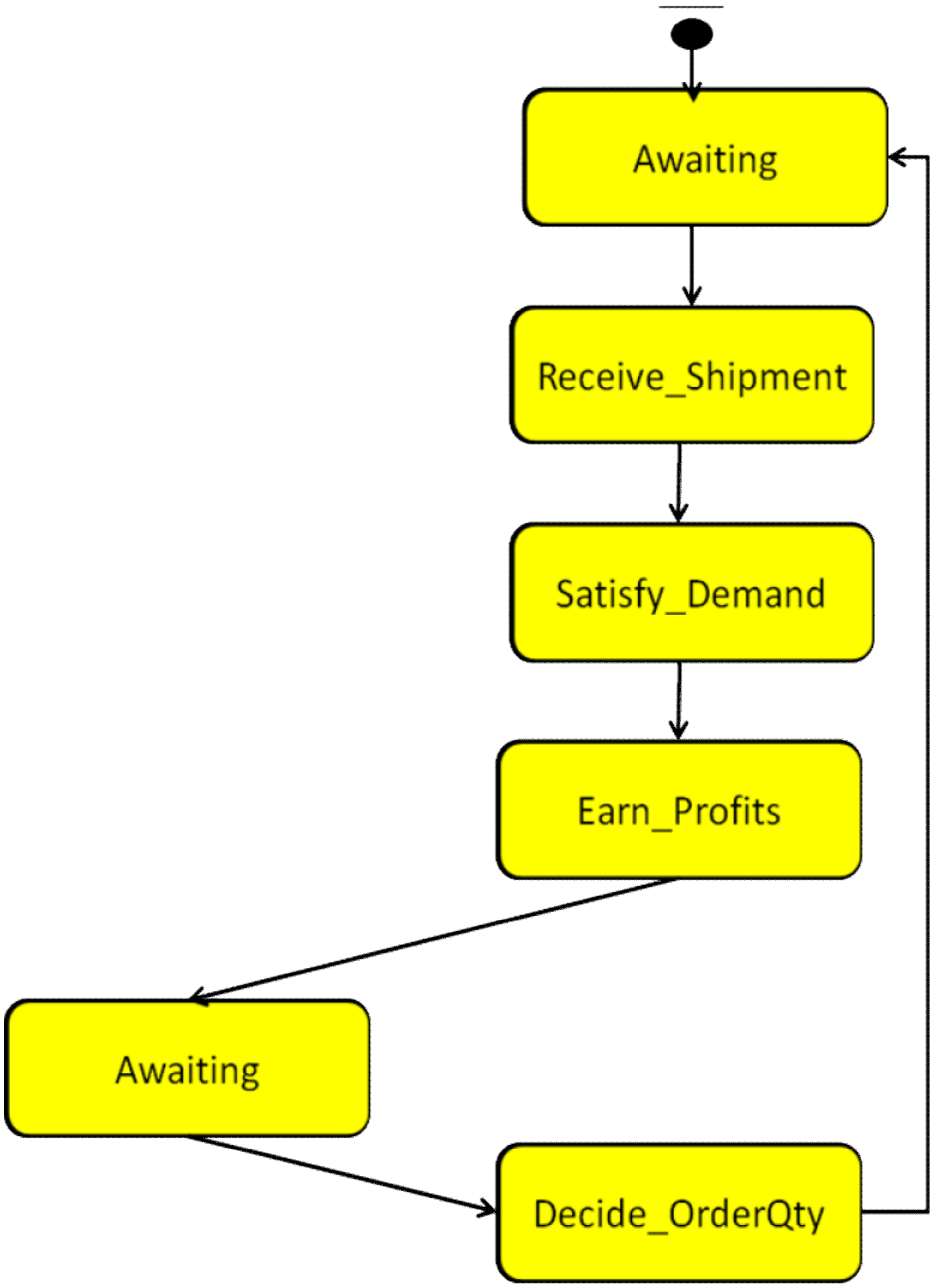


Figure 7.1: The statechart of the *retailer-agent*

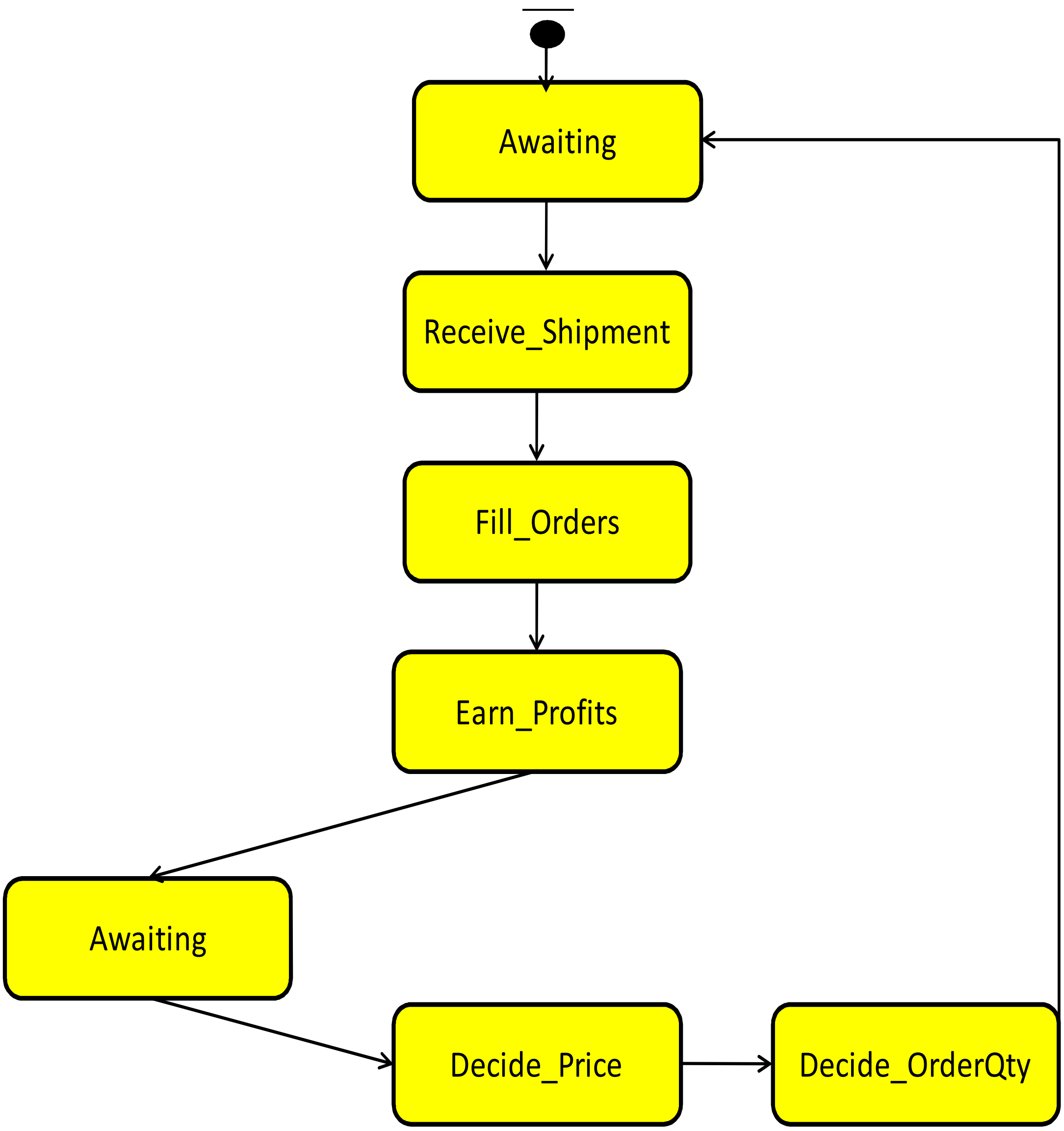


Figure 7.2: The statechart of the *wholesaler-agent*

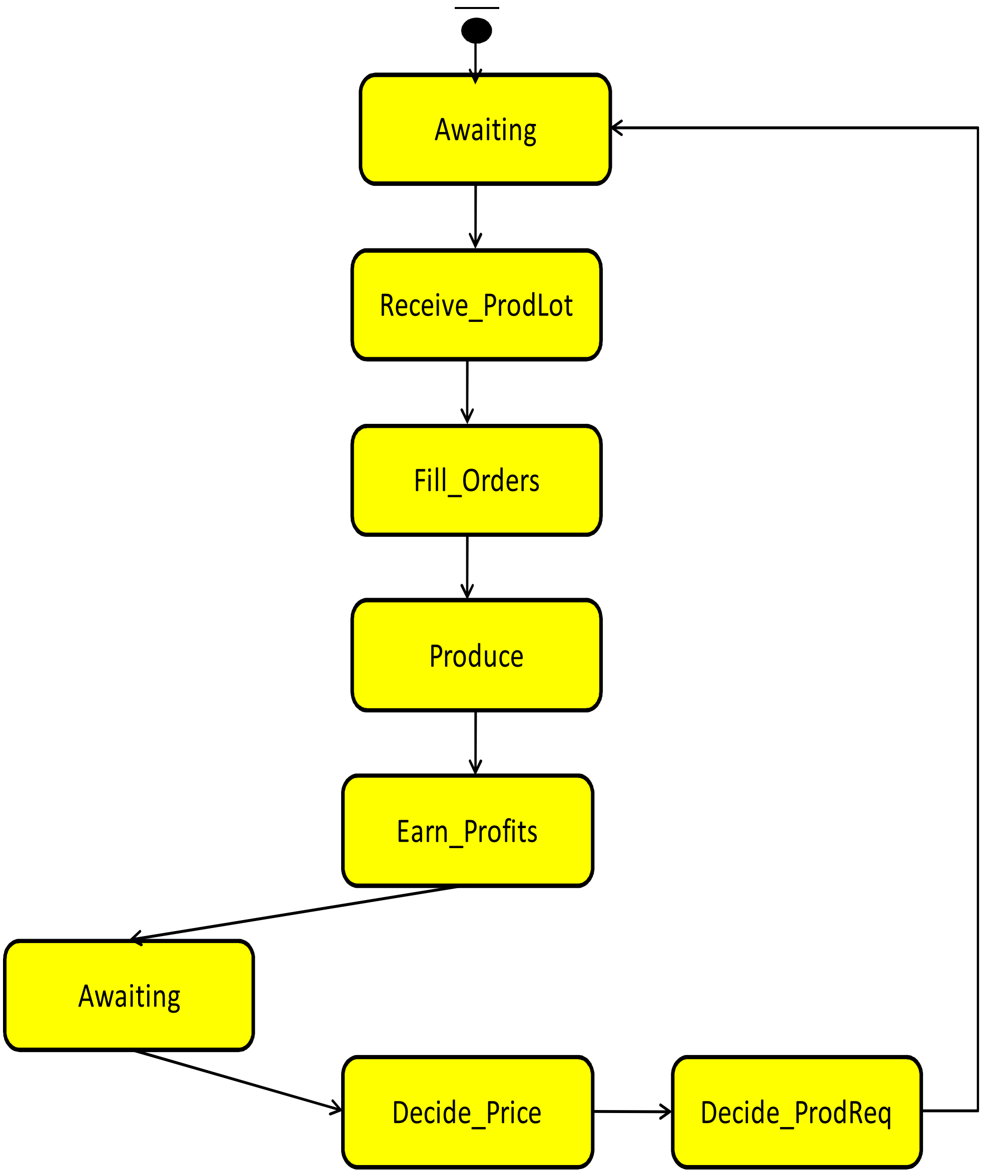


Figure 7.3: The statechart of the *manufacturer-agent*

Figure 7.3 also demonstrates that the *manufacturer-agent* does not need to wait for his/partners decisions in order to make his/her respective decisions. The reasons are that the *manufacturer-agent* incurs a fixed manufacturing cost (c=0.5*m.u.*) and does not place production requests in immediate response to the orders that are placed by the wholesaler. For a detailed explanation the reader is referred to *Steps d)* and *i)* of the *Contract Beer Distribution Game* in *Sub-section 6.2.2*, where it is evident that both the wholesaler and the manufacturer must wait $l_i = 2$ (i = 2, 3) time periods to receive a newly placed order from their respective downstream customer.

The underlying *environment* of the ABS model of the *Contract Beer Distribution Game* symbolizes the market. The environment reflects the customer demand that is uncertain in nature. The element of *combined evolution* is of most relevance to the research hypotheses CBG.3 and CBG.4 that concern whether the *emerging competition penalties* would statistically differ from 0 and the *bullwhip effect* would prevail. In this way, it can be established whether 'globally *efficient*' interactions can *emerge* from the interactions of 'locally poor' decisions.

'Globally *efficient*' interactions would attain overall *competition penalties* that would not differ significantly from 0 and/or where the *bullwhip effect* would not prevail. As for 'locally poor' decisions, these concern price and order quantity decisions that would substantially differ from the corresponding rationally optimising counterparts' decisions, as specified by research questions CBG.1 and CBG.2 respectively.

Based on the above specifications, given the problem's small size and mostly for reasons of speed of model build, ease of use and familiarity with the data presentation, a spreadsheet version of the model (in Excel-VBA) has been developed (Robinson, 2004; North and Macal, 2007).

7.3.2 Stage 2: The Gaming Sessions

The objective of the second stage is to collect data for each human decision maker. Table 7.4 summarises the key aspects of all gaming sessions that were conducted to this end, namely, the sample of subjects, the version of the game along with the corresponding computer interfaces, the duration and distinct components of each session, the underlying customer demand, the provision of financial incentives to participants and the response sets or else *scenarios* that were provided to the human subjects in each session.

Table 7.4: Summary of Gaming Sessions

Sample	From a pool of 2009 Warwick Business School students (*i.e.* MSc in Management, MSc in Management Science and Operational Research and MSc in Business Analytics and Consulting): • MAN_0 to MAN_3 • WHL_0 to WHL_3 • RET_0 *to* RET_3 Demographic characteristics of all participants are provided in Tables 7.5-7.7.
Computer Interface	• *"Base Session"*(*i.e. Session No. 1* in Table 7.8) *:* over the board • *Remaining sessions* (*i.e. Sessions No. 2 - No. 10* in Table 7.8): computerized simulation games. • Screenshots of the computer interfaces that were presented to participants are attached in Figures 7.4 - 7.6.
Customer Demand	• Sterman's (1989, 1992) step-up function • Only the human retailers were aware of true customer demand realizations • The participants were not aware of demand distribution
Duration of Sessions	• 2hrs • 10 *trial periods* that were evenly spread over the total

	number of different *supply chain configurations* • *N*= 90 consecutive rounds for each participant • The participants were not aware of the exact session's duration, so that end-of-game effects could be eliminated • Debriefing • Post-game interview (For an illustrative example of what constituted the basis of the conversation that took place *s.* Appendix C.2)
Financial Incentives	No financial incentives were offered
Scenarios	Following *Latin Hypercube Design* (4^2, *3*) the experimental protocol is presented in Table 7.8

The sub-sections that follow explain some of these key aspects in greater detail. For even more details the interested reader is referred to Appendix C.1 that provides a detailed account of the gaming sessions.

Sample

Tables 7.5, 7.6 and 7.7 summarize the main demographic characteristics of all human subjects, by the role that was assigned to each of them.

Table 7.5: The human manufacturers - subjects

Factor level	**Course**	**Age**
MAN_0	MSc in Management	24
MAN_1	MSc in Management Science and Operational Research	26
MAN_2	MSc in Business Analytics and Consulting	24
MAN_3	MSc in Management Science and Operational Research	23

Table 7.6: The human wholesalers - subjects

Factor level	Course	Age
WHL_0	MSc in Management	25
WHL_1	MSc in Management	26
WHL_2	MSc in Business Analytics and Consulting	25
WHL_3	MSc in Management Science and Operational Research	23

The participation requirements set were two-fold: *a*). all participants had received formal classroom training in inventory management principles, prior to the experiment, as part of their curriculum requisite; and *b*). none of the participants had played any version of the *Beer Distribution Game* before. Both requirements *intend*ed to control and, thus, ensure a standard, common level of knowledge of the game dynamics from all participants. Given recent empirical studies that confirm the overall analogous performance of well trained students when compared with experienced supply chain managers (Croson and Donohue, 2006; Bolton *et al*, 2008), a graduate level course in inventory management would help the participants to better and faster understand the game underlying dynamics and, therefore, perform as well as possible. As for prior participation in the *Beer Distribution Game,* any pre-conception resulting from this might bias the participants against exploring the full potential of the extra control (*i.e*. the *price* decision) that is offered to them in the *Contract Beer Distribution Game* (that is, in comparison to Sterman's (1989; 1992) traditional version of the game).

Table 7.7: The human retailers - subjects

Factor level	**Course**	**Age**
RET_0	MSc in Management	23
RET_1	MSc in Management Science and Operational Research	22
RET_2	MSc in Management Science and Operational Research	24
RET_3	MSc in Management Science and Operational Research	37

Computer Interface

The first three participants who were invited to the laboratory played the *Contract Beer Distribution Game* facing each other over the board. All other participants were asked to record their decisions in computerized simulation games of the *Contract Beer Distribution Game* with three serial echelons (Steckel *et al*, 2004). They worked with a computer interface that simulated the interacting partners' responses. This computer interface has been adapted from the ABS model of the *Contract Beer Distribution Game* that has been developed at the end of *Stage 1* (*i.e. Outcome 1*). An illustrative screen shot of this computer interface, as shown to the human manufacturers, is illustrated in Figure 7.4; while the corresponding screenshots of the computer interfaces that were presented to the human wholesalers and the human retailers are attached in Figures 7.5 and 7.6 respectively.

As is evident from these screenshots, participants are expected to perform the following sequence of activities: *i.* initialize the application ("start the game"), *ii.* enter their decisions (namely, order quantities for the human retailers; prices and order quantities for the human wholesalers and the human manufacturers) and *iii.* "proceed" the game until, finally, being advised by the researcher to "end the game". When subjects click on "proceed", the application records their decisions, informs the corresponding downstream customers about their selected prices, places their order quantities with their corresponding upstream suppliers, simulates their partners' responses and updates accordingly the game statistics.

After every repetition, participants receive via the computer interface feedback on their previous decisions, their realized profit (or losses), their current inventory position and their incoming order. They are also informed about the price that is currently charged to them by their upstream supplier (that is, if applicable) and the shipment that is in transit to their warehouse. In case they wish to obtain any additional history information, they have access to full history information by clicking on the relevant button of their interface.

Interacting Partners

Written instructions on the required task were distributed to all participants well in advance of their allocated session so that they could get familiar with the task and the available software as quickly as possible. The instructions that were distributed to the subjects who played the role of the retailer are presented in Appendix C.3, while the instructions that were distributed to the subjects who played the roles of the wholesaler and the manufacturer are attached in Appendices C.4 and C.5 respectively.

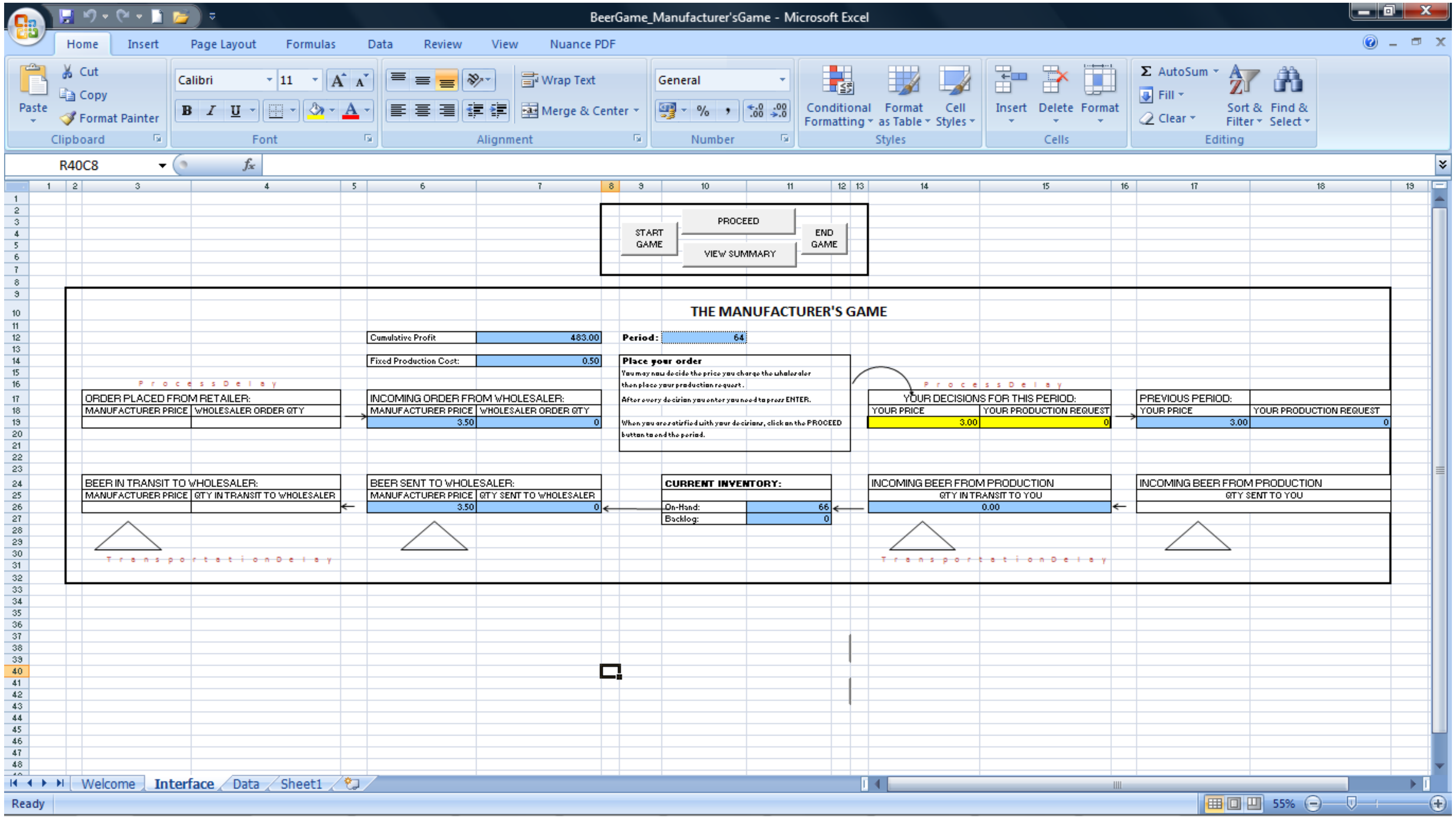


Figure 7.4: The computer interface of the simulation game that is faced by the human manufacturers

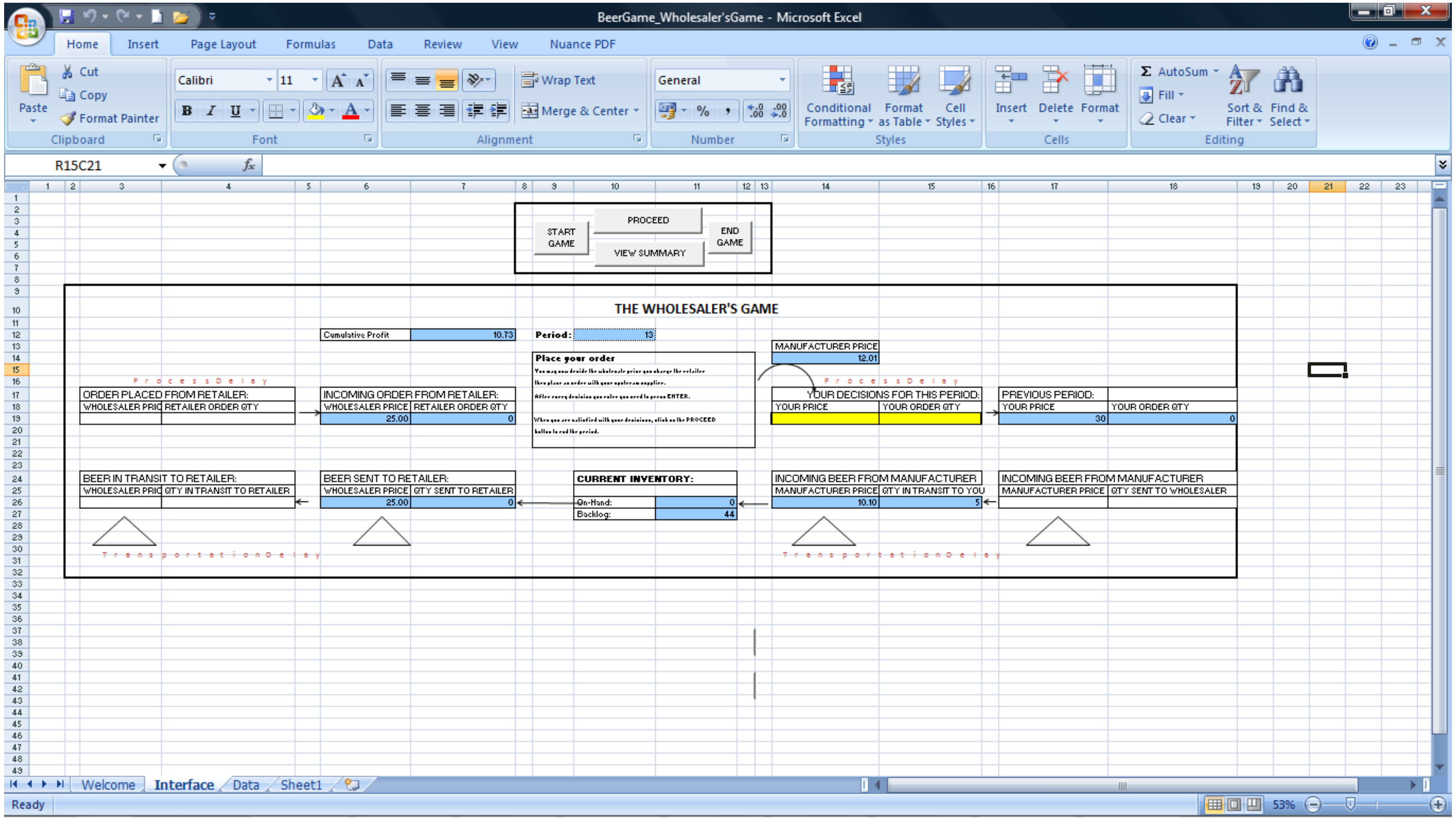


Figure 7.5: The computer interface of the simulation game that is faced by the human wholesalers

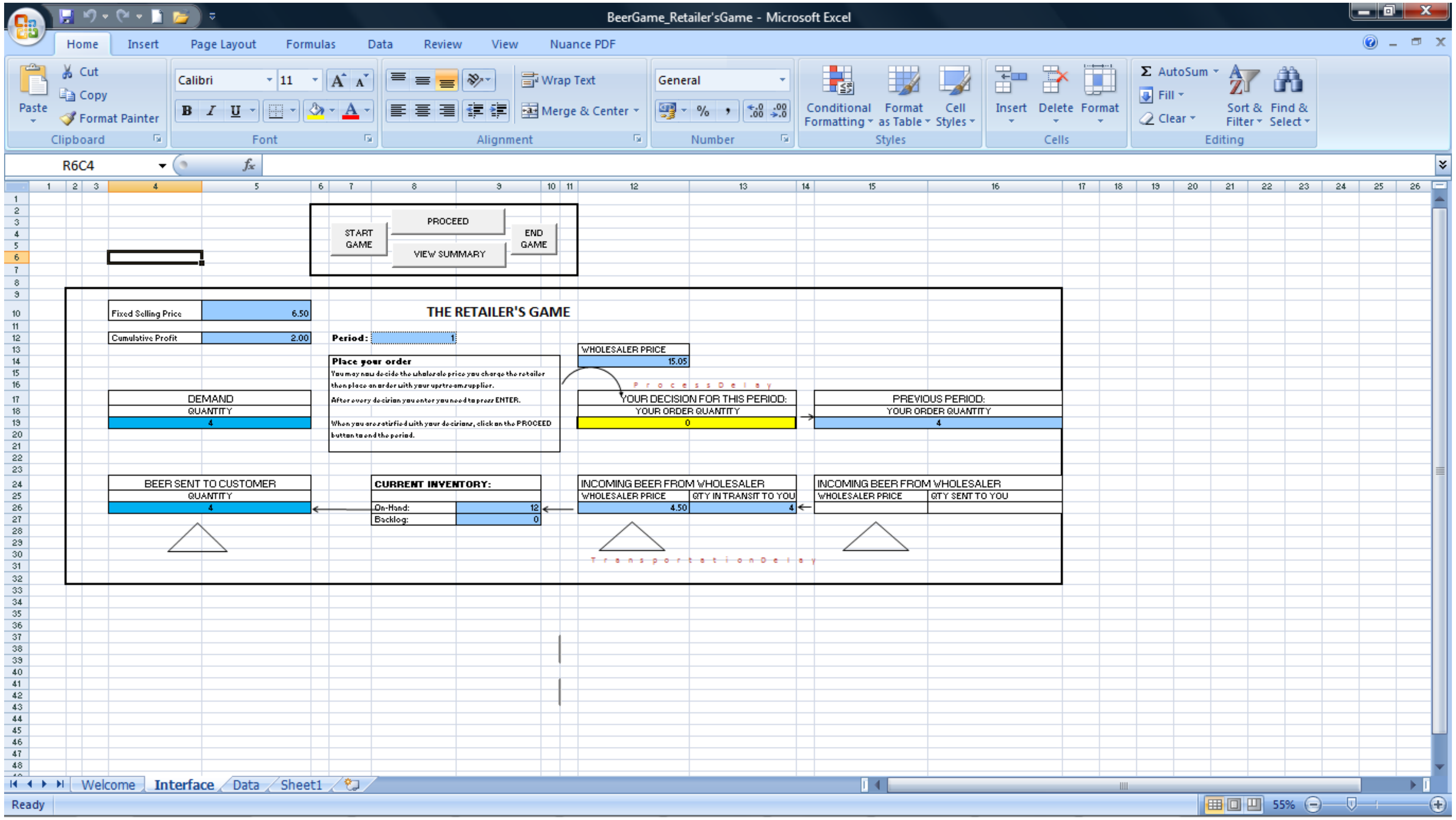


Figure 7.6: The computer interface of the simulation game that is faced by the human retailers

Apart from written instructions, the participants could address questions both before the start of the session and during its course. Nevertheless, the game could not be re-started, once it had began.

Apart from written instructions, the participants could address questions both before the start of the session and during its course. Nevertheless, the game could not be re-started, once it had began.

Scenarios

Table 7.8 outlines the gaming sessions that were conducted, according to the *Latin Hypercube Experimental Design* of k=3 treatment factors (*i*.*e*. *MAN*, *WHL*, *RET*) at s=4 levels each. More details on the exact way that this experimental protocol derived from the *Latin Hypercube Design* are provided in Appendix C.6. The grey shaded row in Table 7.8 (*i*.*e*. *Session No*. *1*) that is separated from the remaining rows with a dashed line represents the "base" session that was required to let the iteration between gaming sessions and inference of decision making strategies begin.

To this end, one decision model needed to be deduced for each available role: one for the manufacturer (MAN_0), one for the wholesaler (WHL_0) and one for the retailer (RET_0). This is why the subjects who had been randomly assigned to the subject codes MAN_0, WHL_0 and RET_0 were asked to participate in the study first. Since there were no pre-deduced decision models for these subjects to interact with, they were asked to play with each other interactively over the board. Once the decisions of $MAN_{0,}$ WHL_0 and RET_0 were recorded, the appropriate combinations of decision models that would determine their corresponding decision models $f_i^{WP(t)}$ and $f_i^{OQ(t)}$, according to types (7.1) and

(7.2), were inferred. The exact approach that was used to this end is discussed in *Sub-section 7.3.3*.

Table 7.8 also denotes that in the second gaming session (*i.e Session No. 2*) the decisions of the participant, who had been assigned the code WHL_2, were recorded. This participant was asked to interact with the fitted decision models of MAN_0 and RET_0. The result of this second gaming session was that the decision models $f_i^{WP(t)}$ and $f_i^{OQ(t)}$ that corresponded to WHL_2 could be inferred. Subsequently, in the third gaming session (*i.e Session No. 3*) the decisions of the participant, who had been assigned the code RET_3, were recorded. This participant was in turn asked to interact with the fitted decision models of MAN_0 and WHL_2. Following this third session, the decision model $f_i^{OQ(t)}$ that corresponded to RET_3 was deduced.

In the next, fourth, gaming session (*i.e Session No. 4*) the decisions of the participant, who had been assigned the code RET_1, were recorded. This participant was asked to interact with two different *scenarios* or else *supply chain configurations*: namely, the interaction of the MAN_0 and WHL_2 and the interaction of MAN_0 and WHL_0 interaction. The only difference between this gaming session that comprised of two different *supply chain configurations* and the previous gaming sessions that only included one *supply chain configuration* was that the sample size of total observations (N=90) was equally split over the two *supply chain configurations* that were under study, with 5 trial periods applied at the beginning of each. At each beginning, the participants were informed that they would be interacting with a different set of partners and the game was restarted. The remaining gaming sessions (*Sessions No. 5 - 10)* proceeded in exactly the same way.

Table 7.8: The Experimental Protocol

Session No.	***Participant*** (*i.e.* Decision Making Strategy –ies- to be determined)	***Supply Chain Configuration*** (*i.e.* Known Decision Making Strategies)
1	$\boldsymbol{MAN_0}$, $\boldsymbol{WHL_0}$, $\boldsymbol{RET_0}$	---
2	$\boldsymbol{WHL_2}$	MAN_0, RET_0
3	$\boldsymbol{RET_3}$	WHL_2, MAN_0
4	$\boldsymbol{RET_1}$	MAN_0,WHL_2 MAN_0,WHL_0
5	$\boldsymbol{MAN_1}$	WHL_2, RET_1
6	$\boldsymbol{WHL_3}$	MAN_0, RET_0 MAN_1, RET_0 MAN_1,RET_1
7	$\boldsymbol{WHL_1}$	MAN_1,RET_0
8	$\boldsymbol{RET_2}$	MAN_1, WHL_0
9	$\boldsymbol{MAN_2}$	WHL_1, RET_2 WHL_1, RET_0 WHL_0, RET_3
10	$\boldsymbol{MAN_3}$	WHL_1, RET_2 WHL_0, RET_1 WHL_0, RET_3

Table 7.8 indicates how 50% of the gaming session that were performed consisted of multiple supply chain configurations. In this way, participants were allocated to multiple supply chain configurations. Furthermore, Table 7.8 demonstrates how 17 different supply chain configurations were possible within, in total, 10 gaming sessions. This was accomplished by running multiple supply chain configurations within a single gaming session. In this way, no human subjects were asked to participate in more than one gaming sessions. Because of the way that the sampling observations were split over the different supply chain configurations explored, the session durations were also even.

Outcome 2: The Datasets of Participants' recorded Decisions

Similarly to the *Newsvendor Problem* setting, all participants' recorded decisions are collectively gathered with the associated *decision attribute*s in appropriate datasets.

7.3.3 Stage 3: The Decision Making Strategies

The objective of the third stage is to determine the decision model that corresponds to each participant, namely specify the relations of type (7.1) that correspond to the price decisions $wP_{i_s}(t)$ of each participant i_s (i: *MAN*, *WHL*) and the relations of type (7.2) that correspond to the order quantity decisions $oQ_{i_s}(t)$ of each participant i_s (i: *MAN*, *WHL*, *RET*).

Following the same approach that is used in the *Newsvendor Problem* setting, the decision models that correspond to the price decisions $wP_{i_s}(t)$ get transformed to the $l_{i\text{-}1}$-th order auto-regressive time-series models $AR(l_{i\text{-}1})$ of type (7.3), while the decision models that correspond to the order quantity decisions $oQ_{i_s}(t)$ become the $l_{i\text{-}1}$ – th order auto-regressive time-series models $AR(l_{i\text{-}1})$ of type (7.4) (Mills, 1990; Box *et al*, 1994; Hamilton, 1994; Greene, 2002).

<u>*Types of Decision Models in the Contract Beer Distribution Game*</u>

$$\langle wP(t)\rangle_{i_s} = a_0^{i_s} + a_{wP_{i+1}}^{i_s} \cdot wP_{i+1}(t) + a_{oQ_{t-1}}^{i_s} \cdot oQ_i(t-1) + a_{S_{t-L_i+1}}^{i_s} \cdot S_{i+1}(t-L_i+1) + a_{oQ_{t-l_{i-1}}}^{i_s} \cdot oQ_{i-1}(t-l_{i-1}) + a_{wP_{t-l_{i-1}}}^{i_s} \cdot wP_i(t-l_{i-1}) + a_{IN_t}^{i_s} \cdot \tag{7.3}$$

$$\langle Wp(t)\rangle_{i_s} = a_0^{i_s} + a_{WP_{i+1}}^{i_s} \cdot WP_i(t-1) + \beta_{WP_t}^{i_s} \cdot WP_i(t) + \beta_{WP_{i+1}}^{i_s} \cdot WP_{i+1}(t) + \beta_{OQ_{t-1}}^{i_s} \cdot OQ_i(t-1) + \beta_{S_{t-L_i+1}}^{i_s} \cdot S_{i+1}(t-L_i+1) + \beta_{OQ_{t-l_{i-1}}}^{i_s} \cdot OQ_{i-1}(t-l_{i-1})$$

$$\langle OQ(t)\rangle_{i_s} = \beta_0^{i_s} + \beta_{WP_{t-1}}^{i_s} \cdot WP_i(t-1) + \beta_{WP_t}^{i_s} \cdot WP_i(t) + \beta_{WP_{i+1}}^{i_s} \cdot WP_{i+1}(t) + \beta_{OQ_{t-1}}^{i_s} \cdot OQ_i(t-1) + \beta_{S_{t-L_i+1}}^{i_s} \cdot S_{i+1}(t-L_i+1) + \beta_{OQ_{t-l_{i-1}}}^{i_s} \cdot OQ_{i-1}(t-l_{i-1}) + \beta_{IN_t}^{i_s} \cdot IN_i(t) + \beta_{CP_t}^{i_s} \cdot \sum_{j=1}^{t} P_i(j) \tag{7.4}$$

In these linear models, the value of each coefficient $a_k^{i_s}$ (where $k \in wP_{i+1}$(t)$, oQ_i(t-1), S_{i+1}(t-L_i$+1), $oQ_{i-1}(t-l_{i-1}), WP_\mathrm{i}(t-l_{i-1}), IN_i(t), \sum_{j=1}^{t} P_i(j)$) and $\beta_k^{i_s}$ (where $k \in WP_i(t-1),\ WP_i(t), WP_{i+1}(t), OQ_i(t-1),\ S_{i+1}(t-L_i$+1)$, OQ_{i-1}(t-l_{i-1}), WP_\mathrm{i}(t-l_{i-1}), IN_i(t), \sum_{j=1}^{t} P_i(j)$ reflects the importance that each human participant assigns to each of the *decision attribute*s that he/she considers for his/her respective decision $\langle WP(t)\rangle_{i_s}$and $\langle OQ(t)\rangle_{i_s}$. A number of departures from *linearity*, *normality* and *hetero-skedasticity* for some of the dependent and independent variables has been identified by the testing procedure that is presented in Appendix C.7 (Weisberg, 2005; Hair *et al*, 2006; Fox, 2008).

In order to address these departures, appropriate modifications need to be applied to the simple linear regression models of types (7.3) and (7.4). Appendix C.8 discusses the main reasons for which the earlier example of a number of related papers is not followed; these papers (*e.g*. Bostian *et al*, 2008; Su, 2008; Ho *et al*, 2009; Lurie and Swaminathan, 2009) apply Generalised Linear Models (GLMs) (Nelder and Wedderburn, 1972) to remedy the aforementioned violations. In this study the following two remedies are instead put in force. The *first* remedy is that the participants' order quantity decisions are viewed as two distinct decisions: (*i*) whether they wish to place a strictly positive order and, provided that they do, (*ii*) exactly to how much would this order quantity amount to. This remedy addresses the *non-normality* of the order quantity decisions $\langle oQ(t) \rangle_{i_s}$ of most human participants, namely the added mass at the value of zero that most participants' order quantity decisions have. The *second* remedy is that appropriate transformations are enforced to the values of the *decision attributes* that violate *normality*. In this way, *non-linearity* and *hetero-skedasticity* are additionally accounted for (Weisberg, 2005; Hair et al, 2006). The paragraphs that follow discuss these two remedies in more detail.

In order to model participants' decision to place a non-zero or zero order, the logistic regression model of type (7.5) is used. In equation (7.5) any deriving probability value above the cut-off threshold of 0.5 naturally represents the placement of a strictly positive order, while any value below 0.5 respectively implies a refusal to place a non-zero order (Tsokos and DiCrose, 1992; Hosmer and Lemeshow, 2000; Hair *et al*, 2006). Moreover, the coefficients of the logistic regression (γ_0, γ_1,...,γ_κ) reflect the importance that each participant assigns to each of his/her *decision attribute*s for his/her decision to place a non-zero order (Hosmer and Lemeshow, 2000;Hair *et al*, 2006).

The main advantage of this model is that the existing violations of *normality*, *linearity* and *homo-skedasticity* do not pose any concerns about the applicability of the logistic regression model (Hosmer and Lemeshow, 2000; Hair *et al*, 2006). The reader should at this point also be reassured that since in the gaming sessions that were conducted at least 10 observations were collected for each explanatory variable (*s.* S*ub-section 7.3.2*), the risk of over-fitting was to a great part eliminated (*i.e*. the minimum sample size requirements of logistic regression were satisfied: Hosmer and Lemeshow, 2000).

<u>The Decision of placing a strictly positive Order in the Contract Beer Distribution Game</u>

$$\langle logit(OQ(t))\rangle_{i_s} = \gamma_0^{i_s} + \gamma_{WP_{t-1}}^{i_s} \cdot WP_i(t-1) + \gamma_{WP_t}^{i_s} \cdot WP_i(t) + \gamma_{WP_{i+1}}^{i_s} \cdot V$$
$$\varphi_{i_s}\left\{\lambda_{OQ_i(t-1)}^{i_s}, OQ_i(t-1)\right\} + \gamma_{S_{t-L_i+1}}^{i_s} \cdot \varphi_{i_s}\left\{\lambda_{S_{i+1}(t-L_i+1)}^{i_s}, \ S_{i+1}(t-L_i+1)\right\} \cdot \tag{7.5}$$
$$\varphi_{i_s}\left\{\lambda_{OQ_{i-1}(t-l_{i-1})}^{i_s}, OQ_{i-1}(t-l_{i-1})\right\} + \gamma_{IN_t}^{i_s} \cdot \varphi_{i_s}\left\{\lambda_{IN_i(t)}^{i_s}, IN_i(t)\right\} + \gamma_{CP_t}^{i_s} \cdot \varphi_{i_s}\{$$

Among the available families of transformations, the Yeo-Johnson (2000) transformation is applied to the values of the *decision attributes* that violate *normality* or *linearity*. The main reason is it extends the good properties of the Box-Cox transformation (Box and Cox, 1964) to the whole real line (Thode, 2002; Weisberg, 2005; Hair *et al*, 2006). Relation (7.6) defines the family of the Yeo-Johnson trasformations. Relation (7.6) indicates that if the data values of y are strictly positive, then the Yeo-Johnson transformation is the same as the Box-Cox power transformation of (y+1). If y is strictly negative, then the Yeo-Johnson transformation is the same as the Box-Cox power transformation of (-y+1), but with the power of 2-λ, where λ represents the chosen power value. Therefore, in case both positive and negative values are existent, different power values of λ are used for positive and negative values. In order to identify the appropriate power values $\boldsymbol{\lambda}^* = \langle\lambda_1^*, \dots, \lambda_K^*\rangle = \langle\lambda_\kappa^*\rangle$ for different participants' *decision variable*s and *decision attribute*s, Velilla's (1993) recommendation is followed. According to this, among the most usual power values, that is [-3,...,3]

(Weisberg, 2005; Hair et al, 2006), the set of transformation parameters λ_{κ}^{*} that minimise the logarithm of the determinant of the sample covariance matrix of the transformed data $\varphi(\boldsymbol{\lambda}^{*}, \boldsymbol{Y})$ is chosen.

<u>*Yeo-Johnson (2000) Transformation*</u>

$$\varphi(\lambda, y) = \begin{cases} \dfrac{(y+1)^{\lambda} - 1}{\lambda}, & if\ \lambda \neq 0, y \geq 0 \\ log\ (y+1), & if\ \lambda = 0, y \geq 0 \\ -\left[\dfrac{(-y+1)^{2-\lambda} - 1}{2-\lambda}\right], & if\ \lambda \neq 2, y < 0 \\ -log\ (-y+1), & if\ \lambda = 2, y < 0 \end{cases} \tag{7.6}$$

The relations (7.7) – (7.9) that follow present the revised types of decision models that exist in the *Contract Beer Distribution Game*. In greater detail, the type (7.7) reflects the participants' pricing decision models, the type (7.8) outlines the order placement decision models, while the type (7.9) indicates the exact order quantity decision models (that is, provided that the participants do wish to place a strictly positive order). In these decision models the violations of *normality*, *linearity* and *homo-skedasticity* are addressed via: *i*. the provision of participants' potential desire to place a zero order (*i.e*. logit model of type (7.5)) and *ii*. the appropriate Yeo-Johnson (2000) transformations of type (7.6). In the models (7.7) – (7.9) these transformations are incorporated via the modified regression coefficients $\tilde{\alpha}^{i}$s, $\tilde{\gamma}^{i}$s and $\tilde{\beta}^{i}$s respectively. In relation (7.9) it is also checked whether the binary transformation of the *decision attributes* (namely λ= $I\{x > 0\} \stackrel{\text{def}}{=} \begin{cases} 0, \text{if } x = 0 \\ 1, \text{if } x > 0 \end{cases}$) would increase the explanatory power of the logistic regression model (Hosmer and Lemeshow, 2000; Hair *et al*, 2006; Fox, 2008).

<u>Revised Types of Decision Models in the Contract Beer Distribution Game</u>

$$\langle WP(t)\rangle_{i_s} = a_0^{i_s} + a_{WP_{i+1}}^{i_s} \cdot WP_{i+1}(t) + \tilde{a}_{OQ_{t-1}}^{i_s} \cdot \varphi_{i_s}\left\{\lambda_{OQ_i(t-1)}^{i_s}, OQ_i(t-1)\right\} + \tilde{a}_{S_{t-L_i+1}}^{i_s} \cdot \varphi_{i_s}\left\{\lambda_{S_{i+1}(t-L_i+1)}^{i_s},\ \ S_{i+1}(t-L_i+1)\right\} + \tilde{a}_{OQ_{t-l_{i-1}}}^{i_s} \cdot \varphi_{i_s}\left\{\lambda_{OQ_{i-1}(t-l_{i-1})}^{i_s}, OQ_{i-1}(t-l_{i-1})\right\} + a_{WP_{t-l_{i-1}}}^{i_s} \cdot WP_{i}(t-l_{i-1}) + \tilde{a}_{IN_t}^{i_s} \cdot \varphi_{i_s}\left\{\lambda_{IN_i(t)}^{i_s}, IN_i(t)\right\} + \tilde{a}_{CP_t}^{i_s} \cdot \varphi_{i_s}\left\{\lambda_{CP_t}^{i_s}, \textstyle\sum_{j=1}^{t} P_i(j)\right\} \tag{7.7}$$

$$\langle logit(OQ(t))\rangle_{i_s} = \gamma_0^{i_s} + \gamma_{WP_{t-1}}^{i_s} \cdot WP_i(t-1) + \gamma_{WP_t}^{i_s} \cdot WP_i(t) + \gamma_{WP_{i+1}}^{i_s} \cdot\ WP_{i+1}(t) + \tilde{\gamma} \ \varphi_{i_s}\left\{\lambda_{OQ_i(t-1)}^{i_s}, OQ_i(t-1)\right\} + \tilde{\gamma}_{S_{t-L_i+1}}^{i_s} \cdot \varphi_{i_s}\left\{\lambda_{S_{i+1}(t-L_i+1)}^{i_s},\ \ S_{i+1}(t-L_i+1)\right\} + \tilde{\gamma}_{OQ_{t-l_{i-1}}}^{i_s} \cdot \varphi_{i_s}\left\{\lambda_{OQ_{i-1}(t-l_{i-1})}^{i_s}, OQ_{i-1}(t-l_{i-1})\right\} + \gamma_{IN_t}^{i_s} \cdot \varphi_{i_s}\left\{\lambda_{IN_i(t)}^{i_s}, IN_i(t)\right\} + \tilde{\gamma}_{CP_t}^{i_s} \cdot \varphi_{i_s}\left\{\lambda_{CP_t}^{i_s}, \textstyle\sum_{j=1}^{t} \right. \tag{7.8}$$

$$\langle OQ(t)\rangle_{i_s} = \beta_0^{i_s} + \beta_{WP_{t-1}}^{i_s} \cdot WP_i(t-1) + \beta_{WP_t}^{i_s} \cdot WP_i(t) + \beta_{WP_{i+1}}^{i_s} \cdot WP_{i+1}(t) + \tilde{\beta}_{oQ_{t-1}}^{i_s} \cdot \varphi_{i_s}\left\{\lambda_{OQ_i(t-1)}^{i_s}, OQ_i(t-1)\right\} + \tilde{\beta}_{S_{t-L_i+1}}^{i_s} \cdot \varphi_{i_s}\left\{\lambda_{S_{i+1}(t-L_i+1)}^{i_s},\ \ S_{i+1}(t-L_i+1)\right\} + \tilde{\beta}_{OQ_{t-l_{i-1}}}^{i_s} \cdot \varphi_{i_s}\left\{\lambda_{OQ_{i-1}(t-l_{i-1})}^{i_s}, OQ_{i-1}(t-l_{i-1})\right\} + \tilde{\beta}_{IN_t}^{i_s} \cdot \varphi_{i_s}\left\{\lambda_{IN_i(t)}^{i_s}, IN_i(t)\right\} + \tilde{\beta}_{CP_t}^{i_s} \cdot \varphi_{i_s}\left\{\lambda_{CP_t}^{i_s}, \textstyle\sum_{j=1}^{t} P_i(j)\right\} \tag{7.9}$$

Outcome 3: The Participants' Decision Models

Tables 7.9 – 7.16 present the decision models of types (7.7) – (7.9) that have been fitted to the decisions of participants i_s who played the roles of the retailer (*i.e.* *i*=*RET*), the wholesaler (*i.e.* *i*=*WHL*) and the manufacturer (*i.e.* *i*=*MAN*). In greater detail, Tables 7.9-7.10 correspond to the decision models of human retailers(*i.e*. the decision models of type (7.8) and (7.9), respectively). , Tables 7.11-7.13 correspond to the decision models of the human wholesalers (*i.e*.

thedecision models of type (7.7), (7.8) and (7.9), respectively). Tables 7.14-7.16 correspond to the decision models of the human manufacturers (*i.e.*the decision models of type (7.7), (7.8) and (7.9), respectively). The paragraphs that follow discuss in greater detail the information that these tables in turn provide.

In the tables that correspond to the auto-regressive multiple linear regression pricing and order quantity decision models of type (7.7) and (7.9) (namely Tables 7.10, 7.11, 7.13, 7.14, 7.16), column (*1*) outlines the regression coefficients $\tilde{\alpha}^{i_s}$and $\tilde{\beta}^{i_s}$(with *i* taking the values of *RET*, *WHL* and *MAN* and *s* taking the values 0-3), respectively, that have been fitted to the corresponding participant's recorded decisions. These regression coefficients represent the significance that the participant under study appears to assign to his/her corresponding *decision attributes*. A value of 0 indicates that the corresponding *decision attribute* has been eliminated from the decision model. Column (*2*) presents the transformation parameter λ^{i_s} (with *i* taking the values of *RET*, *WHL* and *MAN* and *s* taking the values 0-3) that is associated with each *decision attribute*. Column (*3*) portrays the *t*-values of each *decision attribute*, which demonstrate how significant the effect of each *decision attribute* is on the actual decision. Column (4) presents the associated *p*-values, which in turn represent the lowest significance level for which the effect of a *decision attribute* is statistically insignificant. The reason that the *p*-values are reported is that the critical rejection values depend on the total number of valid observations, where the exact number of non-zero quantity orders varies across different subjects. This is why the exact number of non-zero orders is reported separately below each subject's code. In general, the *decision attributes* with *p*-values that are higher than 5% have not been kept in the multiple linear regression decision models of types (7.7) and

(7.9). The last row of Tables 7.10, 7.11, 7.13, 7.14, 7.16 presents the *adjusted coefficient of determination* (*adj*. R^2) for each decision model. Since the *adj*. R^2 takes into account sample sizes, it is considered as an accurate measure of overall model fit (Weisberg, 2005; Hair *et al*, 2006).

The tables that correspond to the logit order placement decision models of type (7.8) (namely, Tables 7.9, 7.12 and 7.15) provide the following information: Column (*1*) reflects the logistic regression coefficients $\tilde{\gamma}^{i_s}$ (with *i* taking the values of *RET*, *WHL* and *MAN* and *s* taking the values 0-3) that have been fitted to the corresponding participant's recorded decisions. These coefficients represent the impact that a unit change in a *decision attribute*'s value has on the logarithm of each participant's order placement decision. Given the difficulty in interpreting and, thus, understanding the impact of *decision attribute*s on logarithms, column (*2*) outlines the corresponding exponentiated values. These exponentiated values represent the importance that each participant seems to assign to his/her order placement decision. Column (*3*) summarizes the transformation parameter λ^{i_s} (with *i* taking the values of *RET*, *WHL* and *MAN* and *s* taking the values 0-3) that corresponds to each *decision attribute*. Column (*4*) portrays the *Wald-test* statistic value that concerns each *decision attribute*. The *Wald-test* statistic indicates the statistical significance of a *decision attribute*. Column (5) presents the associated *p*-value, which in turn represents the lowest significance level for which the effect of a *decision attribute* derives as statistically insignificant. The reader is at this point informed that *decision attributes* with *p*-values that are higher than 5% have been eliminated from the logit decision models of type (7.8). The last two rows of Tables 7.9, 7.12 and 7.15 assess the overall logistic model fit via two different indicators: that is, the attained Nagelkerke pseudo-R^2 measure and the proportional accuracy rate. The *Nagelkerke* R^2 measure demonstrates the percentage of total variation that is explained by the logistic model of type (7.8). The reason that the *Nagelkerke pseudo*-R^2 measure is reported is it is consistent with the linear regression's *adjusted coefficient of determination adj*. R^2 in that it indicates a perfect model fit by taking the value of 1 (Hosmer and Lemeshow, 2000; Hair *et al*, 2006; Fox, 2008). The *accuracy rate* (or else hit ratio) measures the proportion of cases that have been correctly classified (Hosmer and Lemeshow, 2000; Hair *et al*, 2006). The *accuracy rate* that is attained is subsequently compared with the corresponding proportional by chance accuracy criterion. The *proportional by chance accuracy criterion* is calculated from the product of proportional accuracy rate that would be achieved by chance alone (*i*.*e*. sum of squares of proportion of non-zero orders over total orders and proportion of zero orders over total orders) and 1.25, for reasons of stronger evidence. Attaining an *accuracy rate* that is strictly higher than the *proportional by chance accuracy rate* indicates a reasonable fit of the logistic model of type (7.8). Overall, the logistic models of type (7.8) that have been fitted to the decision of the human participants explain more than 60% of the existent variation (*s*. Nagelkerke R^2) and satisfy the *by chance accuracy criterion*. Each of these tables is now discussed in some detail.

Table 7.9 summarises the order placement decision models of type (7.8) that have been fitted to the human retailers' RET_s recorded decisions. The fact that the *p*-values of $wP_W(t)$ are strictly lower than 0.05 indicates that all human retailers (RET_0 - RET_3) seem to take into account the price that is currently charged to them in their respective order placement decisions. In addition, RET_0, RET_2 and RET_3 significantly consider the previously ordered quantity $OQ_R(t -$

$1)$, while RET_1, on the contrary, prefers instead to rely on the shipment that is in transit towards his warehouse $S_W(t - L_R + 1)$, which the other three retailers (RET_0, RET_2, RET_3) largely ignore. This supports that RET_0, RET_2 and RET_3 correctly perceive their previous order quantities as a more reliable indicator of their outstanding orders than the shipments that are in transit towards their warehouse. Last but not least, all human retailers (RET_0 - RET_3) only marginally consider their current inventory positions $IN_R(t)$ and cumulatively realized profits $\sum_{j=1}^{t} P_R(j)$. This supports that RET_0, RET_2 and RET_3 also correctly perceive their previous order. The above observations can explain the labels that have been assigned to the human retailers in Table 7.9. In this regard, RET_0, RET_2 and RET_3 are characterized as 'price and cost sensitive', while RET_1 is labeled as 'price sensitive'. More details about the explanation of these labels are provided in Appendix C.9.

Table 7.10 presents the order quantity decision models of type (7.8) that have been fitted to the human retailers' RET_s recorded decisions. The fact that the *p*-values of $wP_W(t)$ are strictly lower than 0. 05 indicates that the human retailers RET_1 - RET_3) appear to take into account the price that is currently charged to them. Nevertheless, RET_0 - RET_3 consider their previous order quantities $oQ_R(t - 1)$ only marginally and seem to almost ignore the shipments that are in transit towards their warehouse $S_W(t - L_R + 1)$. RET_0 additionally considers the current inventory position $IN_R(t)$, while RET_1 and RET_2 significantly consider the cumulative realized profit $\sum_{j=1}^{t} P_R(j)$ for their order quantity decisions. Building on these observations, RET_0 is characterized in Table 7.10 as 'price conscious', RET_1 as 'price and profit conscious', RET_2 as 'price and cost and profit conscious' and RET_3 as 'price and cost conscious'.

Table 7.11 presents the pricing decision models of type (7.7) that have been fitted to the human wholesalers WHL_s. It is evident from Table 7.11 that all human wholesalers (WHL_0 - WHL_3) take into account for every new price decision they make either the price that is currently charged to them $wP_{MAN}(t)$ or (/and) the price that they themselves charged at the time when the incoming order was placed $wP_{WHL}(t - l_R)$. The labels 'price and past order reactive' (WHL_0), 'price and present availability reactive' (WHL_1), 'price and future availability reactive' (WHL_2) and 'profit and present availability reactive' (WHL_3) summarise the most significant *decision attribute*s of each human wholesaler.

Table 7.12 presents the order placement decision models of type (7.8) that have been fitted to the human wholesalers WHL_s. It is evident from Table 7.12 that all human wholesalers (WHL_0 - WHL_3) consider significantly in their order placement decisions both the prices that are charged to them $wP_{MAN}(t)$ and their own current prices $wP_{WHL}(t)$. Yet, there is one exception: WHL_1, who almost ignores her own price and relies only on the manufacturer's current price. Since wholesalers WHL_0 - WHL_3 treat prices as a sufficient measure of realized profits, they tend to ignore their cumulative profits $\sum_{\boldsymbol{j=1}}^{\boldsymbol{t}} P_{WHL}(j)$. But WHL_0 - WHL_3 do take into account some indication of inventory availability. In greater detail, WHL_1 considers the present inventory position $IN_{WHL}(t)$, while the other three wholesalers instead prefer to project this inventory availability in the future (*i.e.* WHL_0, WHL_3 and WHL_3). In this regard, WHL_3 only accounts for his own previous order quantity $oQ_{WHL}(t-1)$, while WHL_0 and WHL_2 see their future inventory as the outcome of the combination between their own previous order quantity $oQ_{WHL}(t-1)$ and their newly received order quantity $oQ_{RET}(t - l_{RET})$. The above observations can explain the labels that have been assigned to the human wholesalers in Table 7.12. In this regard, WHL_0 and WHL_2 are characterized as 'price and future availability sensitive', WHL_1 is labeled as 'price and present availability sensitive', while WHL_3 is viewed as 'price and part future availability sensitive'.

Table 7.13 presents the order quantity decision models of type (7.9) that have been fitted to the recorded decisions of human wholesalers WHL_s. Table 7.13 clearly indicates that all human wholesalers (WHL_0 - WHL_3) account for some measure of profitability and inventory availability in their order quantity decisions. WHL_0 is the exception, because she completely ignores her inventory availability. Instead she relies on the price that is charged to her $wP_{MAN}(t)$ and her cumulatively realized profit $\sum_{j=1}^{t} P_{WHL}(j)$. These observations justify the labels that have been assigned to the human wholesalers WHL_0 - WHL_3 in Table 7.13, which are the following: WHL_0 is characterised as 'profit conscious', WHL_1 as 'price and future availability conscious', WHL_2 as 'price and current availability conscious' and WHL_3 as 'price and present and future availability conscious'.

Table 7.14 presents the pricing decision models of type (7.7) that have been fitted to the human manufacturers MAN_s. It is obvious from Table 7.14 that the manufacturer MAN_3 simplifies his pricing task by constantly charging a fixed price of 3 *m.u.* throughout the entire gaming session. As for the remaining human manufacturers (MAN_0 - MAN_2), in order to determine their new prices, they significantly rely on the incoming order price $WP_{MAN}(t - l_{WHL})$ that they charged l_{WHL} periods ago. Nevertheless, only MAN_2 manages to successfully associate this past price with her incoming order quantity $OQ_{WHL}(t - l_{WHL})$. MAN_1 associates this incoming order price $WP_{MAN}(t - l_{WHL})$ with his own previous order quantity $OQ_{MAN}(t-1)$. As for MAN_0, he completely ignores all indicators of inventory availability and/or previous ordering behaviour that is available. In this regard, as can be seen in Figure 7.14, MAN_0 is characterized as 'incoming price reactive', MAN_1 is labelled as 'past order and incoming price reactive', MAN_2 is identified as 'incoming order and price reactive' and MAN_3 is considered to enforce a 'fixed pricing' scheme.

Table 7.15 presents the order placement decision models of type (7.8) that have been fitted to the recorded decisions of the human manufacturers MAN_s. Table 7.15 demonstrates that MAN_0 and MAN_2 assign great importance to the price that they are currently charging $WP_{MAN}(t)$. In addition, MAN_2 considers her cumulatively realized profit $\sum_{j=1}^{t} P_{MAN}(j)$. MAN_1 limits his attention to the present inventory position $IN_{MAN}(t)$. MAN_3 appears to compensate for his lack of consideration of prices by taking into account all indicators of inventory availability and/or previous ordering behaviour that are available to him. In respect to this, MAN_0 is identified in Table 7.15 as 'price sensitive', MAN_1 is considered 'present availability sensitive', MAN_2 is characterized as 'price and profit sensitive' and MAN_3 is labeled as 'profit and present and future availability sensitive'.

Table 7.16 presents the order quantity decision models of type (7.9) that have been fitted to the recorded decisions of human manufacturers MAN_s. It becomes evident from Table 7.16 that the human manufacturers MAN_0 – MAN_3 in their respective quantity decisions consider at least one indicator of price or profit and at least one indicator of inventory availability. The only exception is MAN_3, who only considers inventory availability, because he steadily charges the fixed price of 3 *m.u.* In this regard, MAN_0 accurately associates his previous price

$WP_{MAN}(t-1)$ with the quantity that he is now requesting and, thus, prioritizes this price. MAN_2 fails to make this connection and, therefore, prioritizes her current price $WP_{MAN}(t)$ instead. But MAN_2 's current price $WP_{MAN}(t)$ could be considered as an indicator of her future incoming order quantities. MAN_1 assigns greater significance to his cumulatively realized profit $\sum_{j=1}^{t} P_{MAN}(j)$. Among the available inventory-related measures, all human manufacturers MAN_0 – MAN_3 appear to take into account their respective current inventory position $IN_{MAN}(t)$. It is very interesting that none of the studied participants perceive the shipment in transit $OQ_{MAN}(t-L_{MAN}-1)$ of relevance, most probably because they have realised the assumed perfect reliability of their production facility. In respect to this, MAN_0 is considered 'past price and present availability conscious', MAN_1 is characterized as 'profit and present and future availability conscious', MAN_2 is identified as 'present price and present availability conscious' and MAN_3 is labeled as 'present and part future availability conscious'.

Even though Tables 7.9-7.16 report the statistical power of the decision models that have been inferred (*i.e*. *Nagelkerke pseudo-R^2* and *accuracy rate* for logistic regression models and *adjusted coefficient of determination adj. R^2* for multiple linear regression), it also needs to be ensured that these decision models realistically reproduce the participants' decisions, that is, as were observed in the laboratory. To this end, Sterman's (1989) suggestion is followed.

Table 7.9: Human retailers' order placement decision models

Decision Model: (7.8)										
	RET₀ *'price and cost sensitive'*					***RET₁*** *'price sensitive'*				
	(*1*) $\tilde{\gamma}^{RET_0}$	(*2*) Odds Change %	(*3*) λ^{RET_0}	(*4*) $W_{\gamma(RET_0)}$	(*5*) $p_{\gamma(R_{ET0})}$	(*1*) $\tilde{\gamma}^{RET_1}$	(*2*) Odds Change %	(*3*) λ^{RET_1}	(*4*) $W_{\gamma(RET_1)}$	(*5*) $p_{\gamma(R_{ET1})}$
$\gamma_0^{RET_s}$	42.094	-	-	0	1	-0.404	-	-	0.353	0.553
$\gamma_{WP_W}^{RET_s}$	-0.171	-70.30	1	0.220	0.639	0.182	19.96	1	3.768	0.052
$\tilde{\gamma}_{OQ_{t-1}}^{RET_s}$	-1.058	-99.94	$I\{oQ_{t-1} > 0\}$	0.543	0.461	-0.022	-2.18	1	3.114	0.078
$\tilde{\gamma}_{S_{t-L_R+1}}^{RET_s}$	6.591	-79.38	$I\{S_{t-L_R+1} > 0\}$	2.338	0.126	-0.055	-5.35	1	5.492	0.019
$\tilde{\gamma}_{IN_t}^{RET_s}$	-0.034	9.97	1	0.141	0.708	-0.003	-0.30	1	1.250	0.264
$\tilde{\gamma}_{CP_t}^{RET_s}$	0.014	3.46	1	3.464	0.063	0.001	0.10	1	16.859	<0.001
Nagelkerke R^2	0.864					0.650				
Accuracy Rate	0.914 (> 0.51=*by chance accuracy criterion*)					0.762 (> 0.648=*by chance accuracy criterion*)				

Table 7.9(Cont.): Human retailers' order placement decision models

Decision Model: (7.8)										
	RET₂ *'price and cost sensitive'*					***RET₃*** *'price and cost sensitive'*				
	(*1*) $\tilde{\gamma}^{RET_2}$	(*2*) Odds Change %	(*3*) λ^{RET_2}	(*4*) $W_{a(R_{ET2})}$	(*5*) $p_{\gamma(R_{ET2})}$	(*1*) $\tilde{\gamma}^{RET_3}$	(*2*) Odds Change %	(*3*) λ^{RET_3}	(*4*) $W_{a(RET_3)}$	(*5*) $p_{\gamma(RET_3)}$
$\gamma_0^{RET_s}$	14.048	-	-	10.566	0.001	2.146	-	-	2.585	0.108
$\gamma_{WP_W}^{RET_s}$	-0.655	-48.06	1	6.696	0.010	-0.183	-16.72	1	1.629	0.202
$\tilde{\gamma}_{OQ_{t-1}}^{RET_s}$	-2.373	-90.68	$I\{oQ_{t-1} > 0\}$	5.221	0.022	-1.469	-76.98	$I\{oQ_{t-1} > 0\}$	5.881	0.015
$\tilde{\gamma}_{S_{t-L_R+1}}^{RET_s}$	-0.481	-38.18	$I\{S_{t-L_R+1} > 0\}$	0.205	0.651	-0.351	-29.60	$I\{S_{t-L_R+1} > 0\}$	0.271	0.602
$\tilde{\gamma}_{IN_t}^{RET_s}$	0.005	0.50	1	0.707	0.4	0	0	$\begin{cases}-3, if\ IN_t \geq 0\\ 1, if\ IN_t < 0\end{cases}$	0.602	0.438
$\tilde{\gamma}_{CP_t}^{RET_s}$	0.001	0.10	1	7.089	0.008	0	0	$\begin{cases}-3, if\ CP_t \geq 0\\ 1, if\ CP_t < 0\end{cases}$	1.209	0.271
Nagelkerke R^2	0.783					0.631				
Accuracy Rate	0.908 (> 0.625=*by chance accuracy criterion*)					0.822 (> 0.818=*by chance accuracy criterion*)				

Table 7.10: Human retailers' order quantity decision models

Decision Model: (7.9)								
	RET₀ *'price conscious'*				***RET₁*** *'price and profit conscious'*			
	N=36				*N=51*			
	(*1*) $\tilde{\beta}^{RET_0}$	(*2*) λ^{RET_0}	(*3*) $t_{\beta(RET_0)}$	(*4*) $p_{\beta(RET_0)}$	(*1*) $\tilde{\beta}^{RET_1}$	(*2*) λ^{RET_1}	(*3*) $t_{\beta(RET_1)}$	(*4*) $p_{\beta(RET_1)}$
$\beta_0^{RET_s}$	14.166	-	1.256	0.003	57.138	-	3.982	0
$\beta_{WP_W}^{RET_s}$	-1.483	1	-1.784	0.102	-6.088	1	-2.213	0.032
$\tilde{\beta}_{OQ_{t-1}}^{RET_s}$	49.258	-4	2.171	0.053	23.988	-3	0.517	0.607
$\tilde{\beta}_{S_{t-L_R+1}}^{RET_s}$	0	-4	-0.233	0.821	9.901	-3	0.239	0.812
$\tilde{\beta}_{IN_t}^{RET_s}$	-0.343	1	-2.168	0.053	14.728	$\begin{cases}-3, if\ IN_t \geq 0 \\ -1, if\ IN_t < 0\end{cases}$	1.293	0.202
$\tilde{\beta}_{CP_t}^{RET_s}$	0	1	0.393	0.704	23.253	$\begin{cases}-3, if\ CP_t \geq 0 \\ -1, if\ CP_t < 0\end{cases}$	-2.453	0.018
Adj. R^2	0.799				0.730			

Table 7.10(Cont.): Human retailers' order quantity decision models

Decision Model: (7.9)								
	RET₂ 'price and profit conscious'				***RET₃*** 'price and cost conscious'			
	N=68				*N=35*			
	(*1*) $\tilde{\beta}^{RET_2}$	(*2*) λ^{RET_2}	(*3*) $t_{\beta(RET_2)}$	(*4*) $p_{\beta(RET_2)}$	(*1*) $\tilde{\beta}^{RET_3}$	(*2*) λ^{RET_3}	(*3*) $t_{\beta(RET_3)}$	(*4*) $p_{\beta(RET_3)}$
$\beta_0^{RET_s}$	130.858	-	4.111	<0.001	23.229	-	3.497	0.002
$\beta_{WP_W}^{RET_s}$	-6.956	1	-4.658	<0.001	-11.858	1	-4.302	<0.001
$\tilde{\beta}_{OQ_{t-1}}^{RET_s}$	39.146	-3	1.127	0.268	40.017	-3	1.707	0.103
$\tilde{\beta}_{S_{t-L_R+1}}^{RET_s}$	36.845	-3	1.072	0.292	-7.463	-3	-0.286	0.778
$\tilde{\beta}_{IN_t}^{RET_s}$	61.949	$\begin{cases}-3, if\ IN_t \geq 0\\ 0.5, if\ IN_t < 0\end{cases}$	1.513	0.139	-0.001	$\begin{cases}-3, if\ IN_t \geq 0\\ 1, if\ IN_t < 0\end{cases}$	-0.931	0.363
$\tilde{\beta}_{CP_t}^{RET_s}$	0.365	$\begin{cases}-3, if\ CP_t \geq 0\\ 0.5, if\ CP_t < 0\end{cases}$	2.542	0.016	0	$\begin{cases}-3, if\ CP_t \geq 0\\ 1, if\ CP_t < 0\end{cases}$	2.656	0.015
Adj. R^2	0.722				0.761			

Table 7.11: Human wholesalers' pricing decision models

Decision Model: (7.7)								
	WHL_0 *'price and past order reactive'*				***WHL_1*** *'price and present availability reactive'*			
	(*1*) $\tilde{\alpha}^{WHL_0}$	(*2*) λ^{WHL_0}	(*3*) $t_{\alpha(WHL_0)}$	(*4*) $p_{\alpha(W_{HL0})}$	(*1*) $\tilde{\alpha}^{WHL_1}$	(*2*) $\lambda^{W_{HL1}}$	(*3*) $t_{\alpha(WHL_1)}$	(*4*) $p_{\alpha(WHL_1)}$
$a_0^{WHL_s}$	0.472	-	0.733	0.470	3.076	-	3.186	0.002
$a_{WP_{MAN}}^{WHL_s}$	1.388	1	7.327	<0.001	0.426	1	3.401	0.001
$\tilde{a}_{OQ_{t-1}}^{WHL_s}$	-1.166	-2	-2.153	0.04	0	-3	0.748	0.457
$\tilde{a}_{S_{t-L_W+1}}^{W_{HLs}}$	-0.254	-2	-0.642	0.526	0	-3	-0.033	0.974
$\tilde{a}_{OQ_{t-l_R}}^{WHL_s}$	-0.283	-2	-0.680	0.502	0	-3	0.290	0.773
$a_{WP_{t-l_R}}^{wHL_s}$	0.588	1	9.594	<0.001	0.416	1	6.782	<0.001
$\tilde{a}_{IN_t}^{WHL_s}$	0.003	1	0.577	0.569	-0.038	$\begin{cases}-3, if\ IN_t \geq 0\\1.5, if\ IN_t < 0\end{cases}$	-3.953	<0.001
$\tilde{a}_{CP_t}^{WHL_s}$	0.002	1	1.268	0.216	0	$\begin{cases}-3, if\ CP_t \geq 0\\1.5, if\ CP_t < 0\end{cases}$	-3.130	0.003
Adj. R^2	0.940				0.851			

Table 7.11(Cont.): Human wholesalers' pricing decision models

Decision Model: (7.7)								
	WHL₂ 'price and future availability reactive'				***WHL₃*** 'profit and present availability reactive'			
	(*1*) $\tilde{\alpha}^{WHL_2}$	(*2*) λ^{WHL_2}	(*3*) $t_{\alpha(WHL_2)}$	(*4*) $p_{\alpha(WHL_2)}$	(*1*) $\tilde{\alpha}^{WHL_3}$	(*2*) λ^{WHL_3}	(*3*) $t_{\alpha(WHL_3)}$	(*4*) $p_{\alpha(WHL_3)}$
$a_0^{WHL_s}$	0.195	-	0.618	0.538	-19.326	-	-1.989	0.050
$a_{WP_{MAN}}^{WHL_s}$	0.05	1	1.080	0.282	0.897	1	6.397	<0.001
$\tilde{a}_{OQ_{t-1}}^{WHL_s}$	-0.615	-2	-1.641	0.103	0	-3	0.431	0.667
$\tilde{a}_{S_{t-L_W+1}}^{WHL_s}$	-0.309	-2	-2.032	0.044	35.808	-3	1.864	0.066
$\tilde{a}_{OQ_{t-l_R}}^{WHL_s}$	-2.755	-2	6.155	<0.001	0	-3	-1.285	0.202
$a_{WP_{t-l_R}}^{WHL_s}$	0.853	1	18.51	<0.001	-0.401	1	-2.533	0.013
$\tilde{a}_{IN_t}^{WHL_s}$	0	$\begin{cases}-2, if\ IN_t \geq 0\\0.5, if\ IN_t < 0\end{cases}$	-0.943	0.348	-15.337	$\begin{cases}-3, if\ IN_t \geq 0\\-1, if\ IN_t < 0\end{cases}$	-3.249	0.002
$\tilde{a}_{CP_t}^{WHL_s}$	0	$\begin{cases}-2, if\ CP_t \geq 0\\0.5, if\ CP_t < 0\end{cases}$	-0.510	0.611	-19.747	$\begin{cases}-3, if\ CP_t \geq 0\\-1, if\ CP_t < 0\end{cases}$	-2.22	0.029
Adj. R^2	0.879				0.655			

Table 7.12: Human wholesalers' order placement decision models

Decision Model: (7.8)										
	WHL₀ *'price and future availability sensitive'*					***WHL₁*** *'price and present availability sensitive'*				
	(*1*) $\tilde{\gamma}^{WHL_0}$	(*2*) Odds Change %	(*3*) λ^{WHL_0}	(*4*) $W_{\gamma(WHL_0)}$	(*5*) $p_{\gamma(WHL_0)}$	(*1*) $\tilde{\gamma}^{WHL_1}$	(*2*) Odds Change %	(*3*) λ^{WHL_1}	(*4*) $W_{\gamma(WHL_1)}$	(*5*) $p_{\gamma(WHL_1)}$
$\gamma_0^{WHL_s}$	98.307	-	-	0	1	7.421	-	-	1.774	0.183
$\gamma_{WP_{t-1}}^{WHL_s}$	-8.363	-99.98	1	0.271	0.602	0	0	1	0.105	0.294
$\gamma_{WP_t}^{WHL_s}$	-6.898	-99.90	1	5.221	0.022	0	0	1	0.382	0.977
$\gamma_{WP_F}^{WHL_s}$	0.524	68.93	1	6.696	0.010	-1.241	-71.09	1	2.927	0.087
$\tilde{\gamma}_{OQ_{t-1}}^{WHL_s}$	0.488	62.82	$I\{oQ_{t-1} > 0\}$	7.089	0.008	0.104	10.96	1	0.694	0.405
$\tilde{\gamma}_{S_{t-L_W+1}}^{WHL_s}$	-3.32	-96.38	$I\{S_{t-L_W+1} > 0\}$	0.205	0.651	-0.048	-4.69	1	1.267	0.267
$\tilde{\gamma}_{OQ_{t-l_R}}^{WHL_s}$	-5.97	-99.74	$I\{oQ_{t-l_R} > 0\}$	7.089	0.008	0	0	1	0.256	0.953
$\tilde{\gamma}_{IN_t}^{WHL_s}$	-0.153	-14.16	1	0.220	0.639	-0.021	-2.08	1	6.397	0.011
$\tilde{\gamma}_{CP_t}^{WHL_s}$	-2.20	-88.92	1	2.338	0.126	0	0	1	1.535	0.215
Nagelkerke R^2	0.989					0.631				
Accuracy Rate	0.996 (>0.65 =*by chance accuracy criterion*)					0.849 (> 0.837 =*by chance accuracy criterion*)				

Table 7.12(Cont.): Human wholesalers' order placement decision models

Decision Model: (7.8)										
	WHL₂ *'price and future availability sensitive'*					***WHL₃*** *'price and part future availability sensitive'*				
	(1) $\tilde{\gamma}^{WHL_2}$	*(2)* Odds Change %	*(3)* λ^{WHL_2}	*(4)* $W_{a(WHL_2)}$	*(5)* $p_{\gamma(WHL_2)}$	*(1)* $\tilde{\gamma}^{WHL_3}$	*(2)* Odds Change %	*(3)* λ^{WHL_3}	*(4)* $W_{a(WHL_3)}$	*(5)* $p_{\gamma(WHL_3)}$
$\gamma_0^{WHL_s}$	6.672	-	-	6.017	0.014	4.097	-	-	3.021	0.082
$\gamma_{WP_{t-1}}^{WHL_s}$	0.11	11.63	1	7.089	0.010	-0.009	-0.90	1	0.013	0.911
$\gamma_{WP_t}^{WHL_s}$	0.987	168.32	1	5.175	0.023	1.196	230.69	1	6.127	0.013
$\gamma_{WP_F}^{WHL_s}$	-2.208	-89.01	1	13.708	<0.001	-1.402	-75.39	1	6.553	0.01
$\tilde{\gamma}_{OQ_{t-1}}^{WHL_s}$	-1.156	-68.53	$I\{oQ_{t-1} > 0\}$	3.104	0.078	-5.789	-99.69	$I\{oQ_{t-1} > 0\}$	4.132	0.042
$\tilde{\gamma}_{S_{t-L_W+1}}^{WHL_s}$	-0.199	-18.05	$I\{S_{t-L_W+1} > 0\}$	0.121	0.728	0	0	$I\{S_{t-L_W+1} > 0\}$	0.1	0.752
$\tilde{\gamma}_{OQ_{t-l_R}}^{WHL_s}$	-1.613	-80.07	$I\{oQ_{t-l_R} > 0\}$	3.104	0.078	0	0	$I\{oQ_{t-l_R} > 0\}$	0.027	0.868
$\tilde{\gamma}_{IN_t}^{WHL_s}$	-0.007	-0.70	1	0.884	0.347	0	0	$\begin{cases}-3, if\ IN_t \geq 0\\ -1, if\ IN_t < 0\end{cases}$	1.509	0.219
$\tilde{\gamma}_{CP_t}^{WHL_s}$	0	0	1	0.805	0.369	0	0	$\begin{cases}-3, if\ CP_t \geq 0\\ -1, if\ CP_t < 0\end{cases}$	0.456	0.5
Nagelkerke R^2	0.682					0.975				
Accuracy Rate	0.837(> 0.794 =*by chance accuracy criterion*)					0.958(> 0.638 =*by chance accuracy criterion*)				

Table 7.13: Human wholesalers' order quantity decision models

Decision Model: (7.9)								
	WHL₀ 'profit conscious'				***WHL₁*** 'price and future availability conscious'			
	N=26				*N=31*			
	(*1*) $\tilde{\beta}^{WHL_0}$	(*2*) λ^{WHL_0}	(*3*) $t_{\beta(WHL_0)}$	(*4*) $p_{\beta(WHL_0)}$	(*1*) $\tilde{\beta}^{WHL_1}$	(*2*) λ^{WHL_1}	(*3*) $t_{\beta(WHL_1)}$	(*4*) $p_{\beta(WHL_1)}$
$\beta_0^{WHL_s}$	90.269	-	3.2	0.008	37,794.65	-	3.532	0.004
$\beta_{WP_{t-1}}^{WHL_s}$	0	1	-1.138	0.307	0.656	1	3.785	0.003
$\beta_{WP_t}^{WHL_s}$	0	1	0.750	0.487	-0.188	1	-2.114	0.056
$\beta_{WP_F}^{W_{WHL}}$	-15.168	1	-2.748	0.019	0	1	0.346	0.736
$\tilde{\beta}_{OQ_{t-1}}^{WHL_s}$	0	-2	0.520	0.626	-98.361	-3	-1.233	0.241
$\tilde{\beta}_{S_{t-L_W+1}}^{WHL_s}$	0	-2	0.293	0.781	-108,286	-3	-3.513	0.004
$\tilde{\beta}_{OQ_{t-l_{W-1}}}^{WHL_s}$	0	-2	-1.155	0.3	-5,158.84	-3	-1.026	0.325
$\tilde{\beta}_{IN_t}^{WHL_s}$	0	1	-1.680	0.154	0	$\begin{cases}-3, if\ IN_t \geq 0\\ 1.5, if\ IN_t < 0\end{cases}$	-0.792	0.447
$\tilde{\beta}_{CP_t}^{WHL_s}$	-0.097	1	-2.497	0.055	0	$\begin{cases}-3, if\ CP_t \geq 0\\ 1.5, if\ CP_t < 0\end{cases}$	0.750	0.464
Adj. R^2	0.714				0.775			

Table 7.13(Cont.): Human wholesalers' order quantity decision models

Decision Model: (7.9)								
	WHL₂ *'price and current availability conscious'*				***WHL₃*** *'price and present and future availability conscious'*			
	N=43				*N=53*			
	(*1*) $\tilde{\beta}^{WHL_2}$	(*2*) λ^{WHL_2}	(*3*) $t_{\beta(WHL_2)}$	(*4*) $p_{\beta(WHL_2)}$	(*1*) $\tilde{\beta}^{WHL_3}$	(*2*) λ^{WHL_3}	(*3*) $t_{\beta(WHL_3)}$	(*4*) $p_{\beta(WHL_3)}$
$\beta_0^{WHL_s}$	27.365	-	2.089	0.047	75.8	-	7.823	<0.001
$\beta_{WP_{t-1}}^{WHL_s}$	4.805	1	1.327	0.197	0	1	-0.309	0.759
$\beta_{WP_t}^{WHL_s}$	-8.14	1	-2.224	0.036	0.963	1	9.295	<0.001
$\beta_{WP_F}^{WHL_s}$	0	1	0.274	0.787	-0.953	1	-1.701	0.098
$\tilde{\beta}_{OQ_{t-1}}^{WHL_s}$	-16.664	-2	-0.739	0.467	53.833	-3	0.979	0.335
$\tilde{\beta}_{S_{t-L_W+1}}^{WHL_s}$	0	-2	-0.025	0.980	-84.465	-3	-2.717	0.01
$\tilde{\beta}_{OQ_{t-l_{W-1}}}^{WHL_s}$	7l.548	-2	3.032	0.006	0	-3	0.096	0.924
$\tilde{\beta}_{IN_t}^{WHL_s}$	-0.053	$\begin{cases}-2, if\ IN_t \geq 0\\0.5, if\ IN_t < 0\end{cases}$	-1.470	0.155	58.345	$\begin{cases}-3, if\ IN_t \geq 0\\-1, if\ IN_t < 0\end{cases}$	3.913	<0.001
$\tilde{\beta}_{CP_t}^{WHL_s}$	0	$\begin{cases}-2, if\ CP_t \geq 0\\0.5, if\ CP_t < 0\end{cases}$	-0.779	0.445	0	$\begin{cases}-3, if\ CP_t \geq 0\\-1, if\ CP_t < 0\end{cases}$	0.461	0.648
Adj. R^2	0.641				0.821			

Table 7.14: Human manufacturers' pricing decision models

Decision Model: (7.7)								
	MAN₀ 'incoming price reactive'				***MAN₁*** 'past order and incoming price reactive'			
	(*1*) $\tilde{\alpha}^{MAN_0}$	(*2*) λ^{MAN_0}	(*3*) $t_{\alpha(MAN_0)}$	(*4*) $p_{\alpha(MAN_0)}$	(*1*) $\tilde{\alpha}^{MAN_1}$	(*2*) λ^{MAN_1}	(*3*) $t_{\alpha(MAN_1)}$	(*4*) $p_{\alpha(MAN_1)}$
$a_0^{MAN_s}$	2.313	-	3.396	0.002	22.314	-	-1.781	0.079
$\tilde{a}_{OQ_{t-1}}^{MAN_s}$	0.179	-2	0.207	0.837	0.029	1.5	2.884	0.005
$\tilde{a}_{OQ_{t-L_F+1}}^{MAN_s}$	-0.090	-2	-0.109	0.914	0	1.5	-0.05	0.96
$\tilde{a}_{OQ_{t-l_W}}^{MAN_s}$	0	-2	0.590	0.560	-0.007	1.5	-0.595	0.554
$a_{WP_{t-l_W}}^{MAN_s}$	0.418	1	2.644	0.013	0.716	1	8.570	<0.001
$\tilde{a}_{IN_t}^{MAN_s}$	-0.009	1	-1.508	0.143	-0.002	$\begin{cases} 1.5, if\ IN_t \geq 0 \\ -0.5, if\ IN_t < 0 \end{cases}$	-0.307	0.760
$\tilde{a}_{CP_t}^{MAN_s}$	0.002	1	1.433	0.163	-0.011	$\begin{cases} 1.5, if\ CP_t \geq 0 \\ -0.5, if\ CP_t < 0 \end{cases}$	-1.782	0.079
Adj. R^2	0.722				0.785			

Table 7.14(Cont.): Human manufacturers' pricing decision models

Decision Model: (7.7)								
	MAN₂ 'incoming order and price reactive'				***MAN₃*** 'fixed pricing'			
	(*1*) $\tilde{\alpha}^{MAN_2}$	(*2*) λ^{MAN_2}	(*3*) $t_{\alpha(MAN_2)}$	(*4*) $p_{\alpha(MAN_2)}$	(*1*) $\tilde{\alpha}^{MAN_3}$	(*2*) λ^{MAN_3}	(*3*) $t_{\alpha(MAN_3)}$	(*4*) $p_{\alpha(MAN_3)}$
$a_0^{MAN_s}$	-2.498	-	-1.237	0.218	3	-	-	-
$\tilde{a}_{OQ_{t-1}}^{MAN_s}$	0	1.5	-1.420	0.158	0	1	-	-
$\tilde{a}_{OQ_{t-L_F+1}}^{MAN_s}$	0	1.5	-0.637	0.525	0	1	-	-
$\tilde{a}_{OQ_{t-l_W}}^{MAN_s}$	0.001	1.5	3.5	0.001	0	1	-	-
$a_{WP_{t-l_W}}^{MAN_s}$	0.647	1	6.522	<0.001	0	1	-	-
$\tilde{a}_{IN_t}^{MAN_s}$	0	$\begin{cases} 1.5, if\ IN_t \geq 0 \\ -0.5, if\ IN_t < 0 \end{cases}$	-2.568	0.011	0	1	-	-
$\tilde{a}_{CP_t}^{MAN_s}$	-1.686	$\begin{cases} 1.5, if\ CP_t \geq 0 \\ -0.5, if\ CP_t < 0 \end{cases}$	-1.563	0.120	0	1	-	-
Adj. R^2	0.705				-			

Table 7.15: Human manufacturers' order placement decision models

Decision Model: (7.8)										
	MAN₀ 'price sensitive'					***MAN₁*** 'present availability sensitive'				
	(*1*) $\tilde{\gamma}^{MAN_0}$	(*2*) Odds Change %	(*3*) λ^{MAN_0}	(*4*) $W_{\gamma(MAN_0)}$	(*5*) $p_{\gamma(MAN_0)}$	(*1*) $\tilde{\gamma}^{MAN_1}$	(*2*) Odds Change %	(*3*) λ^{MAN_1}	(*4*) $W_{\gamma(MAN_1)}$	(*5*) $p_{\gamma(MAN_1)}$
$\gamma_0^{MAN_s}$	1.869	-	-	0.241	0.623	-1.049	-	-	0.793	0.373
$\gamma_{WP_{t-1}}^{MAN_s}$	-1.19	-69.58	1	2.038	0.153	-0.139	-12.98	1	1.313	0.252
$\gamma_{WP_t}^{MAN_s}$	1.224	240.08	1	3.603	0.058	0	0	1	1.832	0.176
$\tilde{\gamma}_{OQ_{t-1}}^{MAN_s}$	-2.783	-93.81	$I\{oQ_{t-1} > 0\}$	2.774	0.096	1.039	182.64	$I\{oQ_{t-1} > 0\}$	2.348	0.125
$\tilde{\gamma}_{OQ_{t-L_F-1}}^{MAN_s}$	2.062	686.17	$I\{S_{t-L_F-1} > 0\}$	1.035	0.309	0	0	$I\{S_{t-L_F-1} > 0\}$	0.779	0.810
$\tilde{\gamma}_{OQ_{t-l_W}}^{MAN_s}$	-0.091	-8.70	$I\{oQ_{t-l_w} > 0\}$	0.003	0.954	-0.481	-38.18	$I\{oQ_{t-l_w} > 0\}$	0.415	0.519
$\tilde{\gamma}_{IN_t}^{MAN_s}$	-0.044	-4.30	1	1.472	0.225	-0.111	-10.51	1	17.477	<0.001
$\tilde{\gamma}_{CP_t}^{MAN_s}$	0	0	1	0.003	0.953	-0.005	-0.50	1	0.861	0.353
Nagelkerke R^2	0.776					0.661				
Accuracy Rate	0.886 (>0.63 =*by chance accuracy criterion*)					0.84 (> 0.638 =*by chance accuracy criterion*)				

Table 7.15(Cont.): Human manufacturers' order placement decision models

Decision Model: (7.8)										
	MAN_2 *'price and profit sensitive'*					***MAN_3*** *'profit and present and future availability sensitive'*				
	(*1*) $\tilde{\gamma}^{MAN_2}$	(*2*) Odds Change %	(*3*) λ^{MAN_2}	(*4*) $W_{a(MAN_2)}$	(*5*) $p_{\gamma(MAN_2)}$	(*1*) $\tilde{\gamma}^{MAN_3}$	(*2*) Odds Change %	(*3*) λ^{MAN_3}	(*4*) $W_{a(MAN_3)}$	(*5*) $p_{\gamma(MAN_3)}$
$\gamma_0^{MAN_s}$	-18.531	-	-	5.155	0.023	1.005	-	-	5.990	0.014
$\gamma_{WP_{t-1}}^{MAN_s}$	0	0	1	-0.677	0.5	-	-	1	-	-
$\gamma_{WP_t}^{MAN_s}$	0.342	40.78	1	17.656	<0.001	-	-	1	-	-
$\tilde{\gamma}_{OQ_{t-1}}^{MAN_s}$	0.007	0.70	1	0.921	0.337	-0.045	-4.40	1	15.078	<0.001
$\tilde{\gamma}_{OQ_{t-L_F-1}}^{MAN_s}$	0	0	1	-0.019	0.985	-0.034	-3.34	1	11.831	0.001
$\tilde{\gamma}_{OQ_{t-l_W}}^{MAN_s}$	0	0	1	0.979	0.329	-0.006	-0.6	1	0.710	0.400
$\tilde{\gamma}_{IN_t}^{MAN_s}$	0	0	$\begin{cases} 1.5, if\ IN_t \geq 0 \\ -0.5, if\ IN_t < 0 \end{cases}$	0.168	0.867	-0.062	-6.01	1	16.946	<0.001
$\tilde{\gamma}_{CP_t}^{MAN_s}$	-7.913	-99.96	$\begin{cases} 1.5, if\ CP_t \geq 0 \\ -0.5\ if\ CP_t < 0 \end{cases}$	3.551	0.06	0.005	0.5	1	11.852	0.001
Nagelkerke R^2	0.666					0.726				
Accuracy Rate	0.707 (> 0.626 =*by chance accuracy criterion*)					0.763 (> 0.631 =*by chance accuracy criterion*)				

Table 7.16: Human manufacturers' order quantity decision models

Decision Model: (7.9)								
	MAN₀ *'past price and present availability conscious'*				***MAN₁*** *'profit and present and future availability conscious'*			
	N=34				*N=24*			
	(*1*) $\tilde{\beta}^{MAN_0}$	(*2*) λ^{MAN_0}	(*3*) $t_{\beta(MAN_0)}$	(*4*) $p_{\beta(MAN_0)}$	(*1*) $\tilde{\beta}^{MAN_1}$	(*2*) λ^{MAN_1}	(*3*) $t_{\beta(MAN_1)}$	(*4*) $p_{\beta(MAN_1)}$
$\beta_0^{MAN_s}$	122.245	-	7.511	<0.001	4.68	-	2.924	0.007
$\beta_{WP_{t-1}}^{MAN_s}$	-22.685	1	-6.228	<0.001	0	1	-0.454	0.654
$\beta_{WP_t}^{MAN_s}$	0	1	0.641	0.533	0	1	0.011	0.991
$\tilde{\beta}_{OQ_{t-1}}^{MAN_s}$	0	-2	0.095	0.926	-0.211	1.5	5.010	<0.001
$\tilde{\beta}_{OQ_{t-L_F-1}}^{MAN_s}$	0	-2	0.175	0.864	-0.086	1.5	-1.533	0.138
$\tilde{\beta}_{OQ_{t-l_W}}^{MAN_s}$	0	-2	0.087	0.932	0.174	1.5	-1.996	0.057
$\tilde{\beta}_{IN_t}^{MAN_s}$	-0.627	1	-4.977	<0.001	-0.306	$\begin{cases} 1.5, if\ IN_t \geq 0 \\ -0.5, if\ IN_t < 0 \end{cases}$	-0.927	0.363
$\tilde{\beta}_{CP_t}^{MAN_s}$	0.054	1	2.193	0.044	-2.382	$\begin{cases} 1.5, if\ CP_t \geq 0 \\ -0.5, if\ CP_t < 0 \end{cases}$	2.916	0.007
Adj. R^2	0.857				0.781			

Table 7.16(Cont.): Human manufacturers' order quantity decision models

Decision Model: (7.9)								
	MAN₂ *'present price and present availability conscious'*				***MAN₃*** *'present and part future availability conscious'*			
	N=53				*N=32*			
	(*1*) $\tilde{\beta}^{MAN_2}$	(*2*) λ^{MAN_2}	(*3*) $t_{\beta(MAN_2)}$	(*4*) $p_{\beta(MAN_2)}$	(*1*) $\tilde{\beta}^{MAN_3}$	(*2*) λ^{MAN_3}	(*3*) $t_{\beta(MAN_3)}$	(*4*) $p_{\beta(MAN_3)}$
$\beta_0^{MAN_s}$	16.565	-	1.077	0.286	96.186	-	3.844	<0.001
$\beta_{WP_{t-1}}^{MAN_s}$	0	1	0.097	0.923	0	1	-	-
$\beta_{WP_t}^{MAN_s}$	32.516	1	6.037	<0.001	0	1	-	-
$\tilde{\beta}_{OQ_{t-1}}^{MAN_s}$	0.033	1.5	1.813	0.075	-14.774	-2	-3.505	0.001
$\tilde{\beta}_{OQ_{t-L_{MAN}-1}}^{MAN_s}$	0	1.5	-0.742	0.461	-53.926	-2	-1.307	0.199
$\tilde{\beta}_{OQ_{t-l_{WHL}}}^{MAN_s}$	0	1.5	0.314	0.755	-66.249	-2	-1.417	0.165
$\tilde{\beta}_{IN_t}^{MAN_s}$	-0.022	$\begin{cases} 1.5, if\ IN_t \geq 0 \\ -0.5, if\ IN_t < 0 \end{cases}$	-1.992	0.051	-42.123	$\begin{cases} -2, if\ IN_t \geq 0 \\ 2.5, if\ IN_t < 0 \end{cases}$	-3.145	0.003
$\tilde{\beta}_{CP_t}^{MAN_s}$	0	$\begin{cases} 1.5, if\ CP_t \geq 0 \\ -0.5\ if\ CP_t < 0 \end{cases}$	0.042	0.967	0	$\begin{cases} -2, if\ CP_t \geq 0 \\ 2.5\ if\ CP_t < 0 \end{cases}$	0.160	0.874
Adj. R^2	0.749				0.621			

In this regard, the deviation between the total profits that were observed during the actual experimental session and the profits that would be realised if each human subject was assumed to be replaced by the corresponding combination of inferred decision models is explored. In this study if a difference of profits of a magnitude that is lower than 20%[1] takes place, a *reliable correspondence* is assumed. Table 7.17 summarises the difference of profits that are observed.

Building on this, Table 7.17 confirms the *reliable correspondence* of the decision models that have fitted to most human participants (according to Tables 7.9-7.16). The reader should at this point be reassured that the slightly higher than 20% deviation (*i.e*. 22%, as can be seen from the first row of Table 7.17) that was observed between the actual "*Base Session*" that MAN_0, WHL_0 and RET_0 conducted over the board and the corresponding simulation run with the inferred decision models is attributed to the fact that the same dataset was used to infer three different decision models. For this reason, this deviation is not considered to be *unreliable*.

Nevertheless, there are two exceptions that need to be treated as *unreliable*: the decision models that have been fitted to the human manufacturers MAN_1 and MAN_3, which generate a 40% and 34.1% difference of profits, respectively. The explanation of this poor predictive power of the decision models that have been fitted to the recorded decisions of MAN_1 and MAN_3 possibly lie at the small

[1]The fact that 20% is assumed to indicate a *reliable correspondence* between the total profits that were observed during the actual experimental session and the profits that would be realised if each human subject was assumed to be replaced by the corresponding combination of inferred decision models originates from the insight that was gained during all actual experimental sessions.

number of non-zero orders that MAN_1 and MAN_3 placed. Table 7.16 confirms that the order quantity decision models of MAN_1 and MAN_3 have been inferred based on the smallest number of valid observations. Due to this *unreliable correspondence*, the decision models that correspond to human manufacturers MAN_1 and MAN_3 (*i.e.* the grey shaded rows in Table 7.17) are eliminated from further consideration. Nevertheless, it is viewed as encouraging that although the decision models that have been fitted to MAN_1 were used in the gaming sessions that WHL_3, WHL_1 and RET_2 participated (*i.e. Sessions No. 6-8*, according to Table 7.8), the decision models that have been fitted to WHL_3, WHL_1 and RET_2 do demonstrate a *reliable correspondence*. For this reason, the decision models that have been fitted to WHL_3, WHL_1 and RET_2 are kept in the subsequent analysis.

Table 7.17: Difference of Profits between actual experimental session and inferred decision models

Session No.	***Participant or Corresponding Decision Models***	***Total Profit realised during the course of actual experimental session***	***Total Profit realised when inferred decision models are in place***	***Difference of Profits (%)***
1	MAN_0, WHL_0, RET_0	-1,500 *m.u.*	-1,170 *m.u.*	22
2	WHL_2	300 *m.u.*	360 *m.u.*	20
3	RET_3	-25,000 *m.u.*	-29,500 *m.u.*	18
4	RET_1	-350 *m.u.*	-283 *m.u.*	19.1
5	MAN_1	-20,000 *m.u.*	-12,000 *m.u.*	40
6	WHL_3	-10,000 *m.u.*	-7,400 *m.u.*	20
7	WHL_1	-12,000 *m.u.*	-9,360 *m.u.*	16
8	RET_2	-28,000 *m.u.*	-22,442 *m.u.*	19.9
9	MAN_2	-15,000 *m.u.*	-17,852 *m.u.*	19
10	MAN_3	-22,000 *m.u.*	-29,520 *m.u.*	34.1

7.3.4 Stage 4: The Agent-Based Simulation Model Runs

The object of the fourth stage is to explore under all possible interactions of inferred decision making strategies the overall performance of the *wholesale* *price contract* in the *Contract Beer Distribution Game setting*. To this end, the ABS model of the *Contract Beer Distribution Game* is run for all possible combinations of decision models. In greater detail, the interacting partners' respective decision models are treated as the treatment factors of analysis (TF_1: retailer, TF_2: wholesaler and TF_3: manufacturer), with TF_1 appearing at s_1=4 levels (RET_i, i=0-3); TF_2 at s_2=4 levels (WHL_j, j=0-3) and TF_3 at s_3=2 levels (MAN_k k=0, 2). The reason that the human manufacturers MAN_1 and MAN_3 are eliminated from the analysis is that a *reliable correspondence* of observed and simulated profits could not be assured. This conclusion is supported by Table 7.17. Since the total number of all possible TF_1 – $TF_{2–}$ TF_3 combinations (TF_1 x TF_2 x TF_3 =32) is not prohibitively high, *Chapter 8* reports the simulation results of the resulting asymmetrical, full factorial experimental design (Robinson, 2000; Toutenburg, 2002; Mukerjee and Wu, 2006).

But in order to draw statistically accurate conclusions and, thus, test the research hypotheses that are formulated in *Section 7.2* and concern the simulated human participants' WP_i- prices (*i.e*. CBG.1) and OQ_i – quantities (*i.e*. C.B.G. 2), the *emerging competition penalties* (*i.e*. C.B.G. 3) and the degree of prevalence of the *bullwhip effect* (*i.e*. C.B.G. 4), a number of conventions need to be applied to all ABS model runs. The run strategy that is followed (*i.e*. warm-up, run length and number of replications) is summarized in the paragraph that follows.

Figures 7.7 and 7.8 demonstrate how the decision models that have been fitted to the recorded decisions of human participants require some time to converge to their steady state mean values (Figures 7.7 and 7.8 present indicatively the first 500 time periods). The reason is that these decision rules start from an initial state that is far removed from the steady state mean value. In order, thus, to ensure that inferences are not made while the "initialization bias" phenomenon (Pidd, 2004; Robinson, 2004; Law, 2007; Hoad *et al*, 2009a) is still present and, in addition, to obtain accurate estimates of mean performances, the following run strategy is implemented: *i*. An estimate of the warm-up length is established according to the MSER-5 method (White, 1997; White and Spratt, 2000). The warm-up length is found from the longest warm-up (*i.e*. of the *retailer order quantities*) for all the output values to amount to 1,400 time periods. *ii*. The model is run for 15,000 time periods, according to Banks *et al*.'s (2005) recommendation to run for at least ten times the length of the warm-up period. *iii*. In order to obtain accurate estimates of mean performances each simulation run is replicated for *n*=50 times, following Hoad *et al*.'s (2009b) replications algorithm.

Figures 7.7 and 7.8 present the price and order quantity decisions of the combination of models that correspond to the interaction of RET_0, WHL_2 and MAN_0. This particular interaction is only selected for illustration purposes, while similar conclusions can be drawn for all the decision models that have been fitted to all participants' decisions.

Figure 7.7: WHL_2 and MAN_0 price decisions, according to the simulation model (treatment combination: RET_0 - WHL_2 - MAN_0)

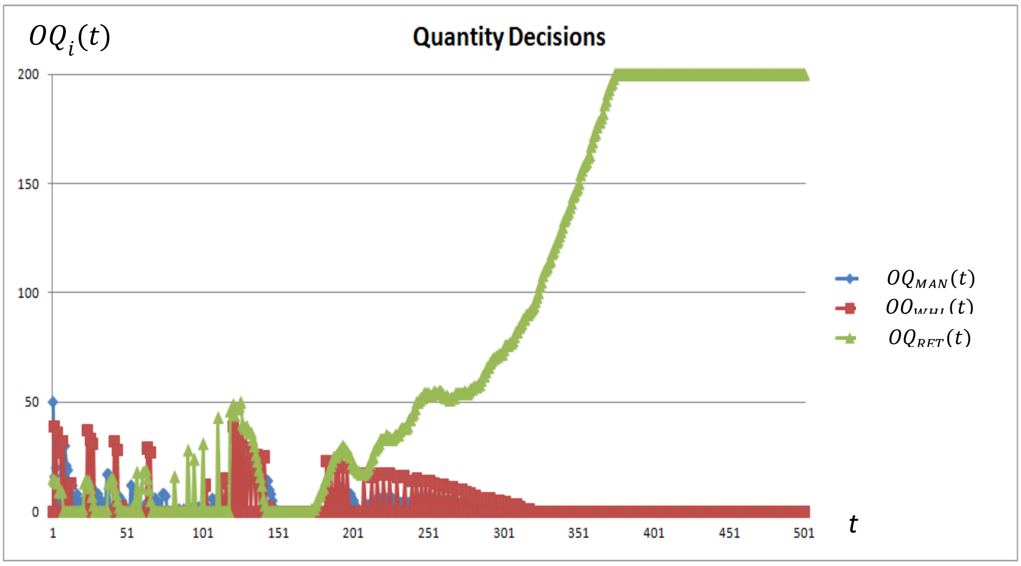


Figure 7.8: RET_0, WHL_2 and MAN_0 order decisions, according to the simulation model (treatment combination: RET_0 - WHL_2 - MAN_0)

Outcome 4: The Key Outcomes

The key outcomes that are obtained from the *ABS Contract Beer Distribution Game* model (*i.e.* the simulated human participants' WP_i- prices and OQ_i – quantities, the *emerging competition penalties* and the dominance of the *bullwhip effect*) are presented in *Chapter* 8.

7.4 Verification and Validation

Although verification and validation have been performed in parallel with developing any version of the ABS *Contract Beer Distribution Game* model (North and Macal, 2007; Robinson, 2008), some steps that have been undertaken to verify and validate the ABS model are summarised in the paragraphs that follow.

As far as verification is concerned, each model function, routine and component, in this order and priority, have been tested separately. Only after all relevant tests have been successful is the entire model tested on the aggregate level. To this end, source code analysis and 'unit testing' have been performed; according to which as many test cases as possible have been covered (Pidd, 2004; North and Macal, 2007). Among these test cases, 'extreme conditions' and 'simplifying assumptions', that enable one to produce results manually, have played a crucial role (Law, 2007). Indicative examples of such 'extreme conditions' and 'simplifying assumptions' are: cases for which no orders are placed from any of the participating agents or no customer demand occurs or fixed deterministic orders are always placed. For example, in the case that no orders are placed from any of the participating agents and the customer demand is assumed fixed at 4 cases of beer, the retailer's inventory should steadily decrease per 4 cases of beer in every time period (*i.e*. take the values of 8, 4, 0, -4 *etc*.) and the wholesaler's and the manufacturer's inventory availability should constantly remain equal to 12. Table 7.18 presents another example, when the manufacturer is assumed to place fixed orders of size 8, the wholesaler and the retailer are enforced to place fixed orders of size 4 and the customer demand is assumed to follow Sterman's (1989) step-up function. In this case, it can be manually calculated that all supply chain partners' corresponding inventory availabilities derive as shown in Table 7.18.

Table 7.18: Example of 'simplifying assumptions' under which the ABS model of the *Contract Beer Distribution Game* is ran

Manufacturer's Orders:	[8,8,8,8,8,8,8,8]
Wholesaler's Orders:	[4,4,4,4,4,4,4,4]
Retailer's Orders:	[4,4,4,4,4,4,4,4]
Demands:	[4,4,4,4,8,8,8,8]
OUTCOME	
Inventory Availability of the Manufacturer:	[12,12,12,16,20,24,28,32]
Inventory Availability of the Wholesaler:	[12,12,12,12,12,12,12,12]
Inventory Availability of the Retailer:	[12,12,12,12,8,4,0,-4]

The results that are produced by the ABS *Contract Beer Distribution Game* model coincide with these manual calculations. These 'extreme conditions' should, nevertheless, not be considered as restrictive, but only serve as illustrative examples. For these scenarios the results that are obtained from the simulation model have been compared with the results that are derived manually. In this way, it has been ensured that the ABS *Contract Beer Distribution Game* model operates as intended.

An additional technique that has been applied to the objective of verification is following 'traces' (Law, 2007: pg. 249). According to this, just after a new shipment is received, the contents of each agent's warehouse is displayed and enumerated. These contents have been subsequently compared with the corresponding manual expectations. As for these expectations, they are built on the inventory balance equations (6.4a) and (6.4b) and the following three balance equations that concern shipments that are received and orders that are in backlog. The aforementioned set of five balance equations should be satisfied in all time periods *t*.

<u>*Balance Equations of Traces*</u>

$$\sum_t DS(j) = [IN_1(t)]^- + \sum_t D(j)$$

$$OQ_i(t - L_i - l_i) + [IN_{i+1}(t-1)]^- = [IN_{i+1}(t-2)]^- + S_{i+1}(t) \text{ for } i = 1, 2$$

$$OQ_3(t - L_3 - l_3) = S_4(t)$$

where $\sum_t DS(j)$ reflects the total demand that has been satisfied by the retailer over *t* periods and $S_4(t)$ represents the total production lot that has been received by the manufacturer at time period *t*. This last balance equation ensures that the manufacturing facility's perfect reliability is actually implemented by the model source code.

With respect to validation, both the agents' distinct behavioural rules and the overall ABS model behaviour have been validated (North and Macal, 2007). In order to validate the agents' decision rules, a *reliable correspondence* between the simulated profits and the actual profits has been ensured. In this way, it has been validated that the agents' decisions don't differ significantly from the corresponding decisions that the participants were observed to make in the laboratory (Sterman, 1989). Table 7.17 summarises all relevant results. In order to validate the overall ABS model behaviour, 'black box validation' has been conducted (Pidd, 2004; Robinson, 2004). To this end, the results that are obtained from the overall model have been compared with existing, confirmed, results. As existing, confirmed, results are treated: *i.* the real world data that were acquired during the course of the "*Base" session* (*i.e*. grey shaded row of Table 7.8) and *ii*. the widely accepted results of the *Beer Distribution Game*. The *reliable correspondence* between the simulated profits and the actual profits that were observed during the "*Base" session* serves as the first successful 'black box validation' test.

As the second successful 'black box validation' test is treated the confirmed ability of the ABS model of the *Contract Beer Distribution Game* to reproduce the full spectrum of possible outcomes from *stability* to *pure chaos* that is reported by North and Macal (2007) in their reproduction of Mosekilde *et al*.'s (1991) implementation of the *Beer Distribution Game.*

i. *Stability:* After some initial transient period, the system eventually settles down to a more stable state. It is evident from Figure 7.9 that after period 26, RET_2, WHL_0, MAN_0 settle down to not placing any new orders with their respective upstream suppliers. Figure 7.9 presents an example of *stability*.

ii. *Transiency:* After some initial unstable behaviour, the system eventually settles down and indefinitely exhibits only small fluctuations. In Figure 7.10 it can be identified that after period 16 RET_3, WHL_3 and MAN_2 cease to vary their order quantity decisions widely.

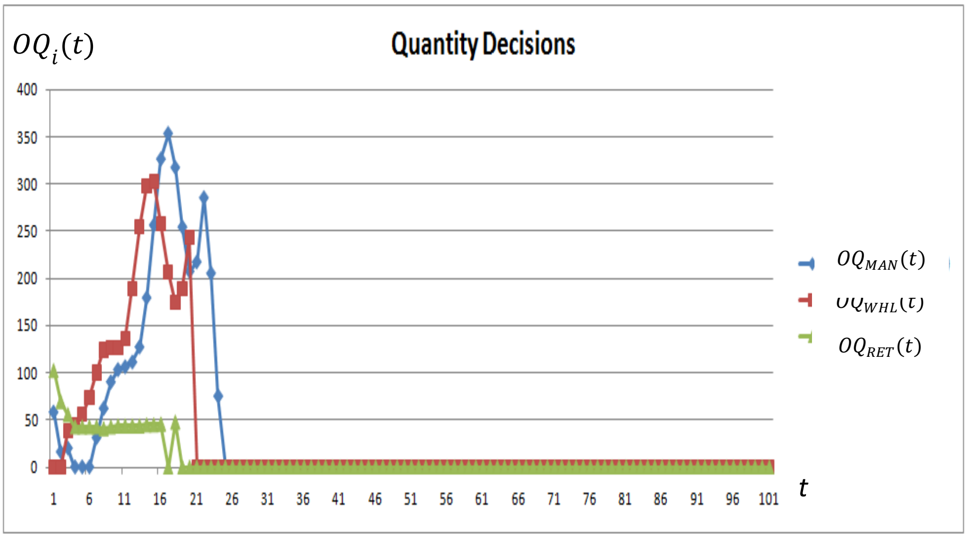


Figure 7.9: *Stability* - Order quantity decisions, according to the simulation model (treatment combination: $RET_3 - WHL_1 - MAN_0$)

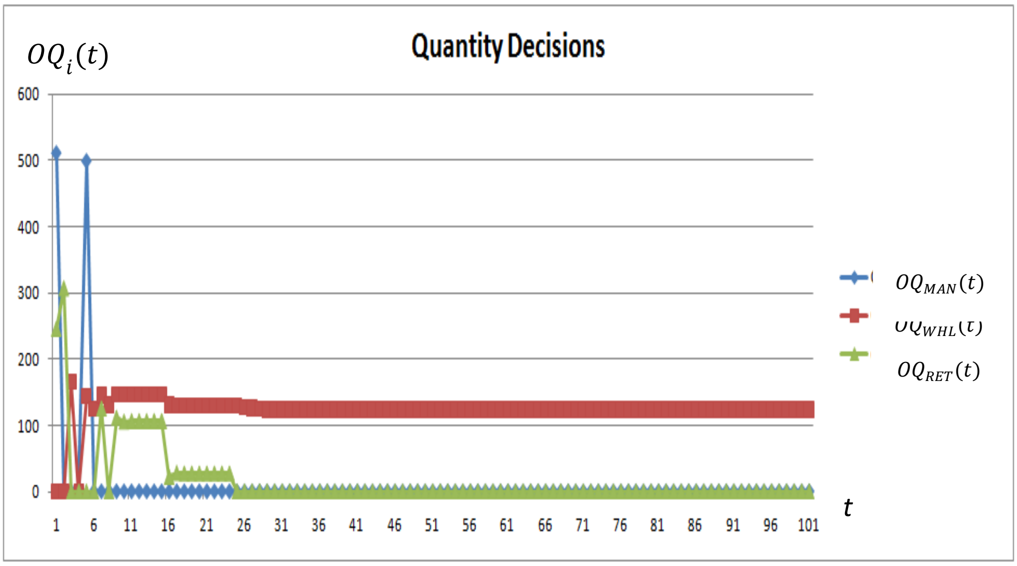


Figure 7.10: *Transiency* - Order quantity decisions, according to the simulation model of the treatment combination: $RET_2 - WHL_3 - MAN_2$

Thus, Figure 7.10 presents an indicative example of *transiency*.

iii. *Periodicity:* The system presents recurring cycles of oscillations that could be easily predicted. In Figure 7.11 WHL_3 and MAN_0 *periodically* reproduce orders of sizes that are of repeating patterns.

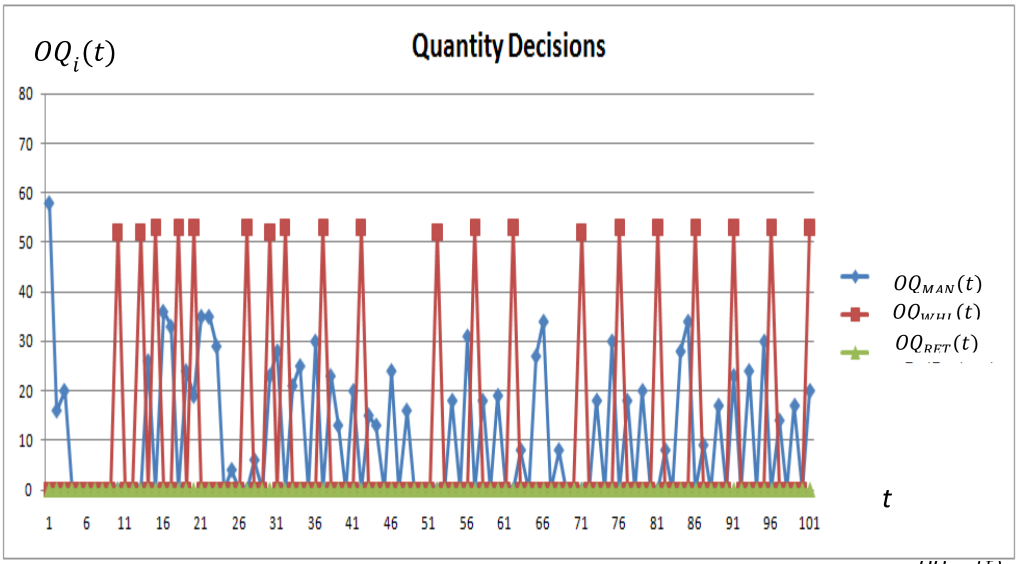


Figure 7.11: *Periodicity* - Order quantity decisions, according to the simulation model of the

iv. *Chaos:* The system suffers from persistent oscillations of no predictable pattern. Figure 7.12 shows that the order decisions of RET_2, WHL_1 and MAN_0 constantly fluctuate and, thus, generate a *chaos*.

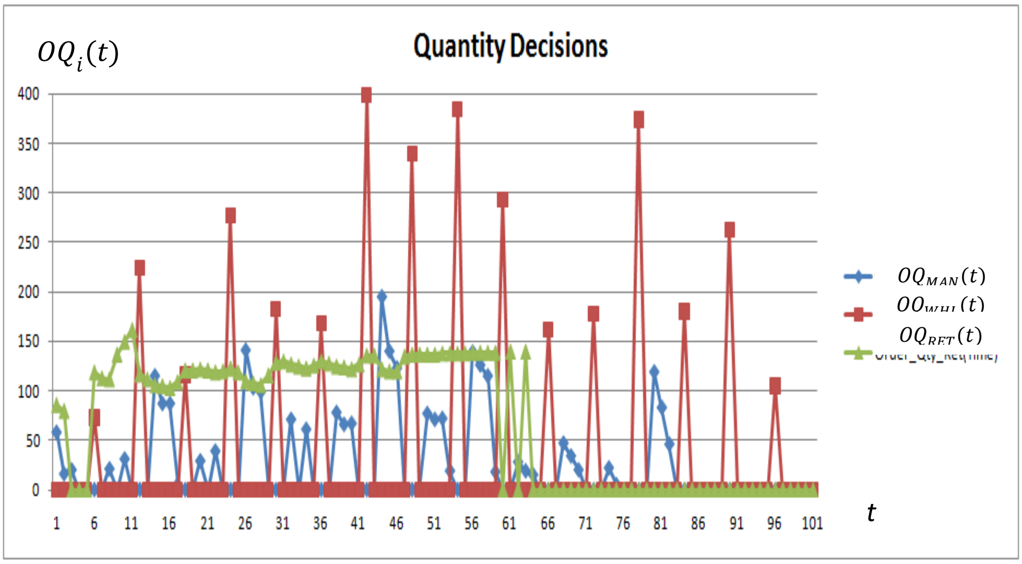


Figure 7.12: *Chaos* - Order quantity decisions, according to the simulation model of the treatment combination: $RET_2 – WHL_1 – MAN_0$

Since the results of these verification and validation activities are encouraging, some confidence is gained in the accuracy of the ABS model of the *Contract Beer Distribution Game*[2].

7.5 Summary

This chapter reminds the reader of the *Contract Beer Distribution Game*'s specification, summarises the analytical results that are developed in *Chapter 6* and the existing relevant experimental results that are known about the traditional *Beer Distribution Game* in *Sub-section 2.2.2.* It then uses these known results to build the research hypotheses about human participants' WP_i- prices being significantly higher than the prices that they are charged (*i.e*. CBG.1), human participants' OQ_i – quantities being significantly different from the quantities that they are requested to deliver (*i.e*. C.B.G. 2), the *emerging competition penalties* being significantly different from 0 (*i.e*. C.B.G. 3) and the degree of prevalence of the *bullwhip effect* (*i.e*. C.B.G. 4).

The chapter subsequently describes in some detail the approach that this PhD thesis has followed to address the aforementioned research hypotheses. In greater detail, this research uses ABS models, which have been calibrated via human experiments. In this way, it builds statistically accurate conclusions about the effect that different prolonged interactions between dynamic, heterogeneous and autonomous decisions of human echelon managers can have on the *wholesale price contract*'s *performance*, when applied to the *Beer Distribution Game* setting. In this way, it manages to accommodate: *i.* human *intentions* that might

[2]The reader should at this point be reassured that the reason that all possible different states are produced is that all possible combinations of inferred decision models are studied. This result that further confirms our main argument here that the system overall behaviour depends on the interplay between the interacting decision making strategies.

be different from profit maximisation, *ii*. human *actions* that might differ from their corresponding *intentions* in heterogeneous ways (*i.e*. heterogeneous *bounded rationality*), *iii*. human *reactions* that might depend on their surrounding environment and changes that occur if any and *iv*. human *decisions* that are *independent* and *autonomous*. In this way, it successfully addresses the literature gaps G.1-G.4 that are identified in Table 2.5 (*s. Section 2.4*) for the *Beer Distribution Game* setting.

Chapter 8 presents the results that are obtained from the ABS *Contract Beer Distribution Game* model, so that statistically accurate conclusions about the research hypotheses CBG.1 – CBG.4 can be drawn.

Chapter 8

The *Contract Beer Distribution Game Results*

The purpose of this chapter is to draw statistically accurate conclusions about the effect that different prolonged interactions between dynamic, heterogeneous and autonomous decisions can have on the *wholesale price contract's performance*, when applied to the *Beer Distribution Game* setting. To this end, this chapter presents and discusses the results that are obtained from the ABS model that is described in *Sub-section 7.3.4*. In this way, *Chapter 8* addresses the research hypotheses that concern human participants' WP_i- prices being significantly higher than the prices that they are charged (*i.e*. CBG.1), OQ_i – quantities being significantly different from the quantities that they are requested to deliver (*i.e*. C.B.G. 2), the *emerging competition penalties* being significantly different from 0 (*i.e*. C.B.G. 3) and the *bullwhip effect* prevailing (*i.e*. C.B.G. 4), as formulated in *Section 7.2*.

This chapter presents the results that are acquired from the ABS model in the same order that the research hypotheses have also been formulated. It starts by discussing the simulated human participants' decisions about wP_i-prices and oQ_i-quantities, proceeds to the *competition penalties* that *emerge* from all possible interactions and finishes by discussing the degree to which the *bullwhip effect* prevails. In this way, the research hypotheses CBG.1-CBG.4, are in turn, tested. The chapter concludes with a brief discussion and a reflection on the managerial implications and the practical significance of the results that are obtained.

The steady state mean results of *n*=50 simulated replications for all *32* possible treatment combinations are presented in the tables of *Sections 8.1-8.4*. In greater detail, Tables 8.1 and 8.2 present the simulated human participants' steady state mean $\overline{WP_i}$ – prices. In the same way Tables 8.4, 8.5 and 8.7 outline the simulated participants' steady state mean $\overline{OQ_i}$ – order quantities respectively. Table 8.9 portrays the steady state mean *competition penalties* that are attained by all studied interactions and Table 8.10 the percentage of cases for which variance amplification is exhibited. More details about the data that are presented in these tables is provided in the sub-sections that follow.

Tables 8.1-8.2, 8.4-8.5, 8.7 and 8.9-8.10 are organised as follows: between parentheses *()* in *italics font* the standard deviation of all different replications' results is given, while between brackets **[] in bold font** the half widths of the corresponding 99% confidence intervals are provided. The reason that all inferences are based on the low significance level of α = 0.01 is on the side of caution in rejecting a null hypothesis and, so, reducing the probability of committing a *Type I* error. For the reasons that are discussed in *Sub-section 7.3.3* the human manufacturers MAN_1 and MAN_3 have been excluded from the analysis.

8.1 Participants' $\overline{WP_i}$ - prices

The object of this section is to test whether the simulated human participants in the *Contract Beer Distribution Game* would make 'locally good' price decisions, namely test the research hypothesis CBG.1. In respect to this, the simulated participants in the *Contract Beer Distribution Game* are expected to charge WP_i-prices that are significantly higher than the prices that they are charged. In this regard, Tables 8.1 and 8.2 present the simulated human manufacturers' and wholesalers' $\overline{WP_i}$ – price decisions. In greater detail, Table 8.1 focuses on the simulated human manufacturers, while Table 8.2 turns attention to the simulated human wholesalers. Table 8.3 compares the prices that are charged by the simulated human manufacturers and the wholesalers. The reason that manufacturers' price decisions are first presented and are subsequently followed by wholesalers' price decisions is that this is the way that prices are transmitted along the *Beer Distribution Game* supply chain.

8.1.1 Manufacturers' $\overline{WP}_{MAN}$ – prices

Table 8.1 portrays the simulated human manufacturers $\overline{WP}_{MAN}$ – price decisions over *n*=50 simulated replications for all 32 treatment combinations studied. Among the *decision attributes* of models of type (7.7) that have been fitted to human manufacturers' price decisions (according to Table 7.14) only the incoming order quantities $OQ_{WHL}(t-l_{WHL})$, the inventory positions $IN_{MAN}(t)$ and the cumulatively realized profits $\sum_{j=1}^{t} P_{MAN}(j)$ are affected by the variation of customer demand that exists between different replications. But since the 'incoming order price reactive' MAN_0 is the only human manufacturer who takes into account the decision attributes the incoming order quantities $OQ_{WHL}(t-l_{WHL})$, the inventory positions $IN_{MAN}(t)$ and the cumulatively realized profits $\sum_{j=1}^{t} P_{MAN}(j)$ in his respective price decisions according to Table 7.14, non-zero standard deviations derive for only some of his interactions that are studied. The remaining interactions of Table 8.1 exhibit standard deviations that are exactly equal to 0. For this reason, all corresponding half-width 99% confidence intervals for all $\overline{WP}_{MAN}$ – price decisions reported become equal to 0.

It can be observed from Table 8.1 that the simulated human manufacturers seem not to vary the prices that they charge depending on the interacting wholesaler and retailer. Therefore, the simulated human manufacturers appear to have their own preferred strategies that are independent of wholesaler-retailer interaction pairs. There is, nevertheless, one exception (*i.e*. the grey shaded row of Table 8.1): the interaction of the 'incoming price reactive' manufacturer MAN_0 and the 'price and future availability reactive' wholesaler WHL_2, in which the interacting simulated human retailer seems to affect MAN_0 price decisions. The reason is that the interaction of WHL_2 with MAN_0 is the only interaction, in which both the interacting wholesaler and the interacting manufacturer consider order quantities in their price decisions (according to Tables 7.11 and 7.14, respectively).

It is very interesting that the simulated human manufacturers MAN_0 and MAN_2 seem to employ two opposite strategies to ensure their profitability. The simulated 'incoming price reactive' MAN_0, solely aware of his own previously charged prices as he is (according to Table 7.14), prefers to attract a demand that is sufficiently high to maximise his individual profit. In order, thus, to achieve this high demand, he insists on charging low prices. In this regard, his pricing strategy could be viewed as 'demand – driven'. As for the simulated 'incoming order and price reactive' MAN_2, she appears to be highly conscious of the incoming order quantities from the wholesaler (according to Table 7.14) and, therefore, aware of the high probability of not receiving orders that are strictly positive. For this reason, she seems to adopt the view that strictly positive margins can ensure profitability. To this end, MAN_2, chooses to charge high prices. This is why her pricing strategy can be characterised as 'profit margin - driven'.

Table 8.1: Simulated manufacturers' $\overline{\boldsymbol{WP}}_{\boldsymbol{MAN}}$ – price decisions[3]

R / W - F	$\boldsymbol{RET_0}$	$\boldsymbol{RET_1}$	$\boldsymbol{RET_2}$	$\boldsymbol{RET_3}$
$\boldsymbol{WHL_0}$ – $\boldsymbol{MAN_0}$	0.5 (*0*) [±**0**]	0.5 (*0*) [±**0**]	0.5 (*0*) [±**0**]	0.5 (*0*) [±**0**]
$\boldsymbol{WHL_0}$ – $\boldsymbol{MAN_2}$	44.59 (0) [±0]	44.58 (*0*) [±**0**]	44.58 (*0*) [±**0**]	44.58 (*0*) [±**0**]
$\boldsymbol{WHL_1}$ – $\boldsymbol{MAN_0}$	0.5 (*0*) [±**0**]	0.5 (*0*) [±**0**]	0.5 (*0*) [±**0**]	0.5 (*0*) [±**0**]
$\boldsymbol{WHL_1}$ – $\boldsymbol{MAN_2}$	44.59 (*0*) [±**0**]	44.58 (*0*) [±**0**]	44.57 (*0*) [±**0**]	44.58 (*0*) [±**0**]
$\boldsymbol{WHL_2}$ – $\boldsymbol{MAN_0}$	26.94 (*1.168*) [±**0.196**]	0.5 (*0*) [±**0**]	10 (*0*) [±**0**]	9.998 (*0.003*) [±**0**]
$\boldsymbol{WHL_2}$ – $\boldsymbol{MAN_2}$	44.57 (*0*) [±**0**]	44.57 (*0*) [±**0**]	44.57 (*0*) [±**0**]	44.57 (*0*) [±**0**]
$\boldsymbol{WHL_3}$ – $\boldsymbol{MAN_0}$	0.5 (*0*) [±**0**]	3.187 (*0*) [±**0**]	0.5 (*0*) [±**0**]	0.5 (*0*) [±**0**]
$\boldsymbol{WHL_3}$ – $\boldsymbol{MAN_2}$	44.59 (*0*) [±**0**]	44.58 (*0*) [±**0**]	44.9 (*0*) [±**0**]	44.9 (*0*) [±**0**]

Since the 'incoming price reactive' manufacturer MAN_0 constantly charges prices that are not significantly different from the manufacturing cost (*i.e.* c = 0.50 *m.u.*), the research hypothesis CBG.1 needs to be rejected for his treatment combinations MAN_0, WHL_i, RET_j with i=0, 1, 3 and j=0,...,3.

However, for ¾ of the interactions in which the 'incoming price reactive' manufacturer MAN_0 interacts with the 'price and future availability reactive'

[3] This table presents the following information about the simulated manufacturers' prices over n=50 replications: *i.* averages in regular font, *ii.* standard deviations in *italics font* (between parentheses), *iii.* the half widths of the corresponding 99% confidence intervals **in bold font** (between brackets).

wholesaler WHL_2 (*i.e.* the grey shaded row of Table 8.1), MAN_0 charges significantly higher prices than his own incurred manufacturing cost. Therefore, for these interactions the research hypothesis CBG.1 cannot be rejected (*i.e.* $\overline{wP}_{MAN} > c$ at $p<0.01$ for: MAN_0, WHL_2, RET_i with i=1, 3, 4). Overall the research hypothesis CBG.1 cannot be rejected for 18.75% of the interactions of MAN_0. However, the research hypothesis CBG.1 needs to be rejected for the remaining 81.25% of the MAN_0 interactions studied. Building on this observation, MAN_0 appears to make 'locally poor' price decisions for the majority of the interactions studied.

Table 8.1 demonstrates that the simulated 'incoming order and price reactive' manufacturer MAN_2 charges prices that are significantly higher than the manufacturing cost, independently of the interacting wholesaler-retailer interaction pair. The result is that the research hypothesis CBG.1 cannot be rejected for any of the treatment combinations, in which MAN_2 participates (*i.e.* $\overline{wP}_{MAN} > c$ at $p<0.01$ for the following interactions: MAN_2, WHL_i, RET_j with i=0...3 and j=0,...,3). Therefore, MAN_2 appears to constantly make 'locally good' price decisions.

8.1.2 Wholesalers' $\overline{WP}_{WHL}$ – prices

Table 8.2 presents the simulated human wholesalers' $\overline{WP}_{WHL}$ – price decisions over n=50 simulated replications for all 32 treatment combinations studied. Among the *decision attributes* of models of type (7.7) that have been fitted to human wholesalers' price decisions (according to Table 7.11) only the shipments to be received $S_{MAN}(t - L_{WHL} + 1)$, the incoming order quantities $OQ_{RET}(t - l_{RET})$ and the current inventory positions $IN_{WHL}(t)$ are affected by the variation of customer demand that exists between different replications. Since WHL_1, WHL_2 and WHL_3 significantly consider these three *decision attributes* in their price decisions (according to Table 7.11), non zero standard deviations occur for some of the interactions in which these simulated human wholesalers come into play, as can be observed from Table 8.2.

Table 8.2: Simulated wholesalers' $\overline{\boldsymbol{WP}}_{\boldsymbol{WHL}}$ – price decisions[4]

R / W - F	$\boldsymbol{RET_0}$	$\boldsymbol{RET_1}$	$\boldsymbol{RET_2}$	$\boldsymbol{RET_3}$
$\boldsymbol{WHL_0}$ – $\boldsymbol{MAN_0}$	0.5 (*0*) [±**0**]	0.5 (*0*) [±**0**]	0.5 (*0*) [±**0**]	0.5 (*0*) [±**0**]
$\boldsymbol{WHL_0}$ – $\boldsymbol{MAN_2}$	44.59 (*0*) [±**0**]	44.58 (*0*) [±**0**]	44.58 (*0*) [±**0**]	44.58 (*0*) [±**0**]
$\boldsymbol{WHL_1}$ – $\boldsymbol{MAN_0}$	249.0 (*0.75*) [±**0.13**]	249.04 (*0.96*) [±**0.16**]	249.47 (*0.20*) [±**0.03**]	249.35 (*0.87*) [±**0.15**]
$\boldsymbol{WHL_1}$ – $\boldsymbol{MAN_2}$	249.69 (*0.80*) [±**0.13**]	249.53 (*0.68*) [±**0.11**]	248.93 (*0.65*) [±**0.11**]	248.22 (*0.88*) [±**0.15**]
$\boldsymbol{WHL_2}$ – $\boldsymbol{MAN_0}$	19.79 (*0.46*) [±**0.08**]	1.59 (*0.01*) [±**0**]	4.837 (*0.002*) [±**0**]	5.952 (*0.007*) [±**0.001**]
$\boldsymbol{WHL_2}$ – $\boldsymbol{MAN_2}$	25.86 (*0*) [±**0**]	17.266 (*0*) [±**0**]	17.27 (*0*) [±**0**]	17.27 (*0*) [±**0**]
$\boldsymbol{WHL_3}$ – $\boldsymbol{MAN_0}$	10.97 (*0*) [±**0**]	3.54 (*0*) [±**0**]	10.97 (*0*) [±**0**]	5.07 (*0.39*) [±**0.07**]
$\boldsymbol{WHL_3}$ – $\boldsymbol{MAN_2}$	34.13 (*0.01*) [±**0.001**]	33.59 (*0.01*) [±**0.001**]	52.66 (*0*) [±**0**]	52.66 (*0*) [±**0**]

[4] This table presents the following information about the simulated wholesalers' prices over n=50 replications: *i.* averages in regular font, *ii.* standard deviations in *italics font* (between parentheses), *iii.* the half widths of the corresponding 99% confidence intervals **in bold font** (between brackets).

But since WHL_0 does not significantly consider any of these three *decision attributes* in her price decisions (according to Table 7.8), the standard deviations of all treatment combinations in which she participates are exactly equal to 0 (*s.* Table 8.2).

It is also very interesting that all simulated human wholesalers seem to follow the manufacturers' example and attempt to ensure their profitability by adopting two distinct strategies. In greater detail, they might prefer to adopt a 'demand – driven' pricing strategy and, hence, charge low prices, in order to induce demand for the downstream retailer. These low prices may even be lower than their own incurred prices. Alternatively, they might choose to employ a 'profit margin - driven' pricing strategy, in accordance with which they charge prices that are sufficiently high to ensure strictly positive margins. In order to identify which of these two pricing strategies the simulated human wholesalers enforce, the research hypothesis CBG.1 needs to be tested for the simulated human wholesalers. To this end, the steady state mean prices that are charged by the simulated human wholesalers need to be compared with the corresponding mean prices of the simulated human manufacturers. Table 8.3 summarises this information.

It is evident from Table 8.3 that WHL_0 is the only simulated human wholesaler, who in steady state charges prices that, irrespective of the interacting manufacturers and retailers, do not differ significantly from her own incurred prices. This is highlighted by the first two grey shaded rows of Table 8.3. So, the 'price and past order reactive' WHL_0 is the only human wholesaler who adopts the 'demand – driven' pricing strategy. The other three simulated human wholesalers, that is WHL_1, WHL_2 and WHL_3, charge in steady state prices that on average are significantly higher than the corresponding manufacturer prices. Thus, they seem to prefer the 'profit margin - driven' pricing strategy.

Table 8.3: Comparison of manufacturers $\overline{WP}_{MAN}$ and wholesalers' $\overline{WP}_{WHL}$ – price decisions

R / W - F	RET_0		RET_1		RET_2		RET_3	
	$\overline{WP}_{MAN}$	$\overline{WP}_{WHL}$	$\overline{WP}_{MAN}$	$\overline{WP}_{WHL}$	$\overline{WP}_{MAN}$	$\overline{WP}_{WHL}$	$\overline{WP}_{MAN}$	$\overline{WP}_{WHL}$
$WHL_0 - MAN_0$	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
$WHL_0 - MAN_2$	44.59	44.59	44.58	44.58	44.58	44.58	44.58	44.58
$WHL_1 - MAN_0$	0.5	249.0	0.5	249.04	0.5	249.47	0.5	249.35
$WHL_1 - MAN_2$	44.59	249.69	44.58	249.53	44.57	248.93	44.58	248.22
$WHL_2 - MAN_0$	26.94	19.79	0.5	1.59	10	4.837	9.998	5.952
$WHL_2 - MAN_2$	44.57	25.86	44.57	17.266	44.57	17.27	44.57	17.27
$WHL_3 - MAN_0$	0.5	10.97	3.187	3.54	0.5	10.97	0.5	5.07
$WHL_3 - MAN_2$	44.59	34.13	44.58	33.59	44.9	52.66	44.9	52.66

The underlying reason for this difference might be that the 'price and past order reactive' WHL_0 is the only wholesaler who relies on her past order quantities to determine her new prices (*s.* Table 7.8). Focusing, thus, on selling the shipments that she expects to receive from the manufacturer (*i.e.* her own past order quantities OQ_{t-1}), she appears to view low prices as inducing demand. This is where the 'demand – driven' pricing strategy might stem from. On the other hand, the 'price and present availability reactive' WHL_1, the 'price and future availability reactive' WHL_2 and the 'profit and present availability reactive' WHL_3 prefer to consider in their price decisions their present or future inventory availabilities instead of their previous order quantities. For this reason, they seem to be highly conscious of inventory costs. Therefore, they might enforce a 'profit margin – driven' pricing strategy, in order to compensate for these costs, from which they cannot be protected.

Based on the above observations from Table 8.3, it naturally follows that the research hypothesis CBG.1 that concerns human wholesalers' prices being significantly higher than the corresponding manufacturer prices needs to be rejected for WHL_0, but cannot be rejected for WHL_1, WHL_2 and WHL_3 (*i.e*. $\overline{wP}_{WHL} > \overline{wP}_{MAN}$ at $p<0.01$). Hence, WHL_0 appears to make 'locally poor' price decisions, while WHL_1, WHL_2 and WHL_3 appear to make 'locally good' price decisions. The only exception for the 'profit and present availability reactive' wholesaler WHL_3 is the interaction with the 'incoming order and price reactive' manufacturer MAN_2, in which WHL_3 charges on average prices that are significantly lower than the prices that he is himself charged by MAN_2. This exception is highlighted by the last grey shaded row of Table 8.3.

The explanation that neither WHL_1 nor WHL_2 charge so low prices when interacting with MAN_2 most possibly lies at the fact that both the the 'price and present availability reactive' WHL_1 and the 'price and future availability reactive' WHL_2 almost ignore their profits in their price decisions. Furthermore, the most probable reason that WHL_3 charges so low prices when he interacts with the 'incoming order and price reactive' manufacturer MAN_2 and not the 'incoming price reactive' manufacturer MAN_0 is because MAN_0's prices are indifferent to the order quantities that WHL_3 places.

In view of these two opposite pricing strategies that the simulated human wholesalers adopt, that is, the 'demand – driven' or the 'profit margin – driven' and the corresponding resulting prices (namely, prices that may be either "too-high" or "too-low"), it becomes very interesting to explore the *emerging competition penalties* that these generate respectively. This question is discussed in *Section 8.3*.

8.2 Participants' $\overline{OQ}_i$ - quantities

The purpose of this section is to test whether the simulated human participants in the *Contract Beer Distribution Game* would make 'locally poor' order quantity decisions, namely test the research hypothesis CBG.2. In respect to this, the simulated participants in the *Contract Beer Distribution Game* are expected to order oQ_i- quantities that are significantly different from the quantities that they are requested to deliver. In this regard, Tables 8.4, 8.5 and 8.7 present the simulated human participants' $\overline{OQ}_i$ – order quantity decisions. Table 8.4 focuses on the simulated human retailers, Table 8.5 turns attention to the simulated human wholesalers, while Table 8.7 concentrates on the simulated human manufacturers. Table 8.6 summarises the steady state mean order quantities of human retailers and wholesalers, so that comparisons can be more easily made. Table 8.8 does so for the simulated human wholesalers and manufacturers.

8.2.1 Retailers' $\overline{OQ}_{RET}$ – order quantities

Table 8.4 portrays the simulated human retailers $\overline{OQ}_{RET}$ – order quantity decisions over *n*=50 simulated replications for all 32 treatment combinations studied.

There is in Table 8.4 a high number of occurrences of non-zero, yet low standard deviations. The simulated human retailers may come in direct contact with stochastic customer demand, which is the only place where variation across different replications exists. As discussed in *Section 6.2*, where the *Contract Beer Distribution Game* is formally specified, customer demand is assumed to follow the truncated at zero normal distribution with μ=5 and σ = 2. But these demand realizations are not included in the order quantity decision models of type (7.9) that have been fitted to the simulated human retailers' true decisions (according to Table 7.10). This is the reason why the standard deviations that are observed in Table 8.4 remain low.

As for why there is a high number of non-zero standard deviations, the answer seems to be the combined effect of demand and supply uncertainty that is applicable to all the simulated human retailers. Demand variation affects retailers' respective inventory positions $IN_R(t)$ and cumulatively realized profits $\sum_{j=1}^{t} P_R(j)$, which are taken into account by all the simulated human retailers in their order quantity decisions (according to Table 7.10). Supply uncertainty is due to the unpredictable pattern of shipments that the retailers receive from their respective upstream wholesalers $S_{WHL}(t - L_{RET} + 1)$. Although not all the simulated human retailers directly consider shipments in their order quantity decisions, the shipments that are in transit to their warehouse $S_{WHL}(t - L_{RET} + 1)$ affect both their inventory position $IN_R(t)$ and their cumulatively realized profits $\sum_{j=1}^{t} P_R(j)$, which are significant determinants of most human retailers' order quantity decisions (according to Table 7.10).

Table 8.4: Simulated retailers' $\boldsymbol{OQ_{RET}}$ – quantity decisions[5]

R / W - F	$\boldsymbol{RET_0}$	$\boldsymbol{RET_1}$	$\boldsymbol{RET_2}$	$\boldsymbol{RET_3}$
$\boldsymbol{WHL_0 - MAN_0}$	4.99 *(0.01)* **[±0.002]**	2.33 *(0.01)* **[±0.001]**	2.27 *(0.01)* **[±0.001]**	30.04 *(0.07)* **[±0.012]**
$\boldsymbol{WHL_0 - MAN_2}$	5.01 *(0.011)* **[±0.002]**	2.34 *(0.008)* **[±0.001]**	2.34 *(0.009)* **[±0.002]**	2.34 *(0.01)* **[±0.001]**
$\boldsymbol{WHL_1 - MAN_0}$	0 *(0)* **[±0]**	2.94 *(0.04)* **[±0.006]**	2.95 *(0.02)* **[±0.003]**	2.96 *(0.01)* **[±0.002]**
$\boldsymbol{WHL_1 - MAN_2}$	2.93 *(0.05)* **[±0.008]**	2.81 *(0.041)* **[±0.007]**	2.88 *(0.012)* **[±0.002]**	2.79 *(0.009)* **[±0.002]**
$\boldsymbol{WHL_2 - MAN_0}$	200.01 *(0)* **[±0]**	2.32 *(0.007)* **[±0.001]**	2.27 *(0.009)* **[±0.002]**	1.22 *(0.02)* **[±0.004]**
$\boldsymbol{WHL_2 - MAN_2}$	200.01 *(0)* **[±0]**	3.42 *(0.02)* **[±0.002]**	3.42 *(0.02)* **[±0.002]**	3.42 *(0.01)* **[±0.002]**
$\boldsymbol{WHL_3 - MAN_0}$	5 *(0.01)* **[±0.002]**	2.34 *(0.008)* **[±0.001]**	2.05 *(0.009)* **[±0.002]**	50 *(0.004)* **[±0.001]**
$\boldsymbol{WHL_3 - MAN_2}$	5 *(0.01)* **[±0.002]**	2.34 *(0.01)* **[±0.001]**	3.33 *(0.01)* **[±0.002]**	3.34 *(0.01)* **[±0.002]**

Still, there is also a number of interactions in Table 8.4 that exhibit standard deviations that are exactly equal to 0, turning the corresponding half-width 99% confidence intervals for all $\overline{OQ}_{RET}$ – order quantity decisions also to zero. These exceptions consist of the interactions in which the simulated 'price conscious' RET_0 interacts with the 'price and current availability conscious' wholesaler WHL_2. The reason is that in these particular interactions RET_0 orders in steady

[5] This table presents the following information about the simulated retailers' order quantities over n=50 replications: *i.* averages in regular font, *ii.* standard deviations in *italics font* (between parentheses), *iii.* the half widths of the corresponding 99% confidence intervals **in bold font** (between brackets).

state quantities that are on average so exceptionally high that they are completely irrelevant to the occurring supply and demand uncertainty.

In order to test the research hypothesis CBG.2 and, thus, assess whether the simulated human retailers make 'locally poor' decisions, their steady state mean $\overline{oQ}_{RET}$ – order quantities need to be compared to the mean customer demand (*i.e.* μ=5).

It is evident from Table 8.4 that only the 'price conscious' retailer RET_0 manages to closely follow true customer demand for a number of interactions. Hence, the research hypothesis CBG.2 needs to be rejected for these particular interactions (*i.e.* $\overline{OQ}_i = \mu$). RET_0 proves to make 'locally good' decisions in these particular interactions.

Nevertheless, the 'price conscious' retailer RET_0 is found to order quantities that are significantly higher than the mean customer demand or else 'over-order' in a number of different interactions. These interactions are also discussed when the occurring zero standard deviations are observed. In these particular interactions that RET_0 'over-orders', he seems to be driven by his strong preference to 'minimise backlogs'. It is very interesting that RET_0 is found to 'over-order' when asked to interact with the 'price and future availability reactive' wholesaler WHL_2. A possible explanation might be that WHL_2 is the lowest charging wholesaler, one who sometimes charges prices that are even lower than the prices that he is himself charged and, therefore, leaves a wide profit margin for RET_0 to exploit (*Sub-section 8.1.2*). For another set of interactions, though, the 'price conscious' retailer RET_0 proves to order quantities that are significantly lower than the mean customer demand or else 'under-order'. In these particular interactions RET_0 seems to prioritize 'minimisation of inventories' and, thus, 'under-orders'. Interestingly, RET_0 appears to 'under-order' when asked to interact with the 'price and present availability reactive' WHL_1, who is found to charge the highest prices. Conscious of prices as he is, he prefers to suffer from backlog penalties rather than being charged excessively high prices. The research hypothesis CBG.2 cannot be rejected for these interactions of RET_0 with WHL_1 and WHL_2 that he either 'under-orders' or 'over-orders'. (*i.e.* $\overline{OQ_i} \neq \mu$ at p<0.01). These particular interactions are highlighted via the grey shaded cells of Table 8.4. A last note on RET_0 ordering strategy that is worthy of further attention is that, 'price conscious' as he is, he exhibits a wide range of ordering strategies, varying from 'under-ordering' to 'over-ordering', depending on the price that he is himself charged. It is a surprise that his ordering decisions seem to be driven from the wholesaler prices and not the actual customer demand.

The fact that RET_0 is the only simulated human retailer who exclusively relies on the price that the wholesaler charges to him for his order decision constitutes a potential explanation for RET_0's potential to make both 'locally good' and 'locally poor' decisions. The other three simulated human retailers additionally resort to this end to either their cumulatively realized profit (*i.e* RET_1 and RET_2) or their inventory holding and backlog cost (*i.e* RET_2 and RET_3). Concerned about profits and costs as the 'price and profit conscious' retailer RET_1, the 'price and cost and profit conscious' retailer RET_2 and the 'price and cost conscious' retailer RET_3 are, they place orders of sizes that are significantly lower than the mean of true customer demand (*s.* Table 8.4). Therefore, in all their interactions RET_1, RET_2 and RET_3 'under-order', that is, order quantities that are significantly lower than the arising customer demand. This 'under-ordering' behaviour seems to be created by their strong preference to 'minimise inventories'. Since RET_1, RET_2 and RET_3 order significantly different quantities than the mean customer demand, the research hypothesis CBG.2 cannot be rejected for all the interactions of RET_1, RET_2 and RET_3 (*i.e.* $\overline{OQ_i} \neq \mu$ at $p<0.01$). These particular interactions are highlighted via the grey shaded cells of Table 8.4. Hence, RET_1, RET_2 and RET_3 make persistently 'locally poor' decisions.

In respect to this, it seems fair to say that it may be the 'price conscious' retailer's RET_0 simplified ordering strategy that enables him to order, on average, as much as his received customer demand entails. This is the first indication that establishes that prices can serve to control order quantities and, thus, inventories. It would be very interesting to explore whether something similar also holds for the wholesaler and the retailer.

8.2.2 Wholesalers' $\overline{oQ}_{WHL}$ – order quantities

Table 8.5 presents the simulated human wholesalers' $\overline{OQ}_{WHL}$ – order quantity decisions over n=50 simulated replications for all 32 treatment combinations studied. There is in Table 8.5 a high number of occurrences of non-zero standard deviations. This originates from the combined effect of demand and supply uncertainty, from which all simulated human wholesalers suffer. Nevertheless, there are certain exceptions that exhibit standard deviations that are exactly equal to 0, turning the corresponding half-width 99% confidence intervals for all $\overline{oQ}_{WHL}$ – order quantity decisions also equal to 0.

Table 8.5: Simulated wholesalers' OQ_{WHL} – quantity decisions[6]

R / W - F	RET_0	RET_1	RET_2	RET_3
$WHL_0 - MAN_0$	5 *(0.02)* **[±0.004]**	2.33 *(0.01)* **[±0.002]**	2.28 *(0.01)* **[±0.001]**	30.04 *(0.08)* **[±0.01]**
$WHL_0 - MAN_2$	5 *(0.02)* **[±0.003]**	2.38 *(0.01)* **[±0.001]**	2.34 *(0.01)* **[±0.001]**	2.38 *(0.01)* **[±0.001]**
$WHL_1 - MAN_0$	5.14 *(0.08)* **[±0.01]**	1.21 *(0.03)* **[±0.005]**	1.20 *(0.02)* **[±0.003]**	1.20 *(0.02)* **[±0.003]**
$WHL_1 - MAN_2$	4.97 *(0.02)* **[±0.03]**	1.41 *(0.05)* **[±0.01]**	1.5 *(0.01)* **[±0.001]**	1.39 *(0.01)* **[±0.001]**
$WHL_2 - MAN_0$	0.04 *(0.04)* **[±0.007]**	4.31 *(0.01)* **[±0.001]**	3.251 *(0.01)*	2.23 *(0.02)* **[±0.004]**
$WHL_2 - MAN_2$	23 (0) [±0]	18.74 (0) [±0]	18.74 (0) [±0]	20.86 (0.004) [±0.001]
$WHL_3 - MAN_0$	9.88 *(0)* **[±0]**	8.57 *(0)* **[±0]**	9.88 *(0.002)* **[±0]**	77.52 *(10.28)* **[±1.73]**
$WHL_3 - MAN_2$	5.01 *(0.02)* **[±0.003]**	2.34 *(0.02)* **[±0.003]**	124.01 *(0)* **[±0]**	124.01 *(0)* **[±0]**

These exceptions entail some of the interactions in which the simulated 'price and present availability conscious' wholesaler WHL_2 and the 'price and present and future availability conscious' wholesaler WHL_3 come into play. One potential explanation could be that WHL_2 and WHL_3 assign a great importance to their current inventory availabilities IN_t for their order quantity decisions (according toTable 7.13), which is not uncertain in nature.

[6] This table presents the following information about the simulated wholesalers' order quantities over n=50 replications: *i.* averages in regular font, *ii.* standard deviations in *italics font* (between parentheses), *iii.* the half widths of the corresponding 99% confidence intervals **in bold font** (between brackets).

In order to test the research hypothesis CBG.2 and, thus, assess whether the simulated human wholesalers make ‘locally poor’ decisions, their steady state mean $\overline{OQ}_{WHL}$ – order quantities need to be compared to the steady state mean $\overline{OQ}_{RET}$ – order quantities of simulated human retailers. In order to facilitate this comparison, Table 8.6 summarises the steady state mean order quantities of human retailers’ $\overline{OQ}_{RET}$ and human wholesalers $\overline{OQ}_{WHL}$.

Table 8.6: Comparison of retailers’ $\overline{\boldsymbol{oQ}}_{\boldsymbol{RET}}$ and wholesalers’ $\overline{\boldsymbol{oQ}}_{\boldsymbol{WHL}}$ – order decisions

R / W - F	$\boldsymbol{RET_0}$		$\boldsymbol{RET_1}$		$\boldsymbol{RET_2}$		$\boldsymbol{RET_3}$	
	$\overline{OQ}_{RET}$	$\overline{OQ}_{WHL}$	$\overline{OQ}_{RET}$	$\overline{OQ}_{WHL}$	$\overline{OQ}_{RET}$	$\overline{OQ}_{WHL}$	$\overline{OQ}_{RET}$	$\overline{OQ}_{WHL}$
$\boldsymbol{WHL_0 – MAN_0}$	4.99	5	2.33	2.33	2.27	2.28	30.04	30.04
$\boldsymbol{WHL_0 – MAN_2}$	5.01	5	2.34	2.38	2.34	2.34	2.34	2.38
$\boldsymbol{WHL_1 – MAN_0}$	0	5.14	2.94	1.21	2.95	1.20	2.96	1.20
$\boldsymbol{WHL_1 – MAN_2}$	2.93	4.97	2.81	1.41	2.88	1.5	2.79	1.39
$\boldsymbol{WHL_2 – MAN_0}$	200.01	0.04	2.32	4.31	2.27	3.251	1.22	2.23
$\boldsymbol{WHL_2 – MAN_2}$	200.01	23.002	3.42	18.741	3.42	18.741	3.42	20.863
$\boldsymbol{WHL_3 – MAN_0}$	5	9.88	2.34	8.57	2.05	9.88	50	77.52
$\boldsymbol{WHL_3 – MAN_2}$	5	5.01	2.34	2.34	3.33	124.01	3.34	124.01

It is evident from Table 8.6 that the ‘profit conscious’ wholesaler *WHL₀* orders as much as she is requested to deliver, irrespectively of the interacting retailer and manufacturer. For this reason, the research hypothesis CBG.2 needs to be rejected for all the interactions in which WHL_0 participates (*i.e.* $\overline{OQ}_{WHL_0} = \overline{OQ}_{RET}$). Therefore, WHL_0 proves to make 'locally good' decisions across all interactions studied. This is also the case for a sub-set of the interactions in which the 'price and current availability conscious' wholesaler WHL_3 participates; namely, RET_0, WHL_3, MAN_2 (*i.e.* $\overline{OQ}_{WHL_3} \neq \overline{OQ}_{RET_0}$) and RET_1, WHL_3, MAN_2 interaction(*i.e.* $\overline{OQ}_{WHL_3} \neq \overline{OQ}_{RET_1}$). For these particular interactions the research hypothesis CBG.2 also needs to be rejected.

But in all remaining interactions the 'price and present and future availability conscious' wholesaler WHL_3 consistently 'over-orders' or else orders quantities that are significantly higher than the mean incoming order quantity. This 'over-ordering' behaviour of WHL_3 may be interpreted as an indicator of an attempt to 'minimise backlogs'. Therefore, the research hypothesis CBG.2 cannot be rejected for these interactions (*i.e.* $\overline{OQ}_{WHL_3} \neq \overline{OQ}_{RET}$ at p<0.01). These particular interactions are highlighted via the grey shaded cells in the last row of Table 8.6. In these interactions WHL_3 appears to make 'locally poor' decisions.

As far as the 'price and future availability conscious' wholesaler WHL_1 and the 'price and current availability conscious' wholesaler WHL_2 are concerned, both WHL_1 and WHL_2 systematically place orders of sizes that are significantly different from the incoming order quantities. For this reason, the research hypothesis CBG.2 cannot be rejected for these particular interactions (*i.e.* $\overline{OQ}_{WHL_j} \neq \overline{OQ}_{RET_i}$ with j=1, 2 and i=0,.., 3 at p<0.01). These interactions are highlighted via the grey shaded cells of Table 8.6. Therefore, WHL_1 and WHL_2 make 'locally poor' decisions, irrespectively of their interacting partners' responses.

In greater detail, the 'price and future availability conscious' wholesaler WHL_1 'over-orders' when she interacts with the 'price conscious' retailer RET_0 and 'under-orders' when she interacts with any of the 'price and profit conscious' retailer RET_1 or the 'price and cost and profit conscious' retailer RET_2 or the 'price and cost conscious' retailer RET_3. As for the the 'price and current availability conscious' wholesaler WHL_2, he follows exactly the complementary approach: namely he 'under-orders' when he interacts with the 'price conscious' retailer RET_0 and 'over-orders' when he interacts with either the 'price and profit conscious' retailer RET_1 or the 'price and cost and profit conscious' retailer RET_2 or the 'price and cost conscious' retailer RET_3. The reason that both WHL_1 and WHL_2 adopt different policies when facing the 'price conscious' retailer RET_0 with respect to the remaining human retailers RET_j with j=1,..3 might be that RET_0 is the only human retailer who exhibits a range of ordering strategies that varies from 'under-ordering' to 'over-ordering'.

Last but not least, the reader should at this point be reminded that in *Sub-section 8.2.1* it is shown that the 'price conscious' retailer RET_0 steadily 'under-orders' when in interaction with the 'price and future availability conscious' wholesaler WHL_1 and 'over-orders' when in interaction with the 'price and current availability conscious' wholesaler WHL_2. In *Sub-section 8.2.1* it is also demonstrated that the 'price and profit conscious' RET_1, the 'price and cost and profit conscious' RET_2 and the 'price and cost conscious' RET_3 'over-order' when in interaction with the 'price and future availability conscious' wholesaler WHL_1 and 'under-order' when in interaction with the 'price and current availability conscious' wholesaler WHL_2. In this regard, the 'price and future availability conscious' wholesaler WHL_1 and the price and current availability conscious' wholesaler WHL_2 seem to adopt the completely opposite ordering strategies with their interacting partners. For this reason, it can be claimed that $WHL_1$and WHL_2 attempt to correct the erroneous ordering policies of their interacting retailers. Whether they do manage to accomplish this, though, depends strongly on the interaction with their corresponding upstream supplier.

But since the 'profit conscious' wholesaler WHL_0 is the only simulated human wholesaler who constantly makes 'locally good' decisions, it becomes very interesting to explore what the underlying reasons for the 'locally good' order quantity decisions might be. Her almost complete ignorance of inventory related measures in her order quantity decisions, combined with her initial pre-conception on placing strictly positive orders, seem to explain her 'locally good' ordering policy. The ignorance on the part of WHL_0 of inventory related measures originates from the simplified ordering strategy that WHL_0 appears to implement. According to this, WHL_0 almost exclusively relies on her realised profit for her exact ordering decisions. The initial pre-conception of placing strictly positive orders that WHL_0 has, is indicated by the fact that she places the highest number of non-zero orders. This is the result of the highest intercept in WHL_0's order placement decision model of type (7.8) according to Table 7.12. It is very interesting that even though 'price consciousness' is an effective strategy for the human retailers, ' profit consciousness' proves to be the equivalent effective strategy for the human wholesalers. It remains to be explored what an equivalent effective strategy for the human manufacturers would be.

8.2.3 Manufacturers' $\overline{OQ}_{MAN}$ – order quantities

Table 8.7 presents the simulated human manufacturers' $\overline{OQ}_{MAN}$ – order quantity decisions over n=50 simulated replications for all 32 treatment combinations studied. The reader is at this point reminded that because of the perfectly reliable manufacturing facility that all simulated human manufacturers are assumed to have in place, they face uncertainty from only the demand side. The results are the low standard deviations that can be observed from Table 8.7.

Table 8.7: Simulated manufacturers' $\boldsymbol{OQ_{MAN}}$ – quantity decisions[7]

R / W - F	RET_0	RET_1	RET_2	RET_3
WHL_0 – MAN_0	5 (*0.025*) [±**0.004**]	2.33 (*0.01*) [±**0.002**]	2.28 (*0.01*) [±**0.001**]	30.05 (*0.08*) [±**0.01**]
WHL_0 – MAN_2	5 (*0.02*) [±**0.003**]	2.28 (*0.01*) [±**0.002**]	2.29 (*0.01*) [±**0.002**]	2.28 (*0.01*) [±**0.002**]
WHL_1 – MAN_0	5.14 (*0.08)* [±**0.01**]	1.21 (*0.03)* [±**0.01**]	1.19 (*0.02)* [±**0.003**]	1.19 (*0.02)* [±**0.003**]
WHL_1 – MAN_2	4.97 (*0.02)* [±**0.003**]	1.34 (*0.02)* [±**0.003**]	1.37 (*0.01)* [±**0.001**]	1.34 (*0.01)* [±**0.001**]
WHL_2 – MAN_0	0.04 (*0.04)* [±**0.01**]	2.31 (*0.01)* [±**0.001**]	2.26 (*0.01)* [±**0.002**]	1.22 (*0.02)* [±**0.004**]
WHL_2 – MAN_2	5.03 (*0.04)* [±**0.01**]	2.34 (*0.04)* [±**0.002**]	1.37 (*0.01)* [±**0.001**]	1.64 (*0.02)* [±**0.001**]
WHL_3 – MAN_0	9.88 (*0*) [±**0**]	8.57 (*0*) [±**0**]	9.88 (*0.001*) [±**0**]	50 (*0*) [±**0**]
WHL_3 – MAN_2	5 (*0.01*) [±**0.001**]	2.29 (*0.04*) [±**0.08**]	2.5 (*0.003*) [±**0.01**]	1.35 (*0.004*) [±**0.0**]

In order to test the research hypothesis CBG.2 and, thus, assess whether the simulated human manufacturers make 'locally poor' decisions, their steady state mean $\overline{OQ}_{MAN}$ – order quantities need to be compared to the steady state

[7] This table presents the following information about the simulated manufacturers' order quantities over *n*=50 replications: *i.* averages in regular font, *ii.* standard deviations in *italics font* (between parentheses), *iii.* the half widths of the corresponding 99% confidence intervals **in bold font** (between brackets).

mean $\overline{OQ}_{WHL}$ – order quantities of the simulated wholesalers. In order to facilitate, thus, this comparison, Table 8.8 summarises the steady state mean order quantities of human wholesalers $\overline{OQ}_{WHL}$ and human manufacturers.

It can be concluded from Table 8.8 that both the 'past price and present availability conscious' MAN_0 and the 'present price and present availability conscious' MAN_2 in most interactions in which they participate (*i.e*. the non-shaded cells of Table 8.8), order in steady state quantities that on average closely follow the corresponding wholesalers' orders. For this reason, the research hypothesis CBG.2 needs to be rejected for these particular interactions ($\overline{OQ}_{MAN} = \overline{OQ}_{WHL}$). Therefore, both MAN_0 and MAN_2 seem to make 'locally good' decisions for the majority of the interactions studied. There are, however, a number of exceptions. These are the interactions for which the 'present price and present availability conscious' MAN_2 'under-orders', namely places orders of sizes that are significantly lower than her incoming order quantities. Table 8.8 highlights these exceptions by shading the corresponding cells in grey colour. For these interactions the research hypothesis CBG.2 cannot be rejected (*i.e*. $\overline{OQ}_{MAN} \neq \overline{OQ}_{WHL}$ at $p<0.05$). Therefore, MAN_2 proves to make 'locally poor' decisions for these particular interactions. As for the 'past price and present availability conscious' MAN_0, he seems to be making 'locally poor' order decisions for only one of the interactions studied (*i.e*. the interaction with WHL_3 and RET_3), most probably because he considers past prices instead of present prices in his order decisions.

Table 8.8: Comparison of wholesalers' $\overline{\boldsymbol{OQ}}_{\boldsymbol{WHL}}$ and manufacturers' $\overline{\boldsymbol{OQ}}_{\boldsymbol{MAN}}$ – order decisions

R / W - F	$\boldsymbol{RET_0}$		$\boldsymbol{RET_1}$		$\boldsymbol{RET_2}$		$\boldsymbol{RET_3}$	
	$\overline{OQ}_{WHL}$	$\overline{OQ}_{MAN}$	$\overline{OQ}_{WHL}$	$\overline{OQ}_{MAN}$	$\overline{OQ}_{WHL}$	$\overline{OQ}_{MAN}$	$\overline{OQ}_{WHL}$	$\overline{OQ}_{MAN}$
$\boldsymbol{WHL_0 - MAN_0}$	5	5	2.33	2.33	2.28	2.28	30.04	30.05
$\boldsymbol{WHL_0 - MAN_2}$	5	5	2.38	2.28	2.34	2.29	2.38	2.28
$\boldsymbol{WHL_1 - MAN_0}$	5.14	5.14	1.21	1.21	1.20	1.19	1.20	1.19
$\boldsymbol{WHL_1 - MAN_2}$	4.97	4.97	1.41	1.34	1.5	1.37	1.39	1.34
$\boldsymbol{WHL_2 - MAN_0}$	0.04	0.04	2.31	2.31	2.25	2.26	1.23	1.22
$\boldsymbol{WHL_2 - MAN_2}$	23.002	5.03	18.74	2.34	18.74	1.37	20.86	1.64
$\boldsymbol{WHL_3 - MAN_0}$	9.88	9.88	8.57	8.57	9.88	9.88	77.52	50
$\boldsymbol{WHL_3 - MAN_2}$	5.01	5	2.34	2.29	124.01	2.5	124.01	1.35

It is very interesting that in these interactions in which the 'present price and present availability conscious'MAN_2 makes 'locally poor' order decisions, she orders almost as if she realized the excessively high order quantities that the wholesaler places. In response to these erroneous orders, MAN_2 attempts to correct them. Whether MAN_2 actually manages to correct these excessive orders or, in contrast, reduce them too much in size is another issue though. It is very interesting to explore why MAN_2 can realise the erroneous ordering behaviour of the 'price and present availability conscious' wholesaler WHL_2 and the 'price and present and future availability conscious' wholesaler WHL_3 and not the 'profit conscious' wholesaler WHL_0, for example. A potential explanation might be that the orders that are placed by WHL_2 and WHL_3 exhibit lower variances. For this reason, MAN_2 might be better willing to leave wholesalers' orders unsatisfied when interacting with WHL_2 and WHL_3. But it does remain an open issue why MAN_2 in these instances orders so low quantities and, thus, leaves such a great portion of the wholesalers' orders unsatisfied.

Since both MAN_0 and MAN_2 seem to make 'locally good' decisions for the majority of the interactions studied, no special effective ordering strategy can be identified for the simulated human manufacturers. Attention is now turned to the *competition penalties* and the degree of prevalence of the *bullwhip effect* that *emerge* from all possible combinations between the different pricing and ordering strategies that are employed by the different simulated human participants in the *Contract Beer Distribution Game*.

8.3 Emergent *Competition Penalties*

The objective of this section is to test whether the *emerging competition penalties* statistically differ from 0, namely test the research hypothesis CBG. 3. In this regard, Table 8.9 presents the mean *competition penalties* ($\overline{CP}$) that are achieved by all 32 treatment combinations studied over n=50 replications. As already discussed in *Sub-Section 7.2.3*, the *competition penalties* that different interactions attain are calculated according to relation (6.14). In relation (6.14), the aggregate channel profit $\hat{P}_C$ is equal to the sum of the individual profits that the interacting partners separately attain according to the ABS model of the *Contract Beer Distribution Game*. The *first-best case maximum* profit $\widehat{P_O^*}$ results from the ABS model, when all interacting decision makers are enforced to follow the decision rules (6.10a) and (6.10b). Based on this, it has a mean of 143,617 *m.u.*, a standard deviation of 1,838 *m.u.*; hence, the resulting half-width of the 99%confidence interval is: ±309 *m.u.*

Table 8.9: The *emergent* steady state *competition penalties*[8]

R / W - F	RET_0	RET_1	RET_2	RET_3
WHL_0 – MAN_0	19.98 (*0.22*) **[±0.04]**	108.97 (*9.86*) **[±1.66]**	104.29 (*8.29*) **[±1.39]**	351.53 (*28.77*) **[±4.84]**
WHL_0 – MAN_2	53.9 (*0.71*) **[±0.12]**	114.32 (*9.77*) **[±1.64]**	113.93 (*9.58*) **[±1.61]**	114.34 (*9.68*) **[±1.63]**
WHL_1 – MAN_0	40.05 (*91.4*) **[±15.37]**	159.16 (*6.57*) **[±1.11]**	159.63 (*10.43*) **[±1.75]**	159.32 (*13.97*) **[±2.35]**
WHL_1 – MAN_2	216.47 (*36.29*) **[±6.10]**	147.95 (*79.02*) **[±13.29]**	162.24 (*13.38*) **[±2.25]**	144.46 (*13.35*) **[±2.24]**
WHL_2 – MAN_0	556.98 (*851.96*) **[±143.28]**	110 (*9.81)* **[±1.65]**	110.24 (*8.95)* **[±1.51]**	764 (*25.69)* **[±4.32]**
WHL_2 – MAN_2	582.61 (*727.8*) **[±122.4]**	198.31 (*15.57*) **[±2.62]**	200.79 (*16.77*) **[±2.82]**	197.54 (*16.36*) **[±2.75]**
WHL_3 – MAN_0	726.78 (*12.78*) **[±2.15]**	213.86 (*23.34*) **[±3.93]**	243.29 (*27.07*) **[±4.55]**	1,470.7 (*1217.16*) **[±204.70]**
WHL_3 – MAN_2	54.18 (*0.76*) **[±0.13]**	113.642 (*9.43*) **[±1.59]**	3,746.776(471.*63*) **[±79.32]**	3,740.76 (473.*68*) **[±79.66]**

It is evident from Table 8.9 that the *competition penalties* that are attained by all treatment combinations studied differ significantly from 0. For this reason, the research hypothesis CBG.3 cannot be rejected for any of the interactions studied ($CP \neq 0$ at $p<0.01$). Thus, no 'globally efficient' interactions seem to

[8] This table presents the following information about the *competition penalties* that are attained by all the simulated interactions over n=50 replications: *i.* averages in regular font, *ii.* standard deviations in *italics font* (between parentheses), *iii.* the half widths of the corresponding 99% confidence intervals **in bold font** (between brackets).

emerge. Nevertheless, there are certain interactions that attain *competition penalties* of significantly lower magnitude than the remaining interactions. These interactions are highlighted in grey shaded colour in Table 8.9 and are thereafter characterised as ‘globally better performing’.

It is very interesting that in most of these ‘globally better performing’ interactions, the ‘price conscious’ retailer RET_0, the ‘profit conscious’ WHL_0 and the ‘price and past order reactive’ wholesaler WHL_1 come into play. Both RET_0 and WHL_0 make ‘locally good’ quantity decisions, while WHL_1 makes ‘locally good’ price decisions. For this reason, the *emergence* of ‘globally better performing’ interactions from their combinations does not come as a surprise. Therefore, there seems to be some evidence that ‘locally good’ decisions induce ‘globally better performances’. Still, it should be noted that neither a ‘demand – driven’ nor a ‘profit margin – driven’ pricing behavior seem to be enhancing the *competition penalties* that are attained overall.

The case of one interaction is now taken as an example. To this end, the case of the interaction of MAN_0 with WHL_0 and RET_0 is taken for illustration purposes. The main reason is that this is the interaction that, among the treatment combinations studied, attains the lowest *competition penalty*. As already discussed, this does not come as a surprise, as in this particular interaction all partners are proven to make ‘locally good’ price and quantity decisions. In greater detail, the ‘incoming order price reactive’MAN_0 and the ‘price and past order reactive’ wholesaler WHL_0 charge prices that do not differ significantly from the incurred manufacturing cost, while the ‘past price and present availability conscious’ manufacturer MAN_0, the ‘profit conscious’ wholesaler WHL_0, and the ‘price conscious’ retailer RET_0 place orders of quantities that do not differ statistically from the mean customer demand. Therefore, all interacting partners seem to follow the *team optimising* decision rules that are given by relations (6.10a) and (6.10b) of *Sub-section 6.4.1.* According to theory, thus, the *first-best case maximum* profit should be attained. Following this, the *competition penalty* that is attained should amount to 0. The first cell of Table 8.9 shows that the *competition penalty* that is attained by the interaction of MAN_0 with WHL_0 and RET_0 may be relatively low (*i.e*. the lowest among all interactions studied), but it remains significantly higher than 0. This is surprising and remains an open question that deserves further exploration.

A potential answer lies in the exact timing of order decisions. Namely, MAN_0, WHL_0, and RET_0 may in the long run order approximately as much as they are requested to deliver, but they may fail to do so in every time period studied. For illustration purposes Figure 8.1 demonstrates the order decisions that the simulated MAN_0, WHL_0, and RET_0 make when they interact in the ABS model of the *Contract Beer Distribution Game* between the 5,500th and 6,000th period (in simulation time). The reason that the average order quantities over n=50 replications within the time interval of 5,500 and 6,000 periods is presented is it is representative of what happens during any simulation run (*i.e*. the warm-up is eliminated and the run remains restricted within the limits of the run length studied).

It is evident from Figure 8.1 that MAN_0, WHL_0, and RET_0 may on average order quantities that are not significantly different from μ = 5, but their decisions that correspond to the different periods do significantly differ from μ = 5. For this reason, the simulated decisions of MAN_0, WHL_0 and RET_0 cannot instantaneously reproduce the *team optimising* rules that are specified by relations (6.10a) and

(6.10b). The result is widely fluctuating inventory levels. . This amplification of inventories and backlogs is due to the fact that some of the retailer's potential backlog might be caused by the wholesaler's backlog, which might in turn be created by the manufacturer's backlog. The result is backlogs that are possibly calculated more than once in the *Contract Beer Distribution Game* supply chain.

This divergence of the order decisions that are inferred from the decision models of type (7.9) from the *team optimising* decision rules may be the explanation of the non-zero *competition penalty* that is attained by the interaction of MAN_0 with WHL_0 and RET_0. Therefore, it may not simply suffice to ensure that decision makers' quantities coincide with the requested quantities on average. It additionally becomes important to force this coincidence on a one-to-one time period basis, that is for every time period of the simulation run, as is specified by the *team optimising* decision rules (6.10a) and (6.10b).

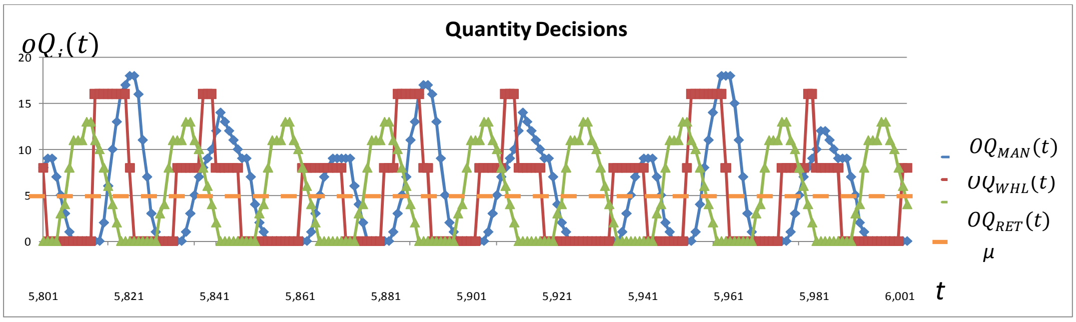


Figure 8.1: The decisions of the simulated MAN_0, WHL_0 and RET_0 between 5,500 and 6,000 time periods (average of ABS model results over n=50 replications)

Figure 8.2 illustrates in the form of stacked column charts the allocation of losses for each supply chain configuration. In this figure, each column reflects a different interaction. In greater detail, R represents the total revenues that are attained by a given interaction; SC the total acquisition costs that are incurred; BP the total backlog penalties that are incurred; IC the total inventory holding costs that are incurred. The reason that these stacked column charts are presented is that since this is the first study that applies the *wholesale price contract* in the *Beer Distribution Game* setting, there are no previous published results on obtained supply chain profits and competition penalties that could be compared with the results that are reported in Table 8.9. In respect to this, the supply chain costs that are incurred are instead of the supply chain profits that are earned illustrated in Figure 8.2.

In the calculation of total supply chain costs, in accordance with the equation (6.2a), the following are cancelled out: *i*. the revenues that are received by the manufacturers and the acquisition costs that are incurred by the wholesalers and *ii*. the revenues that are received by the wholesalers and the acquisition costs that are incurred by the retailers. Therefore, Figure 8.2 only shows the revenues that are received by the retailers and the shipments costs that are incurred by the manufacturers (*i.e*. production costs). It is evident from Figure 8.2 that all interactions studied suffer from huge losses, which are caused by high inventory holding and backlog costs. The latter is in line with the existing experimental research on the traditional *Beer Distribution Game*'s set-up (*e.g*. Kaminsky and Simchi-Levi, 1998; Steckel *et al*, 2004; Nienhaus *et al*, 2006). The reader should at this point be reassured that there are two reasons that explain why inventory holding and backlog costs are not cancelled out. The first reason is that the cost that all supply chain partners need to incur for backlogging (*i.e*. not immediately satisfying) customer demand for one period costs $b_i = 1$ *m.u.*, which is double the cost of keeping inventory in one's warehouse (*i.e*. $h_i = 0.50$ *m.u*). The second reason is that the supply and demand uncertainties that all supply chain partners need to incur affect their net inventory availabilities in such a way that average positive inventories are not necessarily exactly equal to average backlogs.

8.4 *Emergence* of the *Bullwhip effect*

The objective of this section is to test whether the *bullwhip effect* persists in the *Contract Beer Distribution Game*, namely test the research hypothesis CBG.4. The research hypothesis CBG.4 specifies that the *bullwhip effect* persists if and only if the variance of orders increases as one moves away from the retailer. In order, thus, to test the research hypothesis CBG.4, one would need to test whether the variance of orders increases from the retailer to the wholesaler and from the wholesaler to the manufacturer.

To this end is coded as a failure. (A failure includes both the cases of equalities and decreas, every increase of orders observed is coded as a success, while any non-increase observed es of order sizes.) In addition, each time period studied is treated as a separate case. So, the total number of cases (NoC) is equal to the total number of time periods studied (i.e total run length – warm-up period = 15,000-1,400 = 13,600) multiplied by 2 (i.e. one for the retailer-wholesaler pair and one for the wholesaler-retailer pair). Thus: NoC=13,600 x 2 = 27,200. The sample proportion is the number of successes divided by the total number of cases NoC. The average between n = 50 replications is then estimated. Following the earlier example of a number of previous behavioural studies that investigate the dominance of the bullwhip effect in the Beer Distribution Game setting (e.g. Croson and Donohue, 2003; 2005; 2006; Croson et al, 2007), the corresponding non-parametric sign test (Siegel, 1956) is applied. In respect to this, the research hypothesis CBG.4 implies that the sample proportion of success would be significantly higher than 0.5 (*i.e*. $\hat{p} > 0.5$).

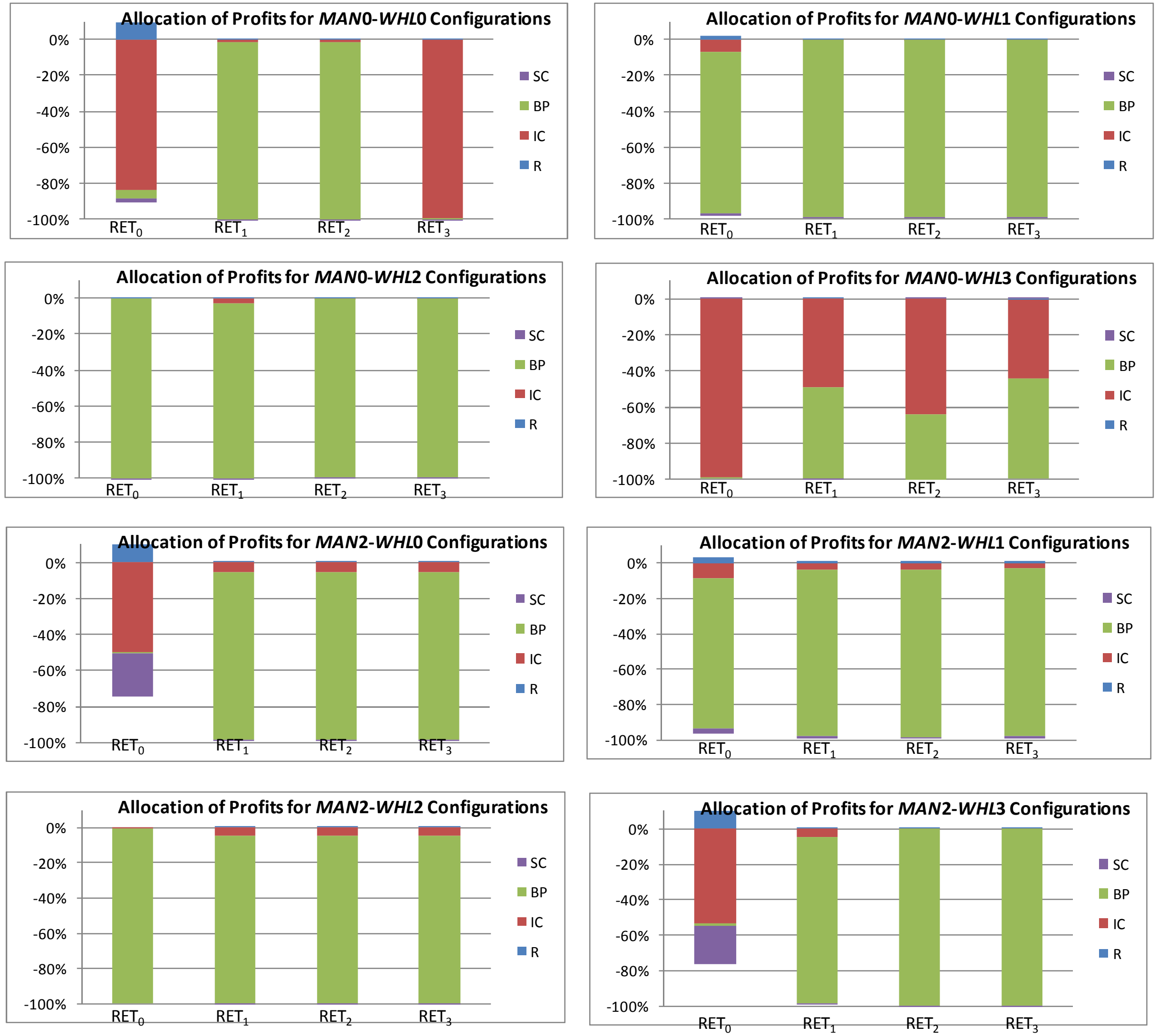


Figure 8.2: *Simulation Results* – Allocation of Costs for all treatment combinations studied

In this regard, Table 8.10 presents the mean success rates or else the mean percentages of successes over *n*=50 for all 32 treatment combinations studied.

It is evident from Table 8.10 that the degree to which the *bullwhip effect* remains is heterogeneous and varies between two extremes, that is, strong prevalence and production smoothing. *Strong prevalence* occurs in the case that the success rate of *bullwhip* existence is significantly higher than 0.5, while *production smoothing* occurs in the case that the *bullwhip effect* is eliminated, or else that the success rate of *bullwhip* existence remains significantly lower than 0.5.

Table 8.10: The *emergent* success rates of the *bullwhip effect*

R / W - F	RET_0	RET_1	RET_2	RET_3
$WHL_0 - MAN_0$	44.44%	72%	98%	64.54%
$WHL_0 - MAN_2$	68%	48%	18%	54%
$WHL_1 - MAN_0$	58%	32%	28%	32%
$WHL_1 - MAN_2$	68%	54%	26%	46%
$WHL_2 - MAN_0$	76.67%	54.44%	58%	56%
$WHL_2 - MAN_2$	12%	23%	44%	32%
$WHL_3 - MAN_0$	100%	58%	53%	52%
$WHL_3 - MAN_2$	68%	26%	24%	33%

Since the success rates that are attained by 62.50% of the studied interactions are significantly higher than 50% (*i.e*. the non-shaded cells of Table 8.10), the research hypothesis CBG.4 cannot be rejected for these particular interactions ($\hat{p} > 50\%$ at p<0.05). These interactions are highlighted in Table 8.10 via grey shaded cells. This conclusion implies that for a significant percentage of the interactions studied, the *bullwhip effect* persists (*i.e. strong prevalence*), which is in line with the existing experimental research on Sterman's (1989, 1992) traditional *Beer Distribution Game* set-up (*e.g.* Croson and Donohue, 2003; 2005; 2006; Croson *et al*, 2007).

Nevertheless, there is another 37.5% of the interactions studied, for which the observed success rate remains significantly lower than 0.5. The research hypothesis CBG.4 needs to be rejected for these particular interactions. These interactions are highlighted in Table 8.10 via the non - shaded cells. But the elimination of the *bullwhip effect* (*i.e. production smoothing*) can be perceived as an indication that a 'globally better performing' interaction is attained (*s.* discussion in *Sub-section 6.4.*3). Therefore, it can be argued that these interactions *emerge* as 'globally near-efficient'. For this reason, the *wholesale price contract*, as applied in the *Contract Beer Distribution Game* setting seems to have the potential to at least partially address the *bullwhip effect*. This result is very important, because it gives evidence that the introduction of the *wholesale price contract* in the *Beer Distribution Game* setting may not attain the *first-best case maximum* profit, but it can seriously reduce the *bullwhip effect* in the case of some interacting participants. Since there is no prior experimental research that confirms the elimination of the *bullwhip effect*, this is considered as a valuable addition to the existing literature.

At this point the reader should be reminded of Su's (2008) earlier theoretical work that is reviewed in *Sub-section 2.2.2* and warned about the main differences with this study. Su offers the formal proof that the existence of at least one non-perfectly rational decision maker constitutes the necessary and sufficient condition for occurrence of the *bullwhip effect* in the *Beer Distribution*

Game setting. The following three differences with Su's study justify the innovative result of this study that the *bullwhip effect* may be at least mitigated. *First,* all human participants are required in the *Contract Beer Distribution Game* to make an extra decision task in comparison with Su's decision makers, that is, choose the prices that they wish to charge to their respective customers. *Second*, participants in the *Contract Beer Distribution Game* are instructed to maximise the aggregate channel profit to their best knowledge and ability. Su's decision makers are assumed to *intend* to minimise their individual cost. *Last but not least*, the decisions of simulated human participants in the *Contract Beer Distribution Game* are inferred from decision models that have been calibrated via actual laboratory evidence. The decisions of Su's decision makers are driven by the same quantal choice analytical formulae. Following these differences, there seems to be some evidence that the inclusion of prices serves to eliminate the *bullwhip effect*. Whether the *wholesale price contract* actually manages to eliminate the *bullwhip effect*, though, depends on the interplay between the different policies of the interacting partners. At this point it should be highlighted that this study's reported result that the degree of prevalence of the *bullwhip effect* is strongly heterogeneous is in line with Cachon *et al*.'s (2007) earlier finding that associates this degree to the industry's seasonality. The main difference of this study with Cachon *et al*.'s is that it is based on a combination of laboratory and simulation experiments, while Cachon *et al.* resort to industry level census data.

A final point that is worthy of further attention is that in the 'globally near-efficient' interactions, that is, the interactions in which the *bullwhip effect* does not prevail (in a statistical sense), not only the simulated human participants who make 'locally good' price and/or order decisions can participate. But in 'globally near-efficient' interactions all simulated human decision makers (*i.e* MAN_i, WHL_i and RET_i with $i = 0,...,3$) can potentially participate. This innovative and counter-intuitive insight originates from the ABS model results that are reported in Table 8.10. Whether 'global near-efficiency' actually *emerges* in a specific interaction depends on the interplay between the interacting partners' policies and is independent from the interacting partners' decisions that may be 'locally poor'. That is exactly why it becomes important to help distinct echelon managers to understand the underlying supply chain dynamics and, thus, train them to make decisions that act against the *bullwhip effect*, so that 'global near-efficiency' can be attained. The simulation experiments of this study demonstrate that the consideration of prices, combined with the concentration on aggregate supply chain profits (instead of individual costs) suffice to reduce to a great extent the occurrence of the *bullwhip effect.* The reader should at this point be reminded that in this study, unlike Cachon *et al*. (2007), as control mechanisms are treated the wholesale prices that the interacting *supply chain partners* charge to each other, and not the price that the retailers sell to end consumers (that mostly operate as promotions and discounts, which amplify the *bullwhip effect*, as Lee *et al.* (1997a) recognise).

8.5 Concluding Discussion

This chapter presents the results that are obtained from the ABS model that is described in *Sub-section 7.3.4* and, therefore, addresses the research hypotheses CBG.1 – CBG.4 that concern human participants' WP_i- prices, OQ_i – quantities, the *emerging competition penalties* and the prevalence of the *bullwhip effect*, as formulated in *Sub-section 7.2*. In this way, *Chapter 8* reports on the first study that explores the effect that different prolonged interactions between dynamic, heterogeneous and autonomous decisions can have on the *wholesale price contract's performance*, in the case that the *wholesale price contract* is enforced to the *Beer Distribution Game* setting.

The simulated human wholesalers and manufacturers are found to make price decisions that vary between 'under-charging' and 'over-charging'. In greater detail, there are simulated human participants in the *Contract Beer Distribution Game* who are found to charge 'locally good' prices. Yet, there is another number of simulated human participants who make 'locally poor' price decisions, namely charge prices that are significantly different from the prices that their rationally optimising counterparts would charge. The underlying reasoning is that there are two distinct pricing strategies that different participants prefer to adopt to ensure profitability. In the case that they take into account their inventory availabilities in their new price decisions, they tend to 'over-charge', thus enforce a 'profit margin – driven' pricing strategy. In the opposite case, that is when they focus instead on their previous order quantities, they are inclined to 'under-charge', hence, implement a 'demand – driven' pricing strategy.

In a similar manner, the simulated human participants are found to make order decisions that vary between 'under-ordering' and 'over-ordering'. There are simulated human participants in the *Contract Beer Distribution Game* who are proven to make 'locally good' order quantity decisions. There is also another number of simulated human participants whose order quantities differ significantly from the quantities that their rationally optimising counterparts would order. In greater detail, the simulated human participants that prioritize 'minimisation of inventories' tend to 'under-order', while the simulated human participants that are driven by 'minimisation of backlogs' tend to 'over-order'.

The results that are obtained from the ABS model of the *Contract Beer Distribution Game* also reveal that there is a systematic pattern of ordering strategies: a simulated human participant seems to make 'locally good' order quantity decisions, provided that he/she takes into account either the prices that are charged to him/her or (/and) the prices that he/she charges. This is the first benefit that the *wholesale price contract* can bring to the *Beer Distribution Game* setting.

Although the combinations of 'locally good' price and quantity decisions fail to attain the *first-best case maximum* profit, they may generate 'global near-efficiency' on the aggregate level. In other words, relatively low *competition penalties* may *emerge* from these combinations. The exact *competition penalties* that are attained by the different interactions strongly depend on the interplay between the interacting partners' priorities and cognitive abilities. The fact that 'global near- efficiency' is possible when prices are taken into account is considered as the second important offering of the *wholesale price contract*, when applied to the *Beer Distribution Game* setting.

All simulated human decision makers have the potential to eliminate the *bullwhip effect*, in spite of their possibly 'locally poor' decisions. The exact degree to which the *bullwhip effect* persists depends on the interplay between the interacting partners' policies. Since there is no prior experimental research that reports the elimination of the *bullwhip effect*, this is attributed to the application of the *wholesale price contract* to the *Beer Distribution Game* setting. This is considered to be the third major advantage of price inclusion in the *Beer Distribution Game* setting.

In summary, this study identifies three distinct benefits that the introduction of prices can bring to the *Beer Distribution Game*: *first*, the *wholesale price contract* can lead to 'locally good' order quantity decisions; *next*, even 'locally poor' prices can potentially generate 'global near efficiency'; and, last, prices can serve as an effective control mechanism to mitigate the *bullwhip effect.*

In addition, this study introduces some innovative ideas that are useful for practitioners. In this regard, the managerial implication of this research is that it can help supply chain managers understand that instead of solely investing in implementing and administering complex, yet efficient, contract types, they could resort to the simple *wholesale price contract*, which seems to have the potential to address at least some of the operational *inefficiencies* that are inherent with supply chains. To this end, they could consider effective management training that focuses on 'global near *efficiency*'. The reason is that in spite of a partner' s 'locally poor' individual decisions, 'global near *efficiencies*' can be achieved and, so, it is important to train decision makers to focus on overall aggregate channel performances instead of their own individual profits, in order to reach these decisions that would give rise to 'global near efficient' interactions. This is exactly where the simulation games developed in this study could help as training tools along the lines of 'business flight simulators' (Sterman, 1992; 2000; van der Zee and Slomp, 2009). The ABS model could also serve as a 'routine decision support' tool in that it can reduce the complexity that is faced by distinct echelon managers and thus, support the required thinking and analysis (Pidd, 2010).

Nevertheless, this study is not deprived from limitations. One potential limitation is that most human participants were asked to play against a computer interface that approximated the decisions of appropriately assigned supply chain configurations. Although this approach is followed to address the usual limitations of experimental approaches (Camerer, 1995; Croson, 2002; Duffy, 2006) and, in addition, eliminate potential biases stemming from social preferences and reputational effects (Loch and Wu, 2008; Katok and Wu, 2009), some of these decisions, as deduced from the decision models that have been fitted to the laboratory data, are unresponsive and inflexible. Human participants might have reacted in different ways, when facing similar conditions. For this reason, asking individuals to play interactively against each other, as is usually done in participatory simulation (North and Macal, 2007), could add some useful insights to the analysis and potentially reduce some of the approach's inherent bias.

Chapter 9

Discussion: Bringing it all Together

The purpose of this chapter is two-fold. The first objective is to summarise the effect that different prolonged interactions between dynamic, heterogeneous and autonomous decisions can have on the *wholesale price contract's performance*, that is, when applied to the *Newsvendor Problem* and the *Beer Distribution Game* setting. The second objective is to discuss, explain and justify the similarities and the differences that are observed between these two settings. The main focus is on the insights and the managerial implications that can be inferred from this PhD thesis.

The chapter starts by summarising the main conclusions that can be drawn from the *Newsvendor Problem* (*Section 9.1*), proceeds to outlining the most important results of the *Beer Distribution Game* (*Section 9.2*). Following this, the differences between the two settings are identified and explained (*Section 9.3)*. Finally (*i.e*. in *Section 9.4*) a discussion on the common themes that seem to emerge from these two settings is provided.

9.1 Conclusions from the Newsvendor Problem

When the *wholesale price contract* is assumed to be in force in the simple *Newsvendor Problem* setting the manufacturer specifies the wholesale price. In response to this, the retailer must choose an order quantity. The manufacturer is assumed to instantaneously deliver to the retailer any quantity requested, while customer demand is also assumed to occur instantaneously.

The relevant standard normative theory is reviewed in *Sub-section 2.1.1.*According to this, the manufacturer is perfectly rational in his/her price decisions and aims to maximise his/her own individual profit. The same also holds for the retailer; namely, he/she places, in response to this price, an order that maximises his/her individual profit. Theory predicts that their resultant interaction is *inefficient*, or else that that the *efficiency score* that is attained by the overall channel is strictly less than 1 (*i.e*. the aggregate profit that is realised is significantly lower than the *first-best case maximum profit*). This phenomenon where neither partner takes into account the effect of his/her decisions on the aggregate channel profit is known as the *double marginalization* problem.

This study explores systematically how different human decisions may be from the above theoretical predictions and what the effect of prolonged interactions between dynamic, heterogeneous and autonomous decisions on the *wholesale price contract's* overall performance is. Since this study is the first that supplements laboratory investigations with ABS experiments, it is the first that simultaneously addresses the requirements of multiple interactions, prolonged interaction lengths and multiple replications. In this way, it infers statistically accurate conclusions that concern: *i.* human *intentions* that might be different from profit maximisation (*i.e*. address the literature gap G.1 of Table 2.5), *ii.* human *actions* that might differ from their corresponding *intention*s in *heterogeneous* ways (*i.e*. heterogeneous *boundedly rational actions*, according to the literature gap G.2 of Table 2.5), *iii*. human *reactions* that might depend on their surrounding environments and any occurring changes to it (*i.e*. address the literature gap G.3 of Table 2.5), *iv*. human *decisions* that might be *independent* and *autonomous (i.e. address the literature gap G.4 of Table 2.5).*

The results that are obtained from these combinations of laboratory and ABS experiments demonstrate systematic deviations from the predictions of the standard normative models in three different aspects, namely, the steady state mean prices that are charged by the simulated manufacturers, the steady state mean quantities that are ordered by the simulated retailers and the steady state mean *efficiency scores* that are attained by the interactions studied. Each of these aspects is now described in some detail.

First, the simulated human manufacturers are shown to make strictly 'locally poor' price decisions, namely charge prices that are significantly different from their rationally optimising counterparts'. In greater detail, they are found to employ two distinct pricing strategies: they either attempt to ensure profitability by attracting retailers' demand or by securing strictly positive profit margins. In the first case they wish to attract customer demand by charging low prices (*i.e*. employ the 'demand – driven' pricing strategy: *s. Section 5.1*) and for this reason tend to 'under-charge'. In the second case they desire to increase their profit margins (*i.e*. employ the 'profit margin – driven' pricing strategy: *s. Section 5.1*) and for this reason tend to 'over-charge'.

Second, although a number of simulated human retailers are found to make 'locally good' order quantity decisions, namely order quantities that would not statistically differ from their respective rationally optimising counterparts', a significant number of them are observed to only make 'locally poor' order quantity decisions. In stark contrast to the predictions of the standard normative theory, some simulated human retailers are even observed to order quantities that do not differ significantly from the quantity that the *integrated newsvendor* would order. As discussed in *Sub-section 2.1.1* the *integrated newsvendor* is entrusted with the task of ordering quantities, when *centralised operation* is assumed to take place, namely when maximisation of the *team overall profit* is sought for. This *centralised operation* is the only instance when the *first-best case maximum* profit is achieved in the analytical version of the *Newsvendor Problem* setting. Overall the simulated human retailers of this study exhibit different preferences that can vary between ‘minimisation of left - overs’ and ‘maximisation of sales’(*s*. *Section 5.2*). In the case that ‘minimisation of left - overs’ is a priority, the simulated human retailers tend to ‘under-order’, while in the case that ‘maximisation of sales’ is a priority; the simulated human retailers tend to ‘over-order’.

Last, the *efficiency scores* that are attained by the combined interactions of the simulated human manufacturers and retailers of this study vary to a great extent. That is, the *efficiency scores emerge* from the interplay between participants’ differing preferences and cognitive limitations and, therefore, are not solely driven by the individual performances of the partners’ distinct decision making strategies. The experiments provide evidence that for a significant number of interactions ‘near efficiency’ is attained, in spite of the interacting partners’ ‘locally poor’ decisions. In addition, it cannot be rejected that there are interactions that may attain *efficiency scores* that are not significantly lower than 1.

In greater detail, there seems to be some evidence that the interests of the simulated human retailers who comply with their individual interpretations of the *pull-to-centre effect* are better aligned with the *first-best case maximum* profit. In terms of conditions that derive as favourable for ‘near’ and/or ‘global efficiency’ the participation of at least one ‘demand – driven’ or ‘sales maximising’ decision maker has the potential to generate a 'nearly efficient' interaction. Indeed, the participation of only 'demand – driven' and 'sales maximising' decision makers in an interaction may generate a higher convergence of aggregate profits to the *first-best case maximum* profit. Among these decision making strategies, the 'better performing' are the ones that exhibit a high responsiveness to the interacting partners' decisions, that is, order quantities in the case of manufacturers and incurred wholesale prices in the case of retailers. As for conditions that are unfavourable for 'near' and/or 'global efficiency', the existence of a 'left - overs minimising' decision maker in an interaction tends to lower significantly the *emerging efficiency scores*.

Following the above results from the laboratory and simulation experiments a number of useful suggestions can be prescribed to supply chain managers. In order to make price and quantity decision that are better aligned with the *team* overall profit maximisation, distinct echelon managers ought to deviate from their isolated views of individual profits and keep the aggregate channel profit in mind. However, since they may not have access to perfect symmetric information to this end, they may instead resort to the relevant information that is available to them; namely, determine prices by prioritizing the previously received order quantities and select order quantities by prioritizing the currently charged wholesale prices. In addition, considering the previous order quantities and wholesale prices may protect them from unnecessarily sacrificing their individual profits.

9.2 Conclusions from the *Contract Beer Distribution Game*

This study is the first that enforces the *wholesale price contract* in the *Beer Distribution Game* setting. In the case that this contract becomes the basis of any interaction between adjacent echelon managers, each echelon manager (apart from the retailer) specifies the price that he/she wishes to charge to his/her downstream customer. Once he/she has received the price that is currently charged by the upstream supplier (apart from the manufacturer, who faces a fixed production cost), he/she decides whether he/she desires to place an order with the upstream supplier or not. If he/she places an order, he/she also determines the exact order quantity. Orders require a total information lead-time of (l_i=) 2 time periods to be processed and there is also a transportation lead-time of (L_i=) 2 time periods for a shipment to be delivered to a partner's site. The total manufacturing time that is required for a requested lot to be produced is (M_3=) 3 time periods. Customer demand arises at the retailer's site and is assumed to occur instantaneously. All participants are assumed to incur inventory holding and backlog costs.

The standard normative models that correspond to the above specification of the *Contract Beer Distribution Game* are developed in *Section 6.4*. According to these, in the case where all distinct echelon managers are assumed to be perfectly rational and exclusively intending to maximise the *team overall* profit (*i.e. centralised operation*), they follow *order-up-to level* inventory policies. Namely, once they reach their optimal inventory target levels, they place orders that follow exactly their incoming order quantities. The result of the interaction of these *order-up-to level* policies is that in steady state the *first-best case maximum* profit is achieved and there is no *bullwhip effect*. The reason is that since incoming orders get reproduced from echelon to echelon in steady state, the order sizes do not get amplified between adjacent supply chain partners.

In the case where all distinct echelon managers have as their only *intention* to maximise their individual profits (*i.e. de-centralised operation*), they charge prices that are strictly higher than the prices that they are charged and follow the same type of *order-up-to level* inventory policies. Their exact optimal inventory target levels may in this case be different from the decisions that that they would make under *centralised operation*. But in steady state they are assumed to have already reached these optimal inventory target levels and, therefore, are subsequently required to simply order as much are they are requested to deliver. Hence, they follow exactly the same decision rules as they would follow under the hypothetical scenario of *centralised operation*. That is exactly why they do achieve in steady state the *first-best case maximum* profit and also avoid the *bullwhip effect* completely. As their combined interaction generates the *first-best case maximum* profit, the *competition penalty* that is attained is exactly equal to 0.

Since this study is the first that supplements laboratory investigations with ABS experiments, it is the first that simultaneously addresses the requirements of multiple interactions, prolonged interaction lengths and multiple replications, which would not have been possible with laboratory experiments alone. The results that are obtained from the combination of laboratory and ABS experiments display persistent divergences from the predictions of standard normative theory in four different aspects: the steady state mean prices that the simulated human participants charge; the steady state mean quantities that the simulated human participants order; the steady state mean *competition penalties* that are attained by the aggregate channel and the degree of prevalence of the *bullwhip effect*. Each of these aspects is now described in some detail.

First, although there are a number of simulated human participants who charge strictly higher prices than the prices that they are charged (*i.e*. make 'locally good' price decisions), there are many simulated human participants who make 'locally poor' price decisions, that is, either charge prices that do not differ significantly from the prices that they are charged or are significantly lower than the prices that they are charged. In greater detail, there are two distinct pricing strategies that the simulated echelon managers seem to employ. In the case where they take into account their inventory availabilities in their price decisions, they tend to be highly conscious of incurred inventory holding and backlog costs and wish to get compensated for these losses. In order, thus, to ensure strictly positive profit margins, they appear to charge prices that are strictly higher than their own prices; namely, they 'over-charge'. In this regard, they make 'locally good' price decisions. For the reasons already explained, this pricing strategy is characterised as 'profit margin – driven' (*s. Section 8.1*). On the contrary, in the case where they prefer to instead base their price decisions on the incoming order quantities, they appear more highly concerned about incoming demand. In order thus, to attract demand from their respective downstream customer, they implement a 'demand – driven' pricing strategy (*s. Section 8.1*) and, hence, 'under-charge', that is, charge prices that may not differ significantly from their own prices or may even be significantly lower than their own prices. Thus, they appear to make 'locally poor' price decisions.

Second, even though there are a number of simulated human participants in the game who on average order quantities that do not differ significantly from the mean incoming order quantities (*i.e*. make 'locally good' order quantity decisions), there are also a significant number of echelon managers who are found to make systematically 'locally poor' order decisions, that is order significantly more (*i.e*. 'over-order') or less (*i.e*. 'under-order') than their rationally optimising counterparts would. More specifically, 'over-ordering' tends to prevail for those simulated human participants who are driven by 'minimisation of backlogs', while 'under-ordering' tends to dominate for those simulated human participants who prioritize 'minimisation of inventories' (*s. Section 8.2*). It is very interesting that there also seems to be a systematic pattern of ordering strategies across different simulated echelon managers. A high accountability with respect to the prices that they charge, the prices that they are charged, or the profit that they have realised cumulatively during the simulation run seems to increase their likelihood of making 'locally good' order quantity decisions.

Third, the interactions of simulated human participants who make 'locally good' price and order quantity decisions fail to attain the *first-best case maximum* profit. The result is that the *emerging competition penalties* are strictly higher than 0, in spite of the interacting partners' 'locally good' decisions. This comes in stark contrast to the analytical predictions of the standard normative models of *Section 6.4*. Nevertheless, it should be noted that there are a significant number of interactions between 'locally good' price and order decisions that generate 'global near efficiencies' on the aggregate channel level (*s. Section 8.3*). In the cases that 'global near efficiencies' are achieved, relatively low *competition penalties* are observed. As for the exact *competition penalties* that are attained by each interaction studied they strongly depend on the interplay between the interacting partners' priorities and cognitive abilities.

Last, the degree of prevalence of the *bullwhip effect* in all simulated human interactions is strongly heterogeneous and varies between two extremes, that is, strong prevalence and production smoothing. *Strong prevalence* occurs in the case that the *bullwhip effect* persists, while *production smoothing* occurs in the case that the *bullwhip effect* is mitigated. Moreover, there is evidence that all simulated echelon managers have the potential to eliminate the *bullwhip effect* in spite of their 'locally poor' decisions. In opposition to the standard normative models' predictions, not only the simulated human participants who make 'locally good' order decisions, but also the simulated human decision makers who make 'locally poor' order decisions can potentially participate in interactions in which the *bullwhip effect* is eliminated. In greater detail, it is the interplay between the interacting partners' policies and not the interacting partners' separate decisions that determine the exact degree to which the *bullwhip effect* persists.

Following the above deviations of the results of the combined laboratory and simulation experiments from the predictions of the standard normative models, a number of conditions are shown to be favourable in decreasing the *emerging competition penalties*. Since the inventory holding and backlog costs that are incurred by all interacting supply chain partners are in great part responsible for the aggregate channel profits, the distinct echelon managers' ordering strategies play a more significant role in the *emerging competition penalties* than their corresponding pricing strategies. In respect to this, a high degree of consciousness of prices and profits brings the simulated echelon managers' order decisions closer to the corresponding decisions of their rationally optimising counterparts' and, hence, significantly reduces the *emerging competition penalties*.

However, no similar favourable conditions for addressing the *bullwhip effect* emerge from the combined laboratory and simulation experiments. The reason is that all simulated echelon managers are shown to be in a position to eliminate the *bullwhip effect*, depending on the interplay with their interacting adjacent partners. Therefore, it becomes important to help distinct echelon managers to understand the underlying supply chain dynamics and, thus, train them to make decisions that act against the *bullwhip effect*.

Building on these findings, a number of useful suggestions can be prescribed to supply chain managers. The purpose of these prescriptions is to provoke price and quantity decision that are better aligned with the decisions that would generate the *first-best case maximum* profit and that, in addition, resist to the amplification of the variance that is often inherent with adjacent partners' orders (*i.e*. *bullwhip effect*). To this end, distinct echelon managers ought to consider prices and aggregate profits instead of individual costs in their respective order decisions. The reason is that they tend to place orders that are consistent with their incoming order quantities, provided that the prices that are charged to them are not excessively high. Hence, a 'demand – driven' pricing strategy favours both 'global near efficiencies' and elimination of the *bullwhip effect*. This conclusion is very interesting, because a similar conclusion has as yet not be drawn for Sterman's (1989) standard *Beer Distribution Game*, given that prices do not come into play in it and, thus, cannot affect order quantity decisions in any way.

9.3 Main Differences between the *Newsvendor Problem* and the *Contract Beer Distribution Game*

The conclusions from the *Newsvendor Problem* and the *Contract Beer Distribution Game* settings that are provided in *Sections 9.1* and *9.2,* respectively, reveal a number of structural differences between the two settings. The numbered list that follows summarises these concisely:

i. While in the *Newsvendor Problem* each participant is entrusted with exactly one decision task (*i.e*. the manufacturer needs to specify the wholesale price and the retailer the order quantity), in the *Contract Beer Distribution Game* each participant is required to make two distinct decisions (*i.e*. the price to be charged to the downstream customer and the order quantity to be placed with the upstream supplier). The only exception is the retailer, who does not need to select a price, because the retailer is assumed to sell at a fixed selling price that is set by competition, as is the case for any commodity product.

ii. Since in the *Newsvendor Problem* the product lasts for only one selling season, there is no inventory. The situation in the *Contract Beer Distribution Game* setting is completely different. Since there is no limit to a product's life, inventory is kept at each echelon. The result is that the associated inventory holding costs are systematically accounted for.

iii. In the *Newsvendor Problem* a demand from a period that is left unsatisfied cannot be satisfied in any subsequent period and, so, all unsatisfied demand is lost. In contrast, in the *Contract Beer Distribution Game* any arising demand needs to be satisfied. Therefore, when demand cannot be satisfied from inventory, it is backlogged and the corresponding backlog penalties are incurred.

iv. In the *Newsvendor Problem* orders get immediately processed, while in the *Contract Beer Distribution Game* there is a fixed information lead-time that is equal to 2 time periods for all orders to get transmitted and processed.

v. In the *Newsvendor Problem* shipments get prepared and delivered immediately. In the *Contract Beer Distribution Game* there are fixed, non-zero production and transportation lead-times that are equal to 3 and 2 time periods, respectively.

vi. Both partners in the *Newsvendor Problem* deal with demand uncertainty only. However, all partners in the *Contract Beer Distribution Game* face uncertainty from both the supply and demand sides. The only exception is the manufacturer of the *Contract Beer Distribution Game*, who is assumed to have a perfectly reliable manufacturing facility in place. All other participants in the game face, in addition to demand stochasticity, supply uncertainty. For example, the exact portion of the requested quantity that the retailer receives (M_i=) 3 time periods after placing the order depends on the wholesaler's inventory availability. The latter in turn depends on the manufacturer's inventory level. But the inventory levels of the wholesaler and manufacturer remain completely outside of the retailer's own control. This is where supply uncertainty stems from.

The above structural differences are responsible for the following main difference that exists between the two settings' analytical results. The relevant theories predict that the *wholesale price contract* may be *inefficient* when applied to the *Newsvendor Problem*, but it is *efficient* in the *Contract Beer Distribution Game*. The reason that the *double marginalization* problem persists in the *Newsvendor Problem* and, therefore, *global efficiency* cannot be attained therein is that the decision making policies of partners are substantially different under *centralised* and *de-centralised* modes of operation.

Nevertheless, the situation is different in the *Contract Beer Distribution Game* setting. The *first-best case maximum* profit can be attained in steady state when the *wholesale price contract* is in force, under both scenarios of *centralised operation* and *de-centralised operation*. Since in this setting inventories and backlogs are accounted for and determine to a great part the overall profit that is attained, the distinct echelon managers can maximise their individual profits by minimising the inventory holding and backlog costs. To this end, they need to follow the same type *order-up-to level* inventory policies that would maximise the *team overall* profit. So, once they have reached their corresponding optimal target inventory levels (*i.e*. in steady state), the decision rules that they need to follow become exactly the same as the decision rules that maximise the *team overall profit*.

It is very interesting that this analytical prediction is built on the simplifying assumption that echelon managers concentrate on only a subset of the components that generate their individual profits, namely those that remain within their own control. In this regard, supply uncertainty is left outside of their individual profit maximising objectives. This simplification brings the *Contract Beer Distribution Game* setting closer to the specification of the *Newsvendor Problem*. Nevertheless, this convergence is still not sufficient to force the analytical predictions of the two settings’ standard normative models to coincide.

The reason is that this simplification affects only the exact optimal inventory targets of the distinct echelon managers of the *Contract Beer Distribution Game*, but leaves the type of the *order-up-to level* inventory policies that are required completely unaffected. In respect to this, ordering as much as requested to deliver leads to attaining the *first-best case maximum* profit.

Furthermore, there are differences in the results that are obtained from the combined laboratory and ABS experiments in the *Newsvendor Problem* and the *Contract Beer Distribution Game*. These differences concern three distinct dimensions: the prices and the order quantities of the simulated human participants and the divergences that occur between *emerging* aggregate channel profits and the *first-best case maximum* profit.

In respect to the prices that the simulated human manufacturers of the *Newsvendor Problem* charge, all of them make ‘locally poor’ price decisions. Although some of them charge prices that are significantly lower than the corresponding price that the rationally optimising manufacturer would charge, all of them prove unwilling to charge the manufacturing cost, which is the only cost component that the *integrated newsvendor* would incur and would generate a zero profit margin. As for the simulated human participants in the *Contract Beer Distribution Game*, a significant number of them charge prices that are not significantly higher than their own incurred prices and, thus, prove willing to tolerate non strictly positive profit margins. This comes as a direct consequence of the setting’s inherent complexity: Since all echelon managers in the *Contract Beer Distribution Game* need to pay for inventory holding costs, they tend to try and avoid accumulating inventories by selling at low prices.

Attention is now turned to the second important difference that is observed from the experimental results of the *Newsvendor Problem* and the *Contract Beer Distribution Game*. Although most simulated human retailers of the *Newsvendor Problem* make ‘locally poor’ order decisions (that is, order quantities that are significantly different from the quantities that would maximise the *team overall* profit), there are a significant number of simulated human participants in the *Contract Beer Distribution Game* that make ‘locally good’ order decisions (namely, order quantities that do not differ significantly from the quantities that would maximise both their respective individual profits and the *team overall* profit). Among the simulated human retailers of the *Newsvendor Problem*, those that prefer to ‘minimise left - overs’ tend to ‘under-order’, while those that prioritize ‘maximisation of sales’ instead tend to ‘over-order. As for the simulated human participants in the *Contract Beer Distribution Game*, those that strongly prefer to ‘minimise inventories’ tend to ‘under-order’, while those that favour ‘minimisation of backlogs’ instead tend to ‘over-order’. Nonetheless, it should at this point be highlighted that the different individual preferences that drive ‘locally poor’ order decisions in the *Newsvendor Problem* and the *Contract Beer Distribution Game* settings most probably originate from the structural differences between the two settings and, more specifically, from the lack of inventories and backlogs in the *Newsvendor Problem* setting. This is why the underlying causes of ‘under-ordering’ behaviours in both the *Newsvendor Problem* and the *Contract Beer Distribution Game* settings (*i.e*. ‘minimisation of left – overs’ and ‘minimisation of inventories’, respectively), as well as the corresponding causes of ‘over-ordering’ behaviours in the *Newsvendor Problem* and the *Contract Beer Distribution Game* (*i.e*. ‘maximisation of sales’ and ‘minimisation of backlogs’, respectively) seem to be equivalent.

The *third* and *last* difference between the experimental results that are acquired from the two settings is that in the *Newsvendor Problem* the *first-best case maximum profit* is attained, while in the *Contract Beer Distribution Game* it is not. The experimental evidence of the *Newsvendor Problem* demonstrates that it is possible that the *efficiency score* of an interaction may not be significantly lower than 1. The exact *efficiency score* that is attained in an interaction greatly varies and, in greater detail, depends on the interplay between the simulated human participants' priorities and cognitive abilities. However, the corresponding evidence of the *Contract Beer Distribution Game* indicates that, irrespectively of the interplay between varying pricing and ordering strategies, the *competition penalties* that are attained by all interactions are significantly higher than 0. This major difference becomes even more interesting since in the *Contract Beer Distribution Game* there are a number of interactions in which all simulated supply chain partners are observed to make 'locally good' price and order quantity decisions, which does not happen in the case of the *Newsvendor Problem*. The underlying reason that explains why compliance with the *team optimising* decision rules in the *Contract Beer Distribution Game* cannot guarantee the *first-best case maximum* profit is the following: some of the simulated human participants in the *Contract Beer Distribution Game* may in steady state order on average as much as they are requested to deliver, but may place these order quantities in time periods that lag from incoming order quantities so significantly that huge inventory and / or backlog costs are generated. Therefore, it may not simply suffice to ensure that decision makers' quantities coincide on average with the requested quantities. It additionally becomes important to force this coincidence on a one-to-one time period basis, namely, ensure that the optimal decision rules (6.10a) and (6.10b) (that incorporate the required order processing time delays) are complied with for every time period of the simulation run. The reader should, nevertheless, be reassured that in spite of the laboratory evidence that has been collected in this PhD study, it cannot be rejected that there might exist a combination that attains a *competition penalty* that may not differ significantly from 0.

In summary, the *wholesale price contract* proves to operate in distinct ways in the *Newsvendor Problem* and the *Contract Beer Distribution Game* settings. These differences pose a concern about the scalability of most existing studies that apply the *wholesale price contract* (as well as any other *supply chain contract*) exclusively to the *Newsvendor Problem* setting. Since the principles that govern the operation of the *Beer Distribution Game* supply chain, and, thus, of any serial multi echelon supply chain, are fundamentally different, analytical and experimental studies of the *wholesale price contract* (and all *supply chain contracts*) should be extended to more complicated and realistic settings than the *Newsvendor Problem*. The setting of the *Contract Beer Distribution Game* presents the first possible extension in this regard.

Yet, in spite of the structural differences that exist between the *Newsvendor Problem* and the *Contract Beer Distribution Game* the combined laboratory and ABS experiments of this PhD thesis also reveal a number of common themes. These similarities, as identified in *Section 9.4*, set the ground for the thesis of this PhD thesis.

9.4 Common Themes between the *Newsvendor Problem* and the *Contract Beer Distribution Game*

It is very interesting that there are systematic divergences between theory and the experiments for both the *Newsvendor Problem* and the *Contract Beer Distribution Game*. The majority of the simulated human participants in both the *Newsvendor Problem* and the *Contract Beer Distribution Game* make price and order quantity decisions that are significantly different from the analytical predictions of the corresponding standard normative models. In addition, there are a significant number of interactions that generate overall performances that also differ significantly from the associated theoretical predictions. In other words, there are interactions in the *Newsvendor Problem* that generate *efficiency scores* that may not be significantly lower than 1 and interactions in the *Contract Beer Distribution Game* that lead to *competition penalties* that may be significantly higher than 0. Given the true price and order decisions of simulated human participants and the true *emerging global efficiencies* of simulated interactions in both the *Newsvendor Problem* and the *Contract Beer Distribution Game* settings, which are systematically different from their corresponding theoretical predictions, the standard normative models cannot be used as accurate predictors of reality.

It is also very interesting that the simulated human participants in both the *Newsvendor Problem* and the *Contract Beer Distribution Game* employ similar pricing strategies to ensure their profitability. In greater detail, the simulated echelon managers in both settings turn to either ‘demand - driven’ or ‘profit margin – driven’ pricing schemes or some adequate combination of them.

Given the equivalence of the ordering strategies in the *Newsvendor Problem* and the *Contract Beer Distribution Game* (that is, 'minimisation of left – overs' and 'minimisation of inventories' and 'maximisation of sales' and 'minimisation of backlogs', respectively), the third commonality between the two settings concerns the underlying causes of simulated human participants' 'under-ordering' and 'over-ordering' behaviours. In greater detail, in both settings the simulated human participants' strong preference to 'minimise inventories' (or 'minimise left – overs') tends to generate orders that are too low (*i.e.* 'under-ordering'), while the simulated human participants' inclination towards 'minimisation of backlogs' (or 'maximisation of sales') mostly produces orders that are too high (*i.e.* 'over-ordering').

A third common pattern that emerges from the combination of laboratory and ABS experiments is the effect of price consciousness on overall supply chain performances in the *Newsvendor Problem* and the *Contract Beer Distribution Game*. In greater detail, the consideration of prices appears to improve both the *efficiency scores* that the different interactions attain in the *Newsvendor Problem* and the degree that the *bullwhip effect* prevails in the *Contract Beer Distribution Game*. Following this, a general prescription that could be suggested to all real echelon managers in both the *Newsvendor Problem* and the *Contract Beer Distribution Game* is that, in order to reduce operational *inefficiencies*, they need to considerably take into account in their order quantity decisions both the prices that they charge and the prices that they are charged. They also ought to deviate from their isolated views of individual profit and keep the aggregate channel profit in mind, when making their respective decisions. This attitude will increase the aggregate channel profit and, so, bring it closer to the *first-best case maximum* profit and, also, reduce the *bullwhip effect*.

The last common insight that emerges from the laboratory and ABS experiments of the *Newsvendor Problem* and the *Contract Beer Distribution Game* is that the *wholesale price contract* can *emerge* as ‘globally efficient’, depending on the interplay between the interacting partners’ cognitive limitations and preferences. Namely, it can generate the *first-best case maximum* profit in the *Newsvendor Problem* and also eliminate the *bullwhip effect* in the *Contract Beer Distribution Game*. That is exactly why supply chain managers should be advised to consider the simple *wholesale price contract*, instead of solely investing in implementing and administering complex, yet efficient, contract types. Not only is it simpler, cheaper and easier to administer, but it can also in practice overcome the main operational *inefficiencies* that are inherent with multi-echelon serial supply chains, that is the *double marginalization* problem and the *bullwhip effect*. This is a very valuable insight, because it may explain the wide popularity of the *wholesale price contract* that is observed in practice, beyond just its simplicity (*e.g*. publishing and movie rental industries: Cachon and Lariviere, 2001; Narayan and Raman, 2004; Cachon and Lariviere, 2005). This insight can also improve the current practice that favours dogmatically the *supply chain contracts* that are theoretically proven as *coordinating*. One such example is the *buyback contract* with a full rebate that seems to prevail in the pharmaceutical industry, irrespectively of the interacting echelon managers’ individual preferences (Katok and Wu, 2009).

Chapter 10 concludes with how the above established common themes of this PhD thesis can be used to infer some general lessons about multi echelon serial supply chains of general type and, hence, serves to answer the main question that motivated this study.

Chapter 10

Conclusions

The purpose of this chapter is to summarise the conclusions that can be drawn from the combined laboratory and ABS experiments that this PhD thesis has conducted in the *Newsvendor Problem* and the *Contract Beer Distribution Game* settings.

In this regard, the chapter starts in *Section 10.1* by extracting the general lessons that can be gained about multi-echelon serial supply chain of general type that can be inferred from the common themes that emerge from the *Newsvendor Problem* and the *Contract Beer Distribution Game* settings. Building on these general lessons, *Section 10.2* proceeds to reflect on whether the objectives of this study have been satisfied; *Section 10.3* then summarises the main contribution of this PhD thesis to knowledge and *Section 10.4* recognises its main limitations. Finally, *Section 10.5* proposes possible directions for future research.

10.1 Insights on general type serial multi-echelon supply chains

Building on the common themes that emerge from the *Newsvendor Problem* and the *Contract Beer Distribution Game*, some general lessons about serial multi-echelon supply chain settings are gained. The reason is that the *Newsvendor Problem* constitutes the fundamental building block of any supply chain configuration, while the *Beer Distribution Game* mimics the material, information and financial flows of any general type, serial multi-echelon supply chain. This is the reason why, once the two settings are combined, they provide learning and insight that can be used in other serial multi-echelon supply chain settings as well.

The *first* learning that can be obtained from this PhD thesis puts forward the limited predictive power of the standard normative models that correspond to general type, multi –echelon serial supply chain systems, when the *wholesale price contract* is assumed to be in force. Since there are systematic divergences between the results that are obtained from the combined laboratory and ABS experiments and the corresponding theoretical predictions, these standard normative models can only to a very a limited degree be used as accurate predictors of real interactions in supply chain systems. In greater detail, human echelon managers make price and order decisions that are significantly different from the corresponding decisions of their perfectly rationally optimising counterparts. There are three underlying reasons that explain this persistence. *First*, real echelon managers do not exclusively *intend* to maximise their respective individual profits; they might also be interested in the entire supply chain's aggregate profit. *In addition*, their *actions* are not necessarily consistent with their *intention*s and their respective degrees of consistency also vary, that is, they are heterogeneously *boundedly rational*. *Last*, they *react* to changes that go on in their surrounding environment and rely to this end on the information that is locally available to them. Since the standard normative models fail to accurately predict the price and order decisions of human echelon managers, their corresponding predictions of the *wholesale price contract's efficiency* also have limited utility for real interactions.

The *second* learning that can be obtained from this PhD thesis concerns the effectiveness of the distinct pricing strategies that the different simulated participants in the *Newsvendor Problem* and the *Contract Beer Distribution Game* adopt. The combined laboratory and ABS experiments demonstrate that whether the simulated echelon managers employ a 'demand – driven' or a 'profit margin – driven' or some mixture of both may not have a significant effect on the aggregate profit that is attained overall. A potential explanations lies at the fact that the aggregate profit that is attained by all echelon managers combined is not affected in any way by the intermediate prices that adjacent supply chain partners charge to each other. Nevertheless, the inclusion of prices does introduce other important benefits; namely, prices serve as an effective control mechanism to induce 'locally good' order quantity decisions, generate 'global near *efficiencies*' and mitigate the *bullwhip effect*. In greater detail, there is significant evidence that among all pricing schemes that can be adopted, the 'demand – driven' pricing strategy, which leads to charging low prices, is the most effective in favouring 'global near *efficiencies*' and eliminating the *bullwhip effect*.

The *third* learning that can be obtained from this PhD thesis about multi – echelon serial supply chains concerns the overall performance of the entire supply chain, as expressed in the form of *efficiency scores* and / or *competition penalties*, and the degree of prevalence of the *bullwhip effect*. In this regard, the overall supply chain performance seems to be affected by two important factors. *First*, the willingness of an echelon manager to sacrifice some of his / her individual profit to the benefit of the aggregate channel profit and, hence, let his/her order quantities converge to the *team overall profit* maximising order quantities appears to have a positive effect on the supply chain's overall performance. *Second*, the significance that an echelon manager assigns to the prices that he / she charges and the prices that he / she is charged also seems to influence the overall performance of the entire supply chain. In greater detail, the simulated human participants' strong preference to 'minimise inventories' tends to generate orders that are significantly lower than the *team overall* profit maximising order quantities (*i.e*. 'under-ordering'), while the simulated human participants' inclination to 'minimise backlogs' mostly produces orders that are significantly higher than the *team overall* profit maximising order quantities (*i.e.* 'over-ordering'). On the contrary, in the case that an echelon manager is willing to sacrifice some of his/her own individual pre-supposition *team overall* profit and, thus, adopt some combination of 'inventories minimising' and 'backlogs minimising' ordering strategy, he/she lets his/her order quantities converge to the *team overall* profit maximising order quantities. This is why the more willing a simulated human participant is to compromise his/her potentially strong preference to some adequate mixture, the better the overall performance of the supply chain. The improvement of the overall supply chain performance is assessed in respect to how close the aggregate channel profit becomes to the *first-best case maximum* profit and to how persistent the *bullwhip effect* remains. Based on this, the general prescription that could be suggested to all real echelon managers is that, in order to reduce operational *inefficiencies*, they need to take into account both the prices that they charge and the prices that they are charged in their order quantity decisions and, also, keep the aggregate channel profit in mind (and not solely their individual profit, as is usually the case), when making their respective decisions.

The *fourth* and *last* learning that derives from this PhD thesis is that the *wholesale price contract* can *emerge* as *globally efficient*, depending on the interplay between the interacting partners' cognitive limitations and preferences. Namely, it can generate the *first-best case maximum* profit and also eliminate the *bullwhip effect*. The result is that the *wholesale price contract* can in practice overcome all the operational *inefficiencies* that are inherent with multi-echelon serial supply chains, that is, the *double marginalization* problem and the *bullwhip effect*. In addition, it is simpler, cheaper and easier to administer than the complicated *transfer payment schemes* that the analytical literature proposes as *efficient*. For this reason, in stark contrast to the recommendations of the existing analytical literature, this study advises supply chain managers to adopt this simple contract, depending on the interacting partners' preferred strategies.

Section 10.2 builds on these insights to test whether the objectives of this PhD thesis have been achieved.

10.2 Reflection on Objectives

The paragraphs that follow remind the reader of the main objectives of this PhD thesis, as stated in *Section 1.4* and discuss the degree to which they have been achieved. The section also reflects on exactly how each stated objective has been accomplished. It concludes with a brief note on whether the underlying motivation of this PhD thesis has been fulfilled.

1. *To develop a methodology that revisits the over-simplifying assumptions of the existing theory-driven, standard normative models in a way that accurately predicts the decisions of human supply chain decision makers.*

This PhD thesis develops and applies a novel approach that revisits the over-simplifying assumptions of the existing analytical models about decision makers' common *intentions*, *actions*, *reactions* and *decisions*. This approach is novel in that it complements the laboratory experiments, that have as yet been exclusively conducted in the studies of the field, with Agent Based Simulation experiments. The corresponding ABS models have been calibrated via the results from the laboratory experiments, which were run with human subjects. In this way, the requirements of multiple interactions, prolonged interaction lengths and multiple replications, which would not have been possible if only experiments with human subjects were run, could be simultaneously addressed.

2. *To assess how different the decisions of supply chain managers are to the corresponding predictions of the standard normative models, when the wholesale price contract is assumed to be in force.*

The combined laboratory and ABS experiments of this PhD thesis demonstrate that in the case where the *wholesale price contract* is enforced, human echelon managers are found to make price and order decisions that deviate systematically from the rationally optimising decisions. The rationally optimising decisions reflect the price and order decisions that the standard normative models predict the perfectly rationally optimising counterparts to make. In greater detail, the simulated human manufacturers in the *Newsvendor Problem* are shown to employ two distinct pricing strategies: either the ‘demand – driven’ or the ‘profit margin – driven’ pricing strategies that both produce price decisions that are significantly different from the predictions of the corresponding standard normative models. The simulated human retailers in the *Newsvendor Problem* exhibit preferences that vary between the two extremes of ‘minimisation of left - overs’ and ‘maximisation of sales’. In stark contrast to the predictions of the standard normative theory, these extremes allow the simulated human retailers to order quantities that do not differ significantly from the quantity that the *integrated newsvendor* would order. As discussed in *Sub-section 2.1.1* in the case that the *integrated newsvendor* makes order quantity decisions is the only instance when the *first-best case maximum profit* is achieved in the analytical version of the *Newsvendor Problem* setting. In the *Contract Beer Distribution Game* setting all simulated human echelon managers employ either a ‘demand-driven' or a 'profit margin-driven' pricing scheme or some adequate combination of these. The result is that most simulated human participants charge prices that are significantly lower than the prices that they are charged. Although the simulated human echelon managers order with a preference to either 'minimise inventories' or 'minimise backlogs', a significant number of them order significantly more (*i.e*. 'over-order') or less (*i.e*. 'under-order') than their rationally optimising counterparts would. Therefore, it can be justifiably argued that the standard normative models that correspond to the *wholesale price contract* do not represent accurately the interactions that can occur between human decision makers in multi-echelon serial supply chain systems.

3. *To investigate the true efficiency of the wholesale price contract, when human supply chain managers interact with each other.*

Since the standard normative models fail to accurately predict the price and order decisions of human echelon managers, their corresponding predictions of the *wholesale price contract's efficiency* also retain a limited predictive power. Furthermore, the true *efficiency of* the *wholesale price contract* varies and is dependent to a great part on the interplay between the interacting partners' cognitive limitations and preferences. In greater detail, the exact *efficiency* (*i.e*. *efficiency score* or *competition penalty* and / or degree of existence of the *bullwhip effect*, whichever is applicable) that the *wholesale price contract* attains is determined by the interplay between the differing pricing and ordering strategies that the interacting supply chain partners prefer to employ. There are a number of interactions in which the *wholesale price contract* can attain the *first-best case maximum* profit and also eliminate the *bullwhip effect*. Therefore, there are interactions for which the *wholesale price contract emerges* as 'globally *efficient*'. Nevertheless, there are also a significant number of interactions in which the *wholesale price contract* achieves very poor overall performances. Since the exact 'global *efficiency*' of the *wholesale price contract* depends on the interplay between the interacting partners' strategies, there cannot be any accurate theoretical predictions of the contract's expected *efficiency*. Yet, it is very interesting that given a pricing and ordering strategy that is adopted by a supply chain partner, the strategies that would turn the contract 'globally *efficient*' are possible to be investigated. This is a valuable addition to the existing experimental research, because it implies that echelon managers should explore the *emerging* 'global *efficiency*' of their interactions before implementing a pricing and ordering strategy. For this reason, they should neither be pre-biased against the *wholesale price* contract nor inclined towards the complicated *transfer payment schemes*, because of their respective theory - driven analytical results. The reason is that the theoretical predictions of *efficiency* retain limited predictive power not only for the *wholesale price contract*, but also for all other *supply chain contracts*. Still, the practical results of other *contracts* in serial multi-echelon supply chains remains to be explored.

4. *To consider the impact that different pricing strategies have on the wholesale price contract's efficiency.*

The combined laboratory and ABS experiments of this PhD thesis demonstrate that the importance that the different echelon managers assign to the prices that are charged by them and to them play a rather significant role on the realised aggregate profits. In greater detail, the higher the significance that an echelon manager assigns to the prices that he/she charges and the prices that he/she is charged, the closer the aggregate channel profit becomes to the *first-best case* *maximum* profit and the less the *bullwhip effect* prevails. Therefore, consideration of prices determines to a great part the global *efficiency* that the *wholesale price contract* attains. In addition, there is significant evidence that a pricing scheme that is concerned more about attracting demand (*i.e*. 'demand – driven') rather than ensuring strictly positive profit margins (*i.e*. 'profit margin – driven') and is, thus, inclined towards charging lower prices serves a dual purpose; namely, favours 'global near *efficiencies*' and mitigates the *bullwhip effect*.

The summary of the above lessons that are gained from this PhD thesis answers the main question that stimulated this study (*s. Section 1.4*), namely:

"Could the wholesale price contract in practice generate the first-best case maximum performance of a supply chain setting and if so, under which specific conditions?".

The main answer that this PhD thesis provides to the aforementioned questions is that supply chain managers are not necessarily advised against the *wholesale price contract*, because it is a potentially globally *efficient* alternative to efficient, yet complex, contract types. The underlying reason is that the *wholesale price contract* has the potential to overcome the main operational *inefficiencies* that are inherent with multi-echelon serial supply chains, namely the *double marginalisation problem* (*i.e*. the *wholesale price contract* can lead to the *first-best case maximum* profit) and the *bullwhip effect*. This comes in stark contrast to the existing analytical results that are built on the common simplifying assumptions of the standard normative models. Some conditions are shown to be favourable, in order to reduce the operational *inefficiencie*s. In greater detail, individual echelon managers are advised to adopt 'demand – driven' pricing strategies and, in respect to this, charge relatively low prices. They also need to considerably take into account both the prices that they charge and the prices that they are charged in their respective decisions. In addition, they ought to deviate from their isolated views of individual profits and keep the aggregate channel profit in mind, when making these decisions.

Section 10.3 summarises the main contributions of this PhD thesis.

10.3 Contributions of the thesis

There are three main contributions of this PhD thesis to existing knowledge.

The *first* contribution of this PhD thesis is that in order to accurately answer the principal research question that motivated this study, namely whether the *wholesale price contract* can in practice attain global *efficiency* and the underlying conditions that seem to favour this, this PhD thesis differs from existing behavioural research in that it does not exclusively rely on laboratory investigations with human subjects to draw statistically accurate conclusions. It instead *develops and applies an original approach that combines laboratory investigations with ABS experiments*. The results that are reported in this PhD thesis originate from experiments with ABS models. These models have been calibrated via evidence that is gained from laboratory experiments with human subjects. In greater detail, the approach that this PhD thesis proposes is adapted from Robinson *et al*.'s (2005) Knowledge Based Improvement methodology and consists of five distinct stages. The first stage concerns recognizing the decision tasks and the factors that influence these decisions on the part of each supply chain role. In the second stage gaming sessions with human subjects are performed so that their respective decisions over time can be recorded. In the third stage the exact mixture of decision models that corresponds to each participant's pricing and ordering decisions is determined. In the fourth stage all possible interactions of participants' decision making strategies are simulated via the ABS model, into which all inferred decision models are input. In the fifth stage conclusions are drawn, based on the simulation results.

Hence, this combination of laboratory – based experiments with human subjects with ABS experiments offers the following benefits. It allows each participant to interact with different response sets, that is, partners with varying *intention*s, over prolonged periods of time and for a number of different replications. In this way, the following possibilities are accommodated: *i.* human echelon managers may not exclusively *intend* to optimise their respective individual objectives, but they may also be interested in the aggregate supply chain performance, for example, *ii.* human echelon managers may not be perfectly rational and, thus undertake *actions* that are not consistent with their *intentions*, *iii.* human echelon managers may *react* to the changes that go on around them and *iv.* human echelon managers may make completely independent and autonomous *decisions*. That is why this novel approach addresses the existing literature gaps about human *intentions*, *actions*, *reactions* and *decisions* that are identified in Table 2.5 (*s. Section 2.4*).

The *second* original contribution of this PhD thesis to existing knowledge is that it introduces the *Contract Beer Distribution Game*, namely it extends the *Beer Distribution Game* in a way that ensures that the basis of any interaction between adjacent supply chain partners is the *wholesale price contract*. It additionally adds to the existing analytical literature, which only explores the effect of complicated *transfer payments schemes* in multi-echelon serial supply chains. It specifically extends the existing analytical literature by developing the standard normative models that correspond to the *Contract Beer Distribution Game*. These models serve to predict the price and order quantity decisions that perfectly rational participants in the *Contract Beer Distribution Game* would make under both scenarios of *centralised* and *de-centralised* modes of operation. These price and order quantity decisions differ from the true decisions of human echelon managers in the following aspects: *i.* they assume that the decision makers exhibit an exclusive interest in maximising the overall supply chain profit, under *centralised operation* (*i.e. team optimal solution*) and their individual aggregate profit, under *de-centralised operation*, *ii.* they assume that all decision makers are perfectly rational and, hence, there is no effect of individual, behavioural biases and *iii*. they assume that all decision makers are completely indifferent to any environmental changes that may occur.

The *third* and *last* contribution of this PhD thesis is its counter-intuitive and interesting result that the exact ‘global efficiency’ that the *wholesale price contract* attains in any given interaction is determined by the interplay between the differing pricing and ordering strategies that the interacting supply chain partners adopt. It is also possible that the *wholesale price contract* attains ‘global efficiency’, in spite of the interacting partners’ ‘locally poor’ price and order quantity decisions. In this regard, since the *efficiency* that the *wholesale price contract* attains greatly varies (*i.e.* there may be a significant number of interactions that achieve ‘global efficiency’, but there are also a significant number of interactions that achieve very poor overall channel performances), there cannot be any accurate theoretical prediction of the contract’s expected *efficiency*. This comes in stark contrast to the existing analytical and empirical literature, which aims at accurately predicting the contract’s expected performance (*e.g.* Lariviere and Porteus, 2001; Cachon, 2003; Keser and

Paleologo, 2004; Kremer, 2008; Katok and Wu, 2009). Moreover, the fact that this PhD thesis recognises price consideration as a favourable condition to increase the contract's *efficiency* is considered as another valuable addition to the existing knowledge, because it serves as a practical advice that can be given to real echelon managers.

10.4 Limitations of the research

This PhD thesis is not without limitations. The first potential limitation of this study concerns the gaming sessions that have been conducted. In respect to these, human participants were asked to play against either computer pre-automated scenarios (*i.e. Newsvendor Problem*: *s. Section 4.3*) or a computer interface that approximated the decisions of appropriately assigned supply chain configurations (*i.e. Contract Beer Distribution Game*: *s. Section 7.3*). This approach has been followed to address the usual limitations of experimental approaches (Camerer, 1995; Croson, 2002; Duffy, 2006) and, in addition, eliminate potential biases stemming from social preferences and reputational effects (Loch and Wu, 2008; Katok and Wu, 2009). Nevertheless, there remains the risk that the computer pre-automated response sets that were presented to the participants in the *Newsvendor Problem* might not have covered all cases that are possible. Moreover, some of these decisions, as deduced from the decision models that have been fitted to the laboratory data of the *Contract Beer Distribution Game*, are simplistic and may suffer from extrapolation. Human participants might have reacted in completely different ways, possibly more realistic, when facing similar conditions. For this reason, asking individuals to play interactively against each other, as is usually done in participatory simulation (North and Macal, 2007), could add some useful insights to the analysis and potentially reduce some of the approach's inherent bias. It would require in retrospect subjects to interact over prolonged session durations and participate in the study for multiple times. But repeated visits to the laboratory are challenging to ask from students who volunteer and are not offered any financial incentives to participate in the study.

An additional limitation of this study is that no evidence is collected for an interaction that attains the *first-best case maximum* profit or else *coordinates* the *Contract Beer Distribution Game* supply chain, as has been anticipated. This is due to the small number of human participants in the *Contract Beer Distribution Game*. Although the first possible solution to this limitation is to conduct an increased number of laboratory investigations with human subjects, it would also suffice to identify appropriate combinations of decision coefficients; by appropriate one would imply such decision coefficients that would generate a *competition penalty* that does not differ significantly from 0. The reader should at this point be made aware that the reason that the sample sizes are so small is because there was no available budget to induce increased interest for the part of students to participate in the study. The time that was available to this end was also limited, which was further complicated by the tight and heavy course load of MSc students at Warwick Business School. A well related problem that also justifies the small samples sizes is that no financial incentives were offered to the participants in the gaming sessions. But provision for specially designed financial incentives that would directly reflect the participants' financial performances in the game might have generated better aligned price and order decisions.

Another limitation of this study is that it limits attention to the *emerging* performance of the interactions, under the assumption that all the simulated echelon managers have reached their corresponding steady state mean decisions.

Nevertheless, it should at this point be admitted to the reader that different insights would possibly be drawn, if the decisions of the simulated echelon managers under the ‘transient period’ were instead investigated. But in this case the theoretical predictions of the standard normative models presented in *Section 6.4* would not provide an accurate basis for comparison and, thus, formulation of hypotheses.

Last but not least, another limitation of this study is that it was not tested whether the steady state mean order quantities of simulated human participants coincided with the *team optimising* decision rules on a one-to-one time period basis, that is, for each and every time period of the simulation run. That is exactly why it remains worthwhile to explore whether a continuous compliance of partners’ decisions with rationally *team optimising* decision rules (*i.e*. in all decision periods) would generate the *first-best case maximum* profit, as is theoretically expected. *Section 10.5* proposes in greater detail some additional possible directions for future research.

10.5 Future Research

As already discussed, a first idea for future research is to test whether continuous compliance of partners’ decisions with rationally *team optimising* decision rules (*i.e*. in all decision periods) would generate the *first-best case maximum* profit. It would also be very interesting to systematically compare the overall performance that is achieved when no provision for price inclusion is made and when provision for price inclusion is specifically made. In this regard, the same human subjects would first be asked to only make order decisions, while subsequently they would be asked to specifically determine prices, in addition to placing orders. In this way, a fairer comparison could be made and, therefore, conclusions that could be generalised would be drawn.

Furthermore, future research in the area may examine the robustness of the results obtained in this study in different settings. Some indicative ideas include, but are not limited to: non-serial supply chains; supply chains, where competition between sites at the same echelon level comes into play; supply chains, where multiple products co-exist; supply chains with varying selling prices to end consumers; and supply chains with seasonal customer demand. In addition, empirical work is undoubtedly required to identify more fully the range of situations over which the experimental results obtained from the ABS model of this study hold. This is where application of the approach that is developed in this PhD thesis to real supply chain cases would be valuable.

Finally, it would be interesting to apply a similar approach and explore the effect of interactions between varying individual preferences and cognitive abilities on the overall performance of different contractual forms, such as, for example, the *buyback contract* (Pasternack, 1985; Lau *et al*, 2007), the *quantity discount contract* (Moorthy, 1987; Kolay *et al*, 2004), the *quantity-flexibility contract* (Tsay, 1999), the *sales rebate contract* (Taylor, 2002; Arcelus *et al*, 2007; Burer *et al*, 2008), the *revenue sharing contract* (Cachon and Lariviere, 2005), the *complicated transfer payment schemes* of Lee and Whang (1999), the *responsibility tokens* of Porteus (2000), the *simple linear transfer payment schemes* of Cachon and Zipkin (1999) and their *generalizations* as suggested by Cachon (2003). In this way, it can be tested more thoroughly whether real echelon managers' decisions systematically deviate from the corresponding predictions of the standard normative models. To this end, the mechanics of the

Contract Beer Distribution Game could be easily adapted to the needs of the above contractual arrangements.

References

Arcelus, F., Kumar, S. Srinivasan, G. 2007. Pricing and rebate policies for the newsvendor problem in the presence of a stochastic redemption rate. *International Journal of Production Economics* 107, 467-482.

Arkes, H. 1996. The psychology of waste. *Journal of Behavioral Decision Making* 9, 213-224.

Axelrod, R. 1997. *The complexity of cooperation – Agent Based Models of competition and collaboration*. Princeton Studies in Complexity, West Sussex.

Axelrod, R. 2005. *Advancing the Art of Simulation in the Social Scienc*es. In: Rennard, J. (Ed), Handbook of Research on Nature Inspired Computing for Economy and Management, Idea Group, Hersey.

Axsäter, A. 2003. Supply chain operations: Serial and distribution inventory systems. In: Kok, A., Graves, S. (Ed), *Supply chain management: Design, coordination and operation*, Elsevier, Amsterdam, 525-559.

Axsäter, A., Rosling, K. 1993. Installation vs. Echelon stock policies for multilevel inventory control. *Management Science* 39(10), 1274-1280.

Banks, J., Carson, J., Nelson, B., Nicol, D. 2005. *Discrete-Event Simulation*. Pearson Prentice Hall, Upper Saddle River, 4th ed.

Barr, D., Sherrill, T. 1999. Mean and Variance of Truncated Normal Distributions. *The American Statistician* 53 (4), 357-361.

Bearden, J. Rapoport, A. 2005. Operations research in experimental psychology, *Tutorials in Operations Research*, INFORMS, New Orleans.

Bell, D. 1982. Regret in decision making under uncertainty. *Operations Research* 30, 961-981.

Bell, D. 1985. Disappointment in decision making under uncertainty. *Operations Research* 33, 1-27.

Bendoly, E., Donohue, K., Schultz, K. 2006. Behavior in operations management: Assessing recent findings and revisiting old assumptions. *Journal of Operations Management* 24, 737-752.

Benzion, U., Cohen, Y., Peled, R., Shavit, T. 2008. Decision-making and the newsvendor problem: an experimental thesis. *Journal of the Operational Research Society* 59, 1281-1287.

Bolton, G., Katok, E. 2008. Learning-by-doing in the newsvendor problem: A laboratory investigation of the role of experience and feedback. *Manufacturing Service Operations Management* 10 (3), 519-538.

Bolton, G., Ockenfels, A., Thonemann, U. 2008. Managers and students as newsvendors: How out-of-task experience matters, *University of Cologne Working Paper*.

Bonabeau, E. 2002. Agent-Based Modeling: Methods and Techniques for Simulating Human Systems. *Proceedings of the National Academy of Sciences of the United States of America* 99 (10, Supplement 3: Colloquium on Adoptive Agents, Intelligence, and Emergent Human Organization: Capturing Complexity though Agent-Based Modeling), 7280-7287.

Bostian, A., Holt, C., Smith, A. 2008. The newsvendor pull-to-center effect: Adaptive learning in a laboratory experiment. *Manufacturing Service Operations Management* 10(4), 590-608.

Boudreau, J., Hopp, W., McClain, J., Thomas, L. 2003. On the Interface between operations and human resources management, *Manufacturing and Service Operations Management* 5(3), 179-202.

Bowman, E. 1963. Consistency and optimality in managerial decision making. *Management Science* 9 (2), 310-321.

Box, G, Jenkins, G., Reinsel, G. 1994. *Time series analysis: Forecasting and control*. Prentice Hall, New Jersey, 3rd Ed.

Box, G., Cox, D. 1964. An analysis of transformations (with discussion). *Journal of the Royal Statistical Society* B(26), 211-252.

Breusch, T. 1978. Testing for autocorrelation in dynamic linear models. *Australian Economics Papers* 17(31), 334-356.

Burer, S., Jones, P., Lowe, T. 2008. Coordinating the supply chain in the agricultural seed industry, *European Journal of Operational Research*, Vol. 185, 354-377.

Cachon, G. 2003. Supply chain coordination with contracts. In: Kok, A., Graves, S. (Ed), *Supply chain management: Design, coordination and operation*, Elsevier, Amsterdam, 229-341.

Cachon, G., Fisher M. 2000. Supply chain inventory management and the value of shared information, *Management Science* 45(8), 1091-1108.

Cachon, G., Lariviere, M. 2001. Turning the supply chain into a revenue chain. *Harvard Business Review* 79(3), 20-21.

Cachon, G., Lariviere, M. 2005. Supply chain coordination with revenue-sharing contracts: Strengths and limitations. *Management Science* 51(1), 30-44.

Cachon, G., Netessine, S. 2004. Game theory in supply chain analysis. In: Simchi-Levi, D., Wu, D., Shen, Z. (Ed), *Handbook of Quantitative Supply Chain Analysis: Modeling in the e-Business Era*, Kluwer Academic Publishers, Boston, 13-66.

Cachon, G., Randall, T., Schmidt, G. 2007. In search of the *bullwhip effect*. *Manufacturing and Service Operations Management* 9(4), 457-479.

Cachon, G., Zipkin, P. 1999. Competitive and cooperative inventory policies in a two-stage supply chain. *Management Science* 45(7), 936-953.

Camerer, C. 1995. Individual decision making. In: Kagel, J., Roth, A. (Ed), *Handbook of Experimental Economics*, Princeton University Press, New Jersey, 313-327.

Camerer, C. 2003. *Behavioral Game Theory: Experiments in Strategic Interactions*, Princeton University Press, New Jersey.

Camerer, C., Hogarth, R. 1999. The effects of financial incentives in experiments: A review and capital-labor-production framework. *Journal of Risk and Uncertainty* 19 (1-3), 7-42.

Carslon, J., O' Keefe, T. 1969. Buffer stocks and *reaction* coefficients: An experiment with decision making under risk. *The Review of Economic Studies* 36(4), 467-484.

Casti, J. 1997. *Would-be worlds: How simulation is changing the frontiers of science*. John Wiley & Sons, New York.

Casti, J. 2002. BizSim: The world of business – in a box. *Complexity International* 08, 1-6.

Chen, F. 1999. De-centralised operation supply chains subject to information delays. *Management Science* 45(8), 1076-1090.

Chen, F. 2003. Information sharing and supply chain coordination In: Kok, A., Graves, S. (Ed), *Supply chain management: Design, coordination and operation*, Elsevier, Amsterdam, 341-421.

Chen, F., Drezner, Z., Ryan, J., Simchi-Levi, D. 1999. The *bullwhip effect*: Managerial insights on the impact of forecasting and information on variability in a supply chain. In: Tayur, S., Ganeshan, R., Magazine, M. (Ed), *Quantitative Models For Supply Chain Management*, Kluwer Academic Publishers, Boston, 299-337.

Chen, F., Zheng, Y.-S. 1994. Lower bounds for multi-echelon stochastic inventory systems. *Management Science* 40(11), 1426-1443.

Choi, T. Dooley, K., Rungtusanatham, M. 2001. Supply Networks and Complex Adoptive Systems: Control Versus Emergence. *Journal of Operations Management* 19(3), 351-366.

Chopra, S., Meindl, P. 2007. *Supply chain management: Strategy, planning and Operation*. Pearson Prentice Hall, Upper Saddle River.

Clark, A., Scarf, H. 1960. Optimal policies for a multi-echelon inventory problem. *Management Science* 6(4), 475-490.

Croson R., Donohue, K. 2006. Behavioral causes of the *bullwhip effect* and the observed value of inventory information. *Management Science* 52(3), 323-336.

Croson, R. 2002. How and why to experiment: Methodologies from experimental economics. *University of Illinoois Law Review* 2, 921-945.

Croson, R., Donohue, K. 2002. Experimental economics and supply-chain management. *Interfaces* 32 (5), 74-82.

Croson, R., Donohue, K. 2003. Impact of POS data sharing on supply chain management: An experimental thesis. *Production and Operations Management* 12 (1), 1-11.

Croson, R., Donohue, K. 2005. Upstream versus downstream information and its impact on the bullwhip effect. *System Dynamics Review* 21 (3), 249-260.

Croson, R., Donohue, K. 2006. Behavioral causes of the *bullwhip effect* and the observed value of inventory information. *Management Science* 52(3), 323-336.

Croson, R., Donohue, K., Katok, E., Sterman, J. 2007. Order stability in supply chains: Coordination risk and the role of coordination stock. *University of Minnesota Working Paper*.

Dejonckheere, J., Disney, S., Lambrecht, M., Towill, D. 2003. Measuring and avoiding the *bullwhip effect*: A control theoretic approach. *European Journal of Operational Research* 147, 567-590.

Duffy, J. 2006. Agent-Based Models and human subject experiments. In: Tesfatsion, L., Judd, K. (Ed), *Handbook of Computational Economics*, Elsevier, Amsterdam.

Eeckhoudt, L., Gollier, C., Schlesinger, H. 1995. The risk-averse (and prudent) newsboy. *Management Science* 41, 786-794.

Epstein,J., Axtell, R. 1996. *Growing Artificial Societies: Social Science from the Bottom Up*. MITPress, Cambridge.

Federgruen, A., Zipkin, P. 1984. Computational issues in an infinite-horizon multi-echelon inventory model. *Operations Research* 32(4), 818-836.

Fischbacher, U. 2007. z-Tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics* 10, 171-178.

Fisher, M., Raman, A. 1996. Reducing the cost of demand uncertainty through accurate response to early sales. *Operations Research* 44 (1), 87-99.

Flanders, H. 1973. Differentiation under the integral sign. *The American Mathematical Monthly* 80(6), 615-627.

Forrester, J. 1958. Industrial dynamics: A major breakthrough for decision makers. *Harvard Business Review*, 37-66.

Forrester, J. 1961. *Industrial dynamics*. The MIT Press and John Wiley and Sons, Massachusetts.

Fox, J. 2008. *Applied Regression Analysis and Generalized Linear Models*, Sage Publications, New York.

Friedman, D., Sunder, S. 1994. *Experimental Methods: A primer for Economists*, Cambridge University Press, Cambridge.

Gallego, G., Moon, I. 1993. The distribution-free newsboy problem: Review and extensions. *Journal of the Operational Research Society* 44(8), 825-834.

Gilbert N. 2008. *Agent-Based Models*. Sage Publications, Los Angeles.

Gilbert, N., Terna, P. 2000. How to Build and use Agent-Based Models in Social Science. *Mind & Society* 1(1), 57-72.

Gino, F., Pisano, G. 2008. Toward a theory of behavioral operations. *Manufacturing Service Operations Management* 10 (4), 676-691.

Godfrey, L. 1978. Testing against general autoregressive and moving average error models when the regressors include lagged dependent variables. *Econometrica* 46(6), 1293-1301.

Greene, W. 2003. *Econometric analysis*. Prentice Hall, New Jersey, 5th Ed.

Hair, J., Black, W., Anderson, Tatham, R. 2006. *Multi-variate data analysis*, Pearson Prentice Hall, New Jersey 6th ed.

Hamilton, J. 1994. *Time series analysis*. Princenton University Press, New Jersey.

Hieber, R., Hartel, I. 2003. Impacts of SCM order strategies evaluated by simulation-based 'Beer Game' approach: the model, concept, and initial experiences. *Production Planning and Control* 14(2), 122-134.

Hirschey, M., J. Pappas, and D. Whigham. 1993. Managerial economics: European Edition. London: The Dryden Press.

Ho, T.-H., Lim, N., Cui, T. 2009. Is Inventory centralization profitable? An experimental investigation. *University of California-Berkeley Working Paper*.

Hoad K., Robinson, S. Davies, R. 2009b. Automated selection of the number of replications for a discrete-event simulation. *Journal of the Operational Research Society*: advance online publication 28 October 2009 (DOI 10.1057/jors.2009.121).

Holland J. 1998. *Emergence: From Chaos to Order*. Oxford University Press, Oxford.

Holmstrom, B., Milgrom, P. 1987. Aggregation and linearity in the provision of inter-temporal incentives, *Econometrica* 55(2), 303-328.

Hopp W., Spearman M. 2001. *Factory Physics,* Irwin/McGraw Hill, New York, 2nd ed.

Horngren, C., Foster, G. 1991. *Cost Accounting: A Managerial Emphasis,* Prentice Hall, New Jersey, 7th ed.

Hosmer, D., Lemeshow, S. 2000. *Applied Logistic Regression*, John Wiley and Sons, New York, 2nd ed.

Janis, I. 1972. *Victims of Groupthink: a psychological study of foreign-policy decisions and fiascoes*, Houghton Mifflin, Boston.

Janis, I. 1982. *Groupthink: Psychological studies of policy decisions and fiascos*, Houghton Mifflin, Boston, 2nd Ed.

Johnson, L., Montgomery, D. 1974. *Operations Research in Production Planning, Scheduling, and Inventory Control*, John Wiley and Sons, New York.

Kahneman, D., Slovic, P., Tversky, A. 1982. *Judgement under uncertainty: Heuristics and biases*. Cambridge University Press, New York.

Kahneman, D., Tversky, A. 1979. Prospect theory: An analysis of decision under risk. *Econometrica* 47, 263-291.

Kaminsky, P., Simchi-Levi, D. A new computerized beer game: A tool for teaching the value of integrated supply chain management. In: Lee, H., Shu Ming, N. (Ed), Supply Chain and Technology Management, *POMS Series in Technology and Operations Management* 1, Production and Operations Management Society, Miami, 216-225.

Kaplan, W. Advanced Calculus. Addison-Wesley Longman, Michigan, 5th ed.

Katok, E., Wu. 2009. Contracting in supply chains: A laboratory investigation. *Management Science* 55(2), 1953-1968.

Kedem, B., Fokianos, K. 2002. *Regression Models for Time Series Analysis*, John Wiley and Sons, New Jersey.

Keser, E., Paleologo, G. 2004. Experimental investigation of manufacturer-retailer contracts: The wholesale price contract. *CIRANO Working Paper*.

Khouja, M. 1999. The single-period (news-vendor) problem: literature review and suggestions for future research. *Omega International Journal of Management Science* 27, 537-553.

Kimbrough, S., Wu, D., Zhong, F. 2002. Computers play the beer game: Can artificial agents manage supply chains?. *Decision Support Systems* 33, 323-333.

Kleijnen, J., Sanchez, S., Lucas, T., Cioppa, T. 2005. A user's guide to the brave new world of designing simulation experiments, *INFORMS Journal on Computing* 17(3), 263-289.

Kolay, S., Shaffer, G., Ordover, J. 2004. All-units discounts in retail contracts. *Journal of Economics & Management Strategy* 13 (3), 429-459.

Kremer, M. 2008. Behavioral perspectives on risk sharing in supply chains. *University of Mannheim Thesis*.

Kremer, M., Minner, S., Van Wassenhove, L. 2008. Anchoring and regret in the newsvendor problem – the impact of task complexity and framing. *University of Mannheim Working Paper*.

Kunc, M., Morecroft, J. 2007. Competitive dynamics and gaming simulation: Lessons from a fishing industry simulator. *Journal of the Operational Research Society* 58, 1146-1155.

Lariviere, M. 1999. Supply chain contracting and coordination with stochastic demand. In: Tayur, S. Ganeshan, R. Magazine, M. (Ed), *Quantitative Models For Supply Chain Management*, Kluwer Academic Publishers, Boston, pp. 233-268.

Lariviere, M., Porteus, E. 2001. Selling to the newsvendor: An analysis of price-only contracts. *Manufacturing Service Operations Management* 3(4), 293-305.

Lau, A., Lau, H., Wang, J. 2007 Some properties of buy-back and other related schemes in a newsvendor-product supply chain with price-sensitive demand. *Journal of the Operational Research Society* 58, 491-504.

Law, A. 2007. *Simulation Modeling and Analysis*. McGraw Hill, New York.

Lee, H. 2004. The Triple-A supply chain. *Harvard business review* 82(10), 102-112.

Lee, H., Padmanabhan, V., Whang S. 1997a. Information distortion in a supply chain: The bullwhip effect, *Management Science* 43(4), 546-558.

Lee, H., Padmanabhan, V., Whang S. 1997b. The bullwhip effect in supply chains, *Sloan Management Review* 38(3), 93-102.

Lee, H., Whang, S. 1999. De-centralised operation multi-echelon supply chains: Incentives and information. *Management Science* 45(5), 633-640.

Levene, H. 1960. Robust tests for equality of variances. In: Olkin, I. (Ed), *Contributions to Probability and Statistics: Essays in Honor of Harold Hotelling*, Stanford University Press, California, 278-292.

Li, X., Wang, Q. 2007. Coordination mechanisms of supply chain systems. *European Journal of Operational Research* 179(1), 1-16.

Loch, C., Wu, Y. 2008. Social preferences and supply chain performance: An experimental study. *Management Science* 54(11), 1835-1849.

Lurie, N., Swaminathan, J. 2009. Is timely information always better? The effect of feedback frequency on decision making. *Organizational Behavior and Human Decision Processes* 108, 315-329.

Lyons, M. 2004. Insights from Complexity: Organizational Change and Systems Modelling. In: Pidd, M. (Ed), *Systems Modelling: Theory and Practice*, John Wiley & Sons, Chichester.

Macal, C., North, M. 2009. Agent-Based Modeling and Simulation. In: Rosetti, M. *et al*. (Ed), *Proceedings of 2009 Winter Simulation Conference*, 116-126.

Massey, F. J. Jr. 1951. The Kolmogorov-Smirnov test of goodness of fit. *Journal of the American Statistical Association* 46, 70.

Matsumoto, M., Nishimura, T. 1998. Mersenne-Twister: A 623-dimensionally equi-distributed uniform pseudo-random number generator. *ACM Transactions on Modeling and Computer Simulation* 8 (1), 3-30.

McCulloch, C., Searle, S., Neuhaus, J. 2008. *Generalized, Linear, and Mixed Models*, John Wiley and Sons, New Jersey, 2nd ed.

McKay, M., Beckman, R., Conover, W. 1979. A comparison of three methods for selecting values of input variables in the analysis of output from a computer code. *Technometrics* 21(2), 239-245.

Mills, T. 1990. *Time series techniques for economists*. Cambridge University Press, Cambridge.

Moorthy, K. 1987. Managing channel profits: comment, *Marketing Science* 6, 375-379.

Mosekilde, E., Larsen, E., Sterman, J. 1991. Coping with complexity: Deterministic chaos in human decision making behavior. In: Casti, J., Karlqvist, A. (Ed), *Beyond Belief: Randomness, Prediction, and Explanation in Science*, CRC Press, Boston, 199-299.

Mukerjee, R., Wu, C. 2006. *A Modern Theory of Factorial Designs*. Springer, New York.

Narayanan, V., Raman, A. 2004. Aligning incentives in supply chains. *Harvard business review* 82(11), 94-102.

Nelder, J., Wedderburn, R. 1972. Generalized linear models. *Journal of the Royal Statistical Society* A(135), 370-384.

Nienhaus, J., Ziegenbein, A., Schoensleben, P. 2006. How human behaviour amplifies the bullwhip effect: A thesis based on the beer distribution game online. *Production Planning and Control* 17(6), 547-557.

North M., Macal, C. 2007. *Managing business complexity*. Oxford University Press, New York.

Pasternack, B. 1985. Optimal pricing and return policies for perishable commodities. *Marketing Science* 4 (2), 166-176.

Pidd, M. 2004. *Computer simulation in management science*. John Wiley and Sons, Chichester.

Pidd, M. 2010. Why modelling and model use matter. *Journal of the Operational Resesarch Society* 61(1), 14-24.

Porteus, E. 2000. Responsibility tokens in supply chain management. *Manufacturing and Service Operations Management* 2(2), 203-219.

Rao, P., Griliches, Z. 1969. Small sample properties of several two-stage regression methods in the context of auto-correlated errors. *Journal of the American Statistical Association* 64(325), 253-272.

Rasmusen, E. 1989. *Games and Information*, Blackwell Publishers, Oxford, 2nd ed.

Remus, W. 1978. Testing Bowman's managerial coefficient theory using a competitive gaming environment. *Management Science* 24(8), 827-835.

Robinson, G. 2000. *Practical Strategies for Experimenting*. John Wiley and Sons, Chichester.

Robinson, S. 2004. *Simulation: The practice of model development and use*, John Wiley & Sons, Chichester.

Robinson, S. 2007. A statistical process control approach to selecting a warm-up period for a discrete-event simulation. *European Journal of Operational Research* 176, 332-346.

Robinson, S. 2008. Conceptual modelling for simulation Part I: definition and requirements. *Journal of the Operational Research Society* 59, 278-290.

Robinson, S. *et al*. 2005. Knowledge-based improvement: Simulation and artificial intelligence for identifying and improving human decision-making in an operations system. *Journal of the Operational Research Society* 56, 912-921.

Samuelson, D., Macal, C. 2006. Agent-Based Simulation Comes of Age. *OR/MS Today*. August.

Sanchez, S. 2005. Work smarter, not harder: Guidelines for designing simulation experiments. In: Kuhl, M., Steiger, N., Armstrong, F., Joines, J. (Ed), *Proceedings of the 2005 Winter Simulation Conference*, 69-82.

Sanchez, S., Lucas T. 2002. Exploring the World of Agent-Based Simulations: Simple Models, Complex Analyses. In: Yücesan, E. (Ed), *Proceedings of 2002 Winter Simulation Conference*, 116-126.

Santner, T., Williams, B., Notz, W. 2003. *The Design and Analysis of Computer Experiments*, Springer Verlag, New York.

Schelling, T. 1978. Micromotives and Macrobehavior, W. W. Norton, New York.

Schultz, K., McClain, J. 2007. The Use of framing in inventory decisions. *Johnson School Research Paper.*

Schwarz, G. 1978. Estimating the dimension of a model. *The Annals of Statistics* 6(2), 461-464.

Schweitzer, M., Cachon, G. 2000. Decision bias in the newsvendor problem with a known demand distribution: Experimental evidence. *Management Science* 46 (3), 404-420.

Siegel, S. 1956. *Non-parametric Statistics for the Behavioral Sciences*, McGraw-Hill, New York.

Simchi-Levi, D., Kaminsky, P., Simchi-Levi, E. 2008. *Designing and managing the supply chain: Concepts, strategies and case studies*, McGraw-Hill Irwin, New York, 3rd ed.

Simon, H. 1957. A behavioural model of rational Choice. In: *Models of Man, Social and Rational: Mathematical Essays on Rational Human Behaviour in a Social Setting*, Wiley, New York.

Simon, H. 1996. *The sciences of the artificial*. MIT Press, Cambridge, 3rd ed.

Smith, V. Walker, J. 1993. Monetary rewards and decision cost in experimental economics. *Economic Inquiry* XXXI, 245-261.

Son, J., Sheu, C. 2008. The impact of replenishment policy deviations in a de-centralised operation supply chain. *International Journal of Production Economics* 113, 785-804.

Spengler, J. 1950. Vertical integration and anti-trust policy. *Journal of Political Economy* 58(4), 347-352.

Stackelberg, H. von. 1934. *Markform and Gleichgewicht*. Springer, Vienna.

Steckel, J., Gupta, S., Banerji, A. 2004. Supply Chain Decision Making: Will Shorter Cycle Times and Shared Point-of-Sale Information Necessarily help?. *Management Science* 50 (4), 458-464.

Sterman, J. 1989. Modeling managerial behavior: Misperceptions of feedback in a dynamic decision making experiment. *Management Science* 35(3), 321-339.

Sterman, J. 1992. Teaching takes off - Flight simulators for management education: “The Beer Game”. *OR/MS Today*, October 1992, 40-44.

Sterman, J. 2000. *Business dynamics: Systems thinking and modeling for a complex world*. Irwin/McGraw-Hill, Boston.

Su, X. 2008. Bounded rationality in newsvendor models. *Manufacturing and Service Operations Management* 10(4), 566-589.

Sucky, E. 2009. The *bullwhip effect* in supply chains – An overestimated problem?. *International Journal of Production Economics* 118, 311-322.

Swaminathan, J., Smith, S., Sadeh, N. 1998. Modelling supply chain dynamics: A Multiagent approach. *Decision Sciences* 29(3), 607-632.

Taylor, T. 2002. Coordination under sales rebate with sales effort effect, *Management Science* 48(8), 992-1007.

Thode, H. Jr. 2002. *Testing for Normality*, Marcel Dekker, New York.

Toutenburg, H. 2002. *Statistical Analysis of Designed Experiments*. Springer, New York.

Tsay A. 1999. Quantity flexibility contract and manufacturer-customer incentives, *Management Science* 45(10), 1339-1358.

Tsay, A., Nahmias, S., Agrawal, N. 1999. Modeling supply chain contracts: A Review. In: Tayur, S., Ganeshan, R., Magazine, M. (Ed), *Quantitative Models For Supply Chain Management*, Kluwer Academic Publishers, Boston, 299-337.

Tsokos, C., DiCrose, P. 1992. Applications in health and social sciences. In: Balakrishnan, N. (Ed), *Handbook of the Logistic Distribution*, Marcel Dekker, New York, 449-494.

Van der Zee, D. Slomp, J. 2009. Simulation as a tool for gaming and training in operations management – a case study, *Journal of Simulation* 3, 17-28.

Velilla, S. 1993. A note on the multivariate Box-Cox transformation to normality. *Statistics and Probability Letters* 17, 259-263.

Weisberg, S. 2005. *Applied linear regression*, John Wiley and Sons, New Jersey, 3rd ed.

White, P. 1997. An effective truncation heuristic for bias reduction in simulation output. *Simulation* 69 (6), 323-334.

White, P., Spratt, S. 2000. A comparison of five steady-state truncation heuristics for simulation. In: Joines, J. *et al*. (Ed), *Proceedings of the 2000 Winter Simulation Conference*, 755-760.

Whitin, T. 1955. Inventory control and price theory. *Management Science* 2(1), 61-68.

Williamson, O. 1981. The economies of organization: the transaction cost approach. *American Journal of Sociology* 87 (3), 548-577.

Wu, D., Katok, E. 2006. Learning, communication and the bullwhip effect. *Journal of Operations Management* 24, 839-850.

XJ Technologies. 2007. AnyLogic® v6.2.2. Available from the world wide web: http://www.xjtek.com/

Yeo, I.-K., Johnson, R. 2000. A new family of power transformations to improve normality or symmetry. *Biometrika* 87(4), 954-959.

Appendix A

The *Newsvendor Problem*

A.1 Manufacturer's Instructions

Date	*Participant Name*	*Code*
XXX	XXX	MAN_{xxx}

In today's study you will participate in a game acting like the manufacturer of a two-stage supply chain that produces and sells perishable widgets over multiple rounds.

The Game Scenario

There are two members in the supply chain you participate to: you (the Manufacturer) and the Retailer, who is automated. You are responsible for producing and delivering to the retailer the widgets that he/she orders from you. You have no capacity constraints and can produce as many widgets as the retailer orders. Each widget that you produce costs c=50 monetary units. You start by proposing a wholesale price w to the retailer and he then responds by placing a specific order quantity. The retailer sells each widget to end consumers for p=250 monetary units.

The Rules of the Game for every round

i. You specify the wholesale price w,

ii. The retailer is informed about w,

iii. Based on the wholesale price w, the retailer decides on the number of units q that he/she orders from you,

iv. You instantaneously produce and deliver to the retailer, before the beginning of the selling season,

v. Customer demand appears at the retailer's site, sales are recorded and profits are calculated.

Profit calculation

Your profit depends on the wholesale price that you are charging your retailer w, as well as the order quantity q that he/she asked you to deliver. More specifically, it is given by the following formula:

$$P_s^t = (w^t - c) \cdot q^t$$

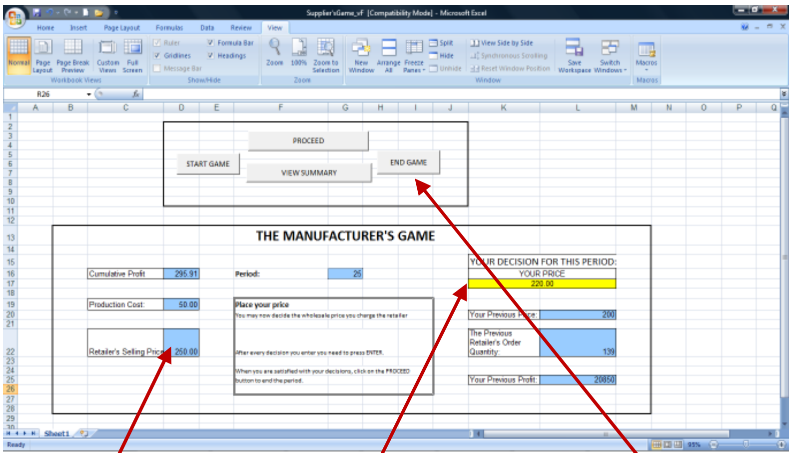
Your task

Your task is to determine the wholesale price that you want to charge your retailer for every widget he/she orders from you. Your purpose is to maximize the overall supply chain profit for the entire session. You will be asked to do so repeatedly until your facilitator informs you of the end of the game.

Feedback information

In each time period, the computer will remind you of past observations.

Your Computer Screen



<u>The Control Panel</u>

1. Click on START GAME to start the game.
2. After you have entered your decision for each round of the game, click on PROCEED.
3. In case you wish to view a summary of all previous periods' results, click on VIEW SUMMARY.
4. When your facilitator informs you to finish the game click on END GAME.

<u>Previous Round's Outcome</u>

You are given all information about the previous period's outcome in the blue cells.

<u>Your decision</u>

You need to enter your decision for every round of the game in the yellow cell.

A.2 Retailer's Instructions

Date	*Participant Name*	*Code*
XXX	XXX	RET_{xxx}

In today's study you will participate in a game acting like the retailer of a two-stage supply chain that produces and sells perishable widgets over multiple rounds.

The Game Scenario

There are two members in the supply chain you participate to: the Manufacturer, who is automated and you (the Retailer). You are responsible for making the widgets available to end consumers. You sell each widget at p=250 monetary units. The manufacturer faces no capacity constraints and, for this reason, you can safely assume that you will receive as many widgets as you order. The manufacturer may charge you a different price in every round.

The Rules of the Game for every round

i. The manufacturer specifies the wholesale price w,

ii. You are informed about w,

iii. Based on this price w, you decide on the number of units q that you want to order from the manufacturer, if any,

iv. The manufacturer instantaneously produces and delivers your requested quantity,

v. Customer demand appears at your site, sales are recorded and profits are calculated.

Customer demand

Each period's demand is random and completely independent of the demand of any earlier round.

T +44 (0)24 7652 4306
F +44 (0)24 7652 3719
E enquiries@wbs.ac.uk
W www.wbs.ac.uk

Warwick Business School
The University of Warwick
Coventry CV4 7AL
United Kingdom

Profit calculation

Your profit depends on the wholesale price the manufacturer is charging you (*w*), the order quantity that you asked him/her to deliver (*q*) and the actual demand *d* that appears.

You also have to incur a cost of lost opportunity *g*=1, in case there is some demand you can not satisfy, because you did not order a sufficient quantity. Your profit is determined by the following formula:

$$P_r^t = p \cdot \min(q^t, d^t) - w \cdot q - g \cdot \max(d^t - q^t, 0)$$

Your task

Your task is to determine the order quantity that you want to place to your manufacturer. Your purpose is to maximize the overall supply chain profit for the entire session. You will be asked to do so repeatedly until your facilitator informs you of the end of the game.

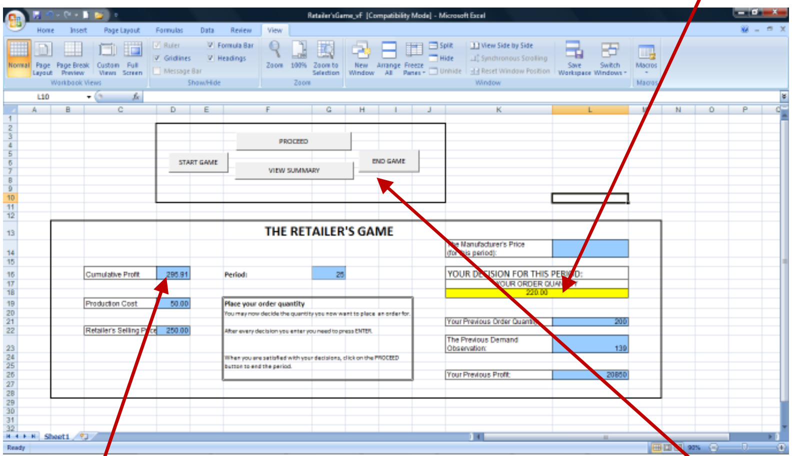
Feedback information

In each time period, the computer will remind you of past observations.

Your Computer Screen

Your decision

You need to enter your decision for every round of the game in the yellow cell.



Previous Round's Outcome

You are given all information about the previous period's outcome in the blue cells.

The Control Panel

1. Click on START GAME to start the game.
2. After you have entered your decision for each round of the game, click on PROCEED.
3. In case you wish to view a summary of all previous periods' results, click on VIEW SUMMARY.
4. When your facilitator informs you to finish the game click on END GAME.

A.3 Dataset of RET_1 Recorded Decisions

	w(t)	q(t-1)	d(t-1)	Pr(t-1)
1	60	140	183	27,257
2	146	140	156	26,584
3	102	140	98	4,060
4	189	120	0	-12,240
5	187	70	212	4,128
6	178	70	5	-11,840
7	125	70	227	4,883
8	192	70	114	8,706
9	223	60	231	3,309
10	60	50	271	1,129
11	116	200	145	24,250
12	188	100	11	-8,850
13	157	40	134	2,386
14	104	100	165	9,235
15	167	120	89	9,770
16	100	70	216	5,664
17	198	120	158	17,962
18	227	50	248	2,402
19	91	0	181	-181
20	226	140	85	8,510
21	146	20	40	460
22	230	100	177	10,323
23	53	20	155	265
24	68	200	39	-850
25	194	200	94	9,900
26	58	70	97	3,893
27	119	200	98	12,900
28	221	130	304	16,856
29	122	30	93	807
30	79	140	61	-1,830
31	166	160	122	17,860
32	124	120	185	10,015
33	109	140	167	17,613
34	87	150	69	900
35	155	160	28	-6,920
36	132	70	245	6,475
37	97	100	203	11,697
38	118	140	96	10,420
39	215	120	167	15,793
40	163	50	126	1,674
41	68	80	152	6,888
42	175	200	249	36,351
43	200	80	0	-14,000
44	148	50	250	2,300
45	127	100	177	10,123
46	140	150	143	16,700
47	133	90	110	9,880
48	123	120	91	6,790
49	60	130	84	5,010
50	226	200	16	-8,000

A.4 Testing the Assumptions of Multiple Linear Regression

The paragraphs that follow discuss the elaborate tests that were conducted to substantiate that all dependent and independent variables of relations (4.5) and (4.6) satisfied the linearity, normality, and homo-skedasticity requirements of multiple linear regression (Weisberg, 2005; Hair *et al*, 2006; Fox, 2008). The corresponding scatterplot matrices were only used as a first indicator to this end. Figure A.4.1 illustratively presents the scatterplot matrix of RET_j=RET_3's (or simply j=3) *decision variable* $\langle q(t)\rangle_{RET_3}$ and the corresponding *decision attributes*. This particular example is only presented for illustration purposes, while exactly the same testing procedure was also applied to all human manufacturers' MAN_i and all other human retailers' RET_j datasets of decisions.

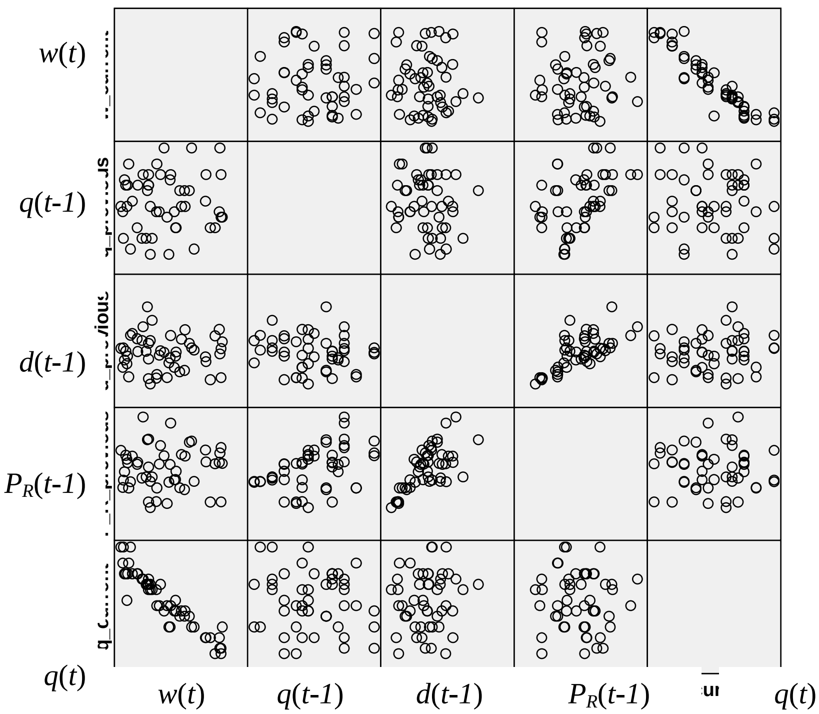


Figure A.4.1: Scatterplot Matrix of RET_3 dependent and independent variables

a) *Linearity*: The rows of the above scatterplot matrix indicated a linear relationship between RET_3 's dependent variable $\langle q(t)\rangle_{RET_3}$ and all independent variables. Although this scatterplot matrix appeared encouraging, the strictly linear relationship between $\langle q(t)\rangle_{RET_3}$ and all independent variables was further confirmed via a visual inspection of all the relevant partial regression plots. Figure A.4.2 indicatively presents the partial regression plot of RET_3's order quantity $\langle q(t)\rangle_{RET_3}$ with $w(t)$. The red line going through the centre of the points slopes down, based on that the regression coefficient of $w(t)$ is negative (-0.952, *acc*. to Table 4.6). The absence of any clear curvi-linear pattern of residuals in this plot established the lack of any non-linear association between $\langle q(t)\rangle_{RET_3}$ and $w(t)$. The same procedure was repeated for all remaining independent variables (*i.e.* $q(t$-1); $d(t$-1); $P_R(t-1)$) and, in this way, it was confirmed that only linear relationships existed between any pair of $\langle q(t)\rangle_{R_3}$and any independent variable.

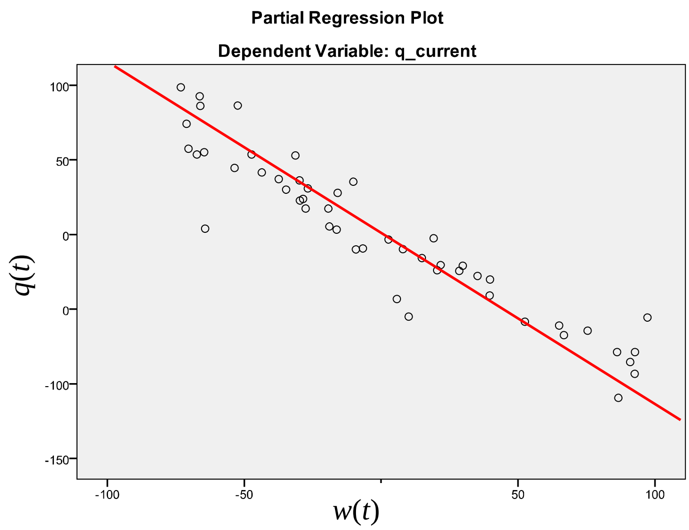


Figure A.4.2: Partial Regression Plot of $\langle q(t)\rangle_{RET_3}$with $w(t)$

b) *Normality*: Figure A.4.3 presents the normal histogram of the residuals of $\langle q(t) \rangle_{RET_3}$. Since this normal histogram was not very clearly formed, the corresponding normal probability plot was additionally visually inspected.

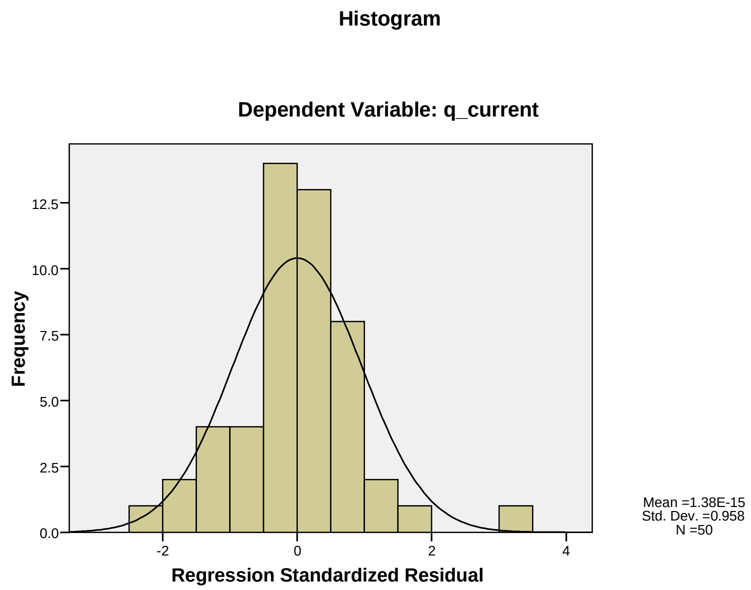


Figure A.4.3: Normal Histogram of $\langle q(t) \rangle_{RET_3}$

Figure A.4.4 graphically plots $\langle q(t) \rangle_{RET_3}$ against the corresponding "expected" quantiles from standard normal distribution; these standard normal distribution's "expected" quantiles are represented on the line of the graph. Therefore, Figure A.4.4 illustrates the quantile-quantile (*Q*-*Q*) plot of $\langle q(t) \rangle_{RET_3}$, which serves to identify any systematic deviation of $\langle q(t) \rangle_{RET_3}$ from the the line of the standard normal distribution (Thode, 2002).

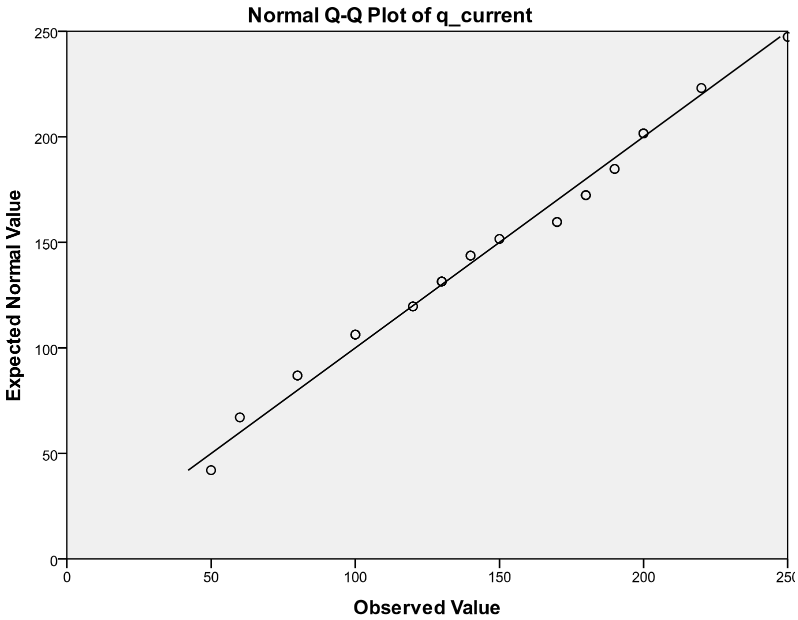


Figure A.4.4: Quantile-Quantile (*Q*-*Q*) plot of $\langle q(t) \rangle_{RET_3}$

Table A.4.1: One-Sample Kolmogorov-Smirnov Test for $\langle q(t) \rangle_{RET_3}$

Characteristics of $\langle q(t) \rangle_{RET_3}$ dataset		
Normal Parameters	Mean	150.9
	Std. Deviation	54.93
Most Extreme Differences	Absolute	0.084
	Positive	0.071
	Negative	-0.084
Kolmogorov-Smirnov Z		0.591
Asymp. Sig. (2-tailed)		.877

From Figure A.4.4 it is evident that no systematic divergences of $\langle q(t) \rangle_{RET_3}$ from the standard normal distribution occur, as can be further supported by the Kolmogorov-Smirnov test, the results of which are presented in Table A.4.1. The Kolmogorov-Smirnov test aims at comparing the largest absolute difference between any empirical observation of $\langle q(t) \rangle_{RET_3}$ and the normal distribution

(Massey, 1951; Thode, 2002). Since the two-tailed significance of the test statistic is relatively large (0.877), it is highly unlikely that $\langle q(t) \rangle_{RET_3}$ originated from a non-normal distribution. The same conclusion about $\langle q(t) \rangle_{RET_3}$ normality could also be drawn from the Anderson – Darling test, which is more powerful, because it places a higher weight on the tails of the distribution (Robinson, 2007). Its results are presented in Figure A.4.5.

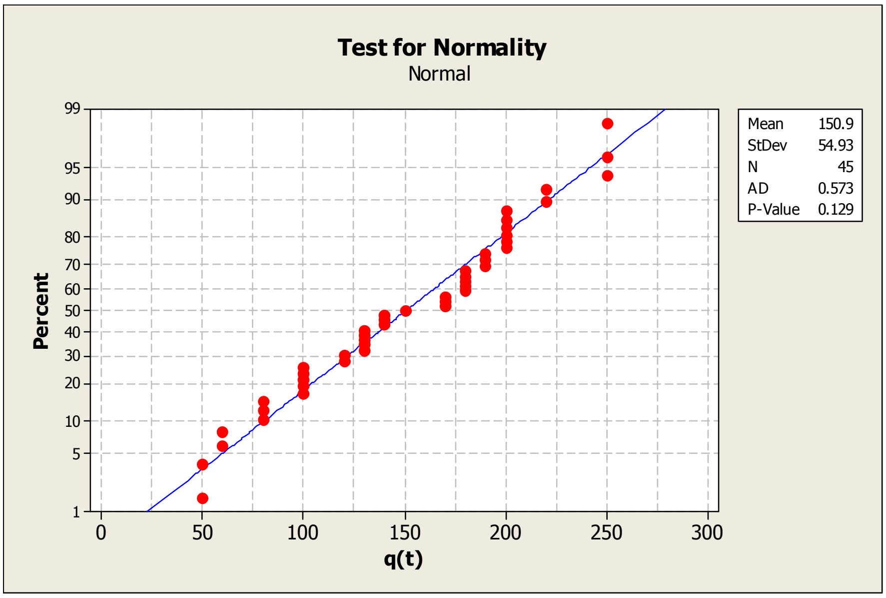


Figure A.4.5: The Darling - Anderson Test for Normality of $\langle q(t) \rangle_{RET_3}$

From Figure A.4.5 can be concluded that $\langle q(t) \rangle_{RET_3}$ follows the normal distribution (p<0.13). Exactly the same procedure was repeated to confirm that R_3's *decision attributes*, *i.e.* $w(t)$, $q(t\text{-}1)$, $d(t\text{-}1)$ and $P_R(t-1)$ also satisfied the normality requirement of multiple regression analysis.

c) *Homo-skedasticity*: Figure A.4.6 illustrates the plot of $\langle q(t) \rangle_{RET_3}$ studentized residuals against the predicted dependent values. This plot's graphical comparison with the null plot, illustrated in red colour, demonstrates that the dispersion of $\langle q(t) \rangle_{RET_3}$ variances is almost equal. For this reason, it was safely assumed that the homo-skedasticity requirement was satisfied for $\langle q(t) \rangle_{RET_3}$. In the same way it was also confirmed that all independent variables of RET_3's *decision* model (4.8), namely $w(t)$, $q(t\text{-}1)$, $d(t\text{-}1)$ and $P_R(t-1)$, also satisfied the homo-skedasticity requirement.

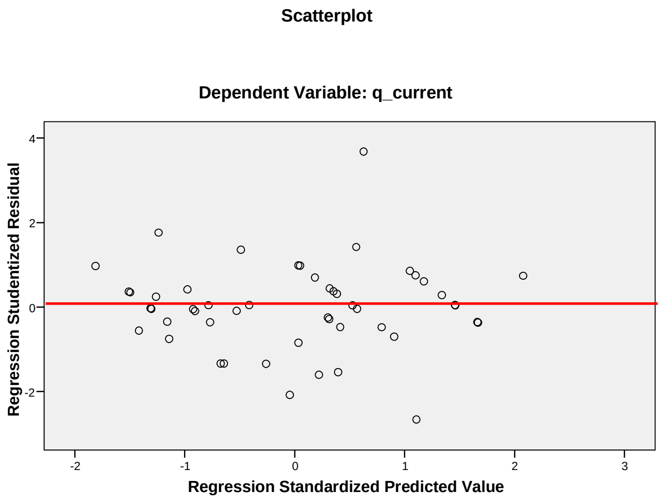


Figure A.4.6: Residual plot of $\langle q(t) \rangle_{R_3}$

After it was established that all human manufacturers' MAN_i and retailers' RET_j *decision variables* and *decision attributes* satisfied the linearity, normality, and homo-skedasticity requirements of multiple linear regression (Weisberg, 2005; Hair *et al*, 2006; Fox, 2008), it was also ensured that their respective decision making strategies could by portrayed by the simple linear models of the form (4.5) and (4.6).

Appendix B

The *Contract Beer Distribution Game*

B.1 Retailer's Instructions

In today's study you will participate in the "Beer game": a role playing simulation designed to investigate management decision making behaviours. There is no beer in the beer game and the game does not promote drinking. Indeed, you will be working with your partners to help the team to which you have been assigned to make the maximum total, system-wide profits possible. You will participate in the game as the Retailer.

The Game Scenario

There are three members in each supply chain configuration: a Manufacturer, a Wholesaler and a Retailer. You will be the retailer; namely you will be responsible for serving end consumers. You are supplied the cases of beer that you order by the wholesaler, who is, in turn, supplied by the manufacturer.

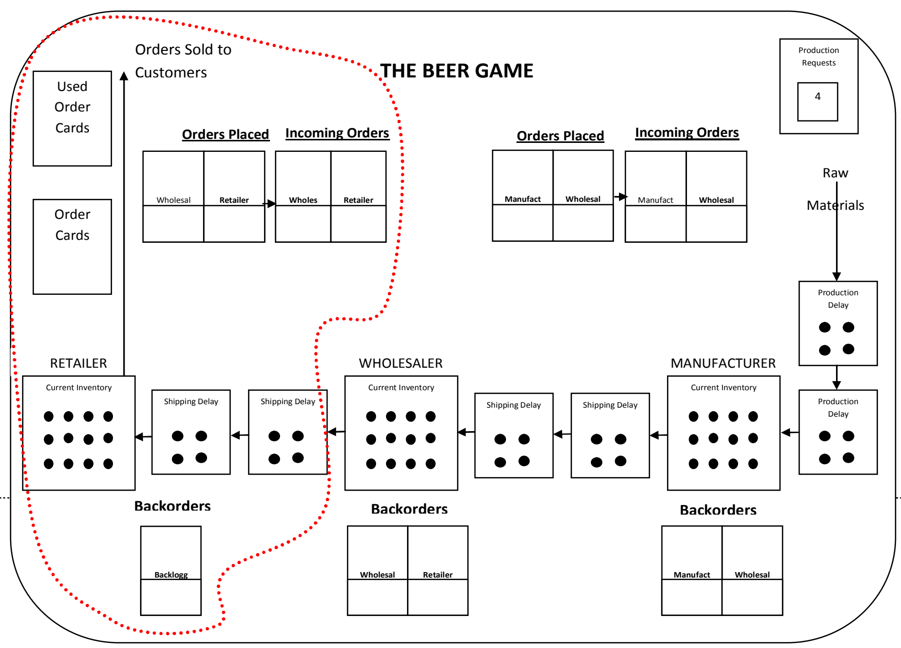
Each round of the game represents a week. Any week's demand is completely independent of the demand of any earlier week. You are the only team member who can actually see and really knows the exact customer demand. For this reason, you are kindly asked not to share this information with any of the other members of your team.

Every week you have to decide: how many cases of beer you want to order.

You pay £0.50 for every case of beer that you keep in your inventory for one week. You also have to pay £1 for every case of beer demanded by your customers, but which you are not able to provide. You receive £3 for every case of beer that you sell to your customers.

What you will need:

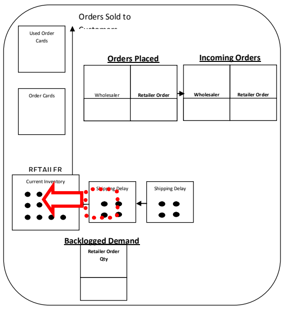
1. ***Your Section of the Game Board***



2. *Your Records sheet*

<u>The Steps of the Game</u> (these steps have to be repeated in *<u>every week</u>*)

Step 1: RECEIVE SHIPMENT



Step 1a

Step 1a: Receive inventory and associated order slip from the first SHIPPING DELAY into your CURRENT INVENTORY.

Step 1b: Find from the associated order slip: *i*. the WHOLESALER PRICE at the left hand side column and *ii*. the RETAILER ORDER QUANTITY received at the right hand side column.

Step 1c: Write in this week's row and column (3) of your records sheet your Delivery Cost, calculated as follows:

Wholesaler Price	Retailer Order Qty
£2	4

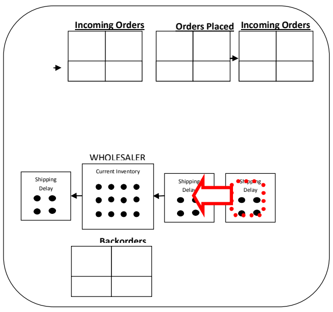
Delivery Cost = RETAILER ORDER QUANTITY x WHOLESALER PRICE

For example for the 1st week you write in the first cell of column (3): 4 x £2= £8, as you can see from the slip at the side.

In case you received more than one order slips with the shipments add all corresponding Delivery Costs, <u>where each</u> is calculated according to the above formula.

Step 1d: Destroy the incoming order slips associated with the cases of beer you just received.

Step 2: ADVANCE SHIPPING DELAYS



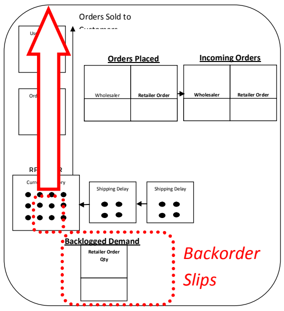
Step 2

Advance the contents of the second SHIPPING DELAY one position to the left.

Step 3: FILL BACKLOG, *if any*, depending on your available inventory.

- *If you don't have any BACKORDER slips, then wait for your partners to complete Step 3, so that you can proceed <u>at the same time with them</u> to Step 4.*
- *For as long as you have BACKORDER slip(s) <u>and</u> available inventory left, perform the following sequence of steps:*

***Step 3a*: Fill as much of your first BACKORDER slip's quantity as you can.**



Step 3a

Back-logged Demand
~~4~~ 1

- If your available inventory entails more cases of beer than your first BACKORDER slip, then move as many cases of beer as written in this BACKORDER slip out of your warehouse.
- If your available inventory entails less cases of beer than your first BACKORDER slip, then move as many cases of beer as you have left in your inventory out of your warehouse.

***Step 3b:* Correct your first BACKORDER slip, *if required*.**

- If you delivered to your customers all the cases of beer written in the first BACKORDER slip, then proceed directly to Step 3c, by keeping the BACKORDER slip in your hands.
- If you delivered to your customers only a part of the quantity written in the first BACKORDER slip, then correct this backorder slip by: *i.* crossing out with your pen the BACKLOGGED DEMAND and *ii.* writing with your pen the exact quantity that you just delivered to your customers. At the side of the previous page you can see an example of a corrected backorder slip, where only 1 out of 4 backlogged cases of beer were delivered. Keep the BACKORDER slip in your hands.

***Step 3c:* Receive corresponding REVENUES from your customers.**

- <u>Add</u> in this week's row and column (4) of your records sheet your corresponding Revenues, calculated as follows:

Back-logged Demand
4

Revenues = BACKLOGGED DEMAND x £3

You will find the backlogged demand at the BACKORDER SLIP you have in your hands.

For the example of the non-corrected backorder slip given at the left you write in the appropriate cell of column (4):+ 4 x £3= £12.

Back-logged Demand
~~4~~ 1

For the example of the corrected backorder slip given at the right, where you only satisfied 1 out of 4 backlogged cases of beer, you write in the appropriate cell of column (4): + 1 x £3= £3.

***Step 3d:* Create a new BACKORDER slip.**

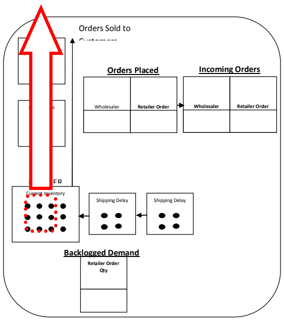
- If you have in your hands a non-corrected BACKORDER slip, then you should go back to Step 3a, for as long as you have remaining BACKORDER slip(s) <u>and</u> available inventory left. You don't need the BACKORDER slip anymore.

Back-logged Demand
3

- If you have in your hands a corrected BACKORDER slip, then you should complete an empty BACKORDER slip with the quantity that you did not have sufficient inventory to ship and place it <u>as the first</u> of your BACKORDER slip(s).You don't need the previous BACKORDER slip anymore. For the example given above, the new BACKORDER slip should look like as is shown at the left. After placing the new BACKORDER slip at the top of all BACKORDER slip(s), you should wait for your partners to complete Step 3, so that you can proceed <u>at the same time with them</u> to Step 4.

- *When you run out of available inventory or you have satisfied all your* ***BACKORDER*** *slip(s), then you should wait for your partners to complete Step 3, so that you can proceed <u>at the same time with them</u> to Step 4.*

Step 4: **FILL CUSTOMER DEMAND, depending *on your available inventory***



Step 4b

***Step 4a*: Lift ORDER card and keep it in your hands.**

***Step 4b:* Fill as much of the ORDER quantity as you can.**

- If your available inventory entails more cases of beer than the ORDER quantity, then move as many cases of beer as written in this ORDER card out of your warehouse.
- If your available inventory entails less cases of beer than the ORDER quantity (or is zero), then move as many cases of beer as you have left in your inventory out of your warehouse.

***Step 4c:* Correct the ORDER card, *if required*.**

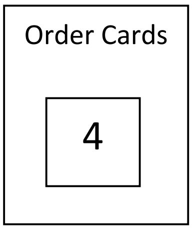
- If you delivered to your customers all the cases of beer written in the ORDER card, then proceed directly to Step 4d.
- If you delivered to your customers only a part of the quantity written in the ORDER card, then correct this ORDER card by: *i*. crossing out with your pen the ORDER QUANTITY and *ii*. writing with your pen the exact quantity that you just delivered to your customers. At the side you can see an example of a corrected ORDER card, where only 1 out of 4 demanded cases of beer were delivered.

Order Cards

~~4~~ 1

- If you did not have any inventory left and, thus, did not send anything to your wholesaler, then place your ORDER card as the last of your BACKORDER SLIP(s), *if any*. Then you should wait for your partners to complete Step 4, so that you can proceed at the same time with them to Step 5.

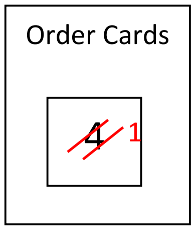
Step 4d: **Receive corresponding REVENUES from your customers.**



- Add in this week's row and column (4) of your records sheet your corresponding Revenues, calculated as follows:

Revenues = ORDER QUANTITY x £3

You will find the order quantity at the ORDER card you have in your hands.

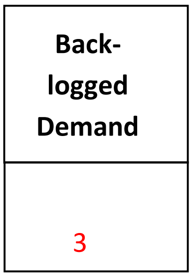


For the example of the non-corrected order card given at the left you write in the appropriate cell of column (4): + 4 x £3= £12.

For the example of the corrected order card given at the right, where you only satisfied 1 out of 4 demanded cases of beer, you write in the appropriate cell of column (4): + 1 x £3= £3.

Step 4e: **Create a new BACKORDER slip.**

- If you have in your hands a non-corrected ORDER card, then you should wait for your partners to complete Step 4, so that you can proceed at the same time with them to Step 5.
- If you have in your hands a corrected ORDER card, then you should complete an empty BACKORDER slip with the quantity that you did not have sufficient inventory to ship and place it as the last of your BACKORDER slip(s). For the example given above, the new BACKORDER slip should look like as is shown at the left.



  - *You don't need the previous ORDER card anymore.*

Step 5: **COMPLETE RECORDS SHEET WITH INVENTORY OR BACKLOG, *if any***

- If you have any inventory left, then:

Step 5a: **Record your inventory.**

Count the number of cases of beer you have left in your inventory and write this number in this week's row and column (1) of your records sheet.

For example for 1st week you write in the first cell of column (1) 12.

- If you have any backorder slips in front of you, then:

Step 5b: Record your backlogged quantity.

Add the quantities included at the right hand side columns of *all* backorder slips you have and write this number in this week's row and column (2) of your records sheet.

- *Please make sure that you either follow Step 5a or Step 5b!*

Step 6: Calculate Profits

Step 6a: Calculate this week's total Revenues$_t$

Add all revenues that you have received from your customers (as written in this week's row and column (4) of your records sheet) and write the result in the same cell.

Step 6b: Calculate this week's profit Profit$_t$.

Calculate this week's profit Profit$_t$, according to the following formula, where all elements (t) can be found in this week's row of your records sheet. In greater detail:
Revenues$_t$ in column (4), Production Cost$_t$ in (3), Backlog$_t$ in (2) and Inventory$_t$ in (1).

$$\boxed{\text{Profit}_t = \text{Revenues}_t - \text{Acquisition cost}_t - \text{Backlog}_t - \text{Inventory}_t / 2}$$

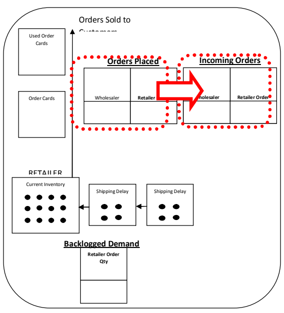
Step 6c: Calculate the cumulative profit Cumulative Profit$_t$.

Add to Profit$_t$ the value that can be found in the previous row of column (5) of your records sheet, namely Cumulative Profit$_{t-1}$, according to the following formula:

$$\boxed{\text{Cumulative Profit}_t = \text{Profit}_t + \text{Cumulative Profit}_{t-1}}$$

Step 6c: Record your cumulative profit.

Write the new cumulative profit in this week's row and column (5) of your records sheet.



Step 7

Step 7: ADVANCE INCOMING ORDERS

Advance order slips from the ORDERS PLACED position to the INCOMING ORDERS position for your wholesaler to be able to see in the next round of the game.

Step 8: DO NOTHING

Step 9: PLACE ORDERS

Step 9a: Receive the order slip that your wholesaler is passing on to you.

Step 9b: Decide your order quantity.

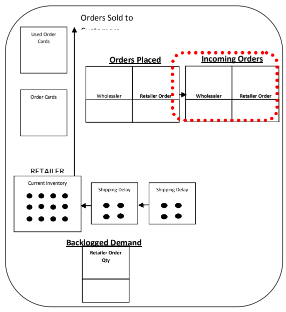
Decide how many cases of beer you want to order. Write this number in this week's row and column (6) of your records sheet.

Step 9c: Complete the order slip with this order quantity.

Complete the right hand side column of the order slip that you just received from your wholesaler with the value you just wrote in column (6) of your records sheet.

Step 9d: Place your order.

Place the above order slip at the appropriate position of your board, as illustrated at the side.



Step 9d

After you have completed Steps 1-9, you should repeat them for the next week, until your facilitator informs you of the last round of the game.

At the end of the game you will be asked to add your end-of-game cumulative profit with all your partners', in order to calculate the total game profit.

GOOD LUCK!!

WARWICK
BUSINESS SCHOOL

GAME RECORDS (BY WEEK)

POSITION: MANUFACTURER **TEAM:** ___________________________

Week	(1) Inventory	(2) Backlog	(3) Production Cost	(4) Revenues	(5) Cumulative Profit	(6) Manufacturer Price	(7) Production Requests
1							
2							
3							
4							
5							
6							
7							
8							
9							
10							
11							
12							
13							
14							
15							
16							
17							
18							
19							
20							
21							
22							
23							
24							
25							
26							
27							
28							
29							
30							

+44 (0)24 7652 4306
+44 (0)24 7652 3719

THE UNIVERSITY OF WARWICK

The University of Warwick
Coventry CV4 7AL
United Kingdom

WARWICK
BUSINESS SCHOOL

Week	(1) Inventory	(2) Backlog	(3) Production Cost	(4) Revenues	(5) Cumulative Profit	(6) Manufacturer Price	(7) Production Requests
31							
32							
33							
34							
35							
36							
37							
38							
39							
40							
41							
42							
43							
44							
45							
46							
47							
48							
49							
50							

In every week (t) Profit is given by:

$\text{Profit}_t = \text{Revenues}_t - \text{Production Cost}_t - \text{Backlog}_t - \text{Inventory}_t / 2$

or

$\text{Profit}_t = \quad \textbf{(4)} \quad - \quad \textbf{(3)} \quad - \quad \textbf{(2)} \quad - \quad \textbf{(1)} \quad /2$

The corresponding cumulative profit derives as:

$\text{Cumulative Profit}_t = \text{Profit}_t + \text{Cumulative Profit}_{t-1}$.

T +44 (0)24 7652 4306
F +44 (0)24 7652 3719
E enquiries@wbs.ac.uk
W www.wbs.ac.uk

THE UNIVERSITY OF
WARWICK

Warwick Business School
The University of Warwick
Coventry CV4 7AL
United Kingdom

B.2 Wholesaler's Instructions

In today's study you will participate in the "Beer game": a role playing simulation designed to investigate management decision making behaviours. There is no beer in the beer game and the game does not promote drinking. Indeed, you will be working with your partners to help the team to which you have been assigned to make the maximum total, system-wide profits possible. You will participate in the game as the Wholesaler.

The Game Scenario

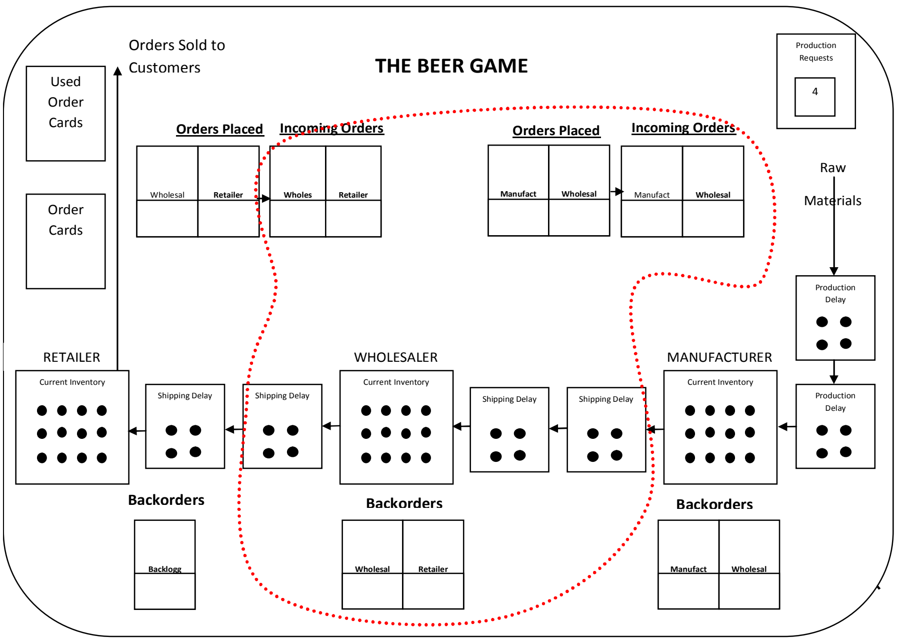
There are three members in each supply chain configuration: a Manufacturer, a Wholesaler and a Retailer. You will be the wholesaler; namely you will be responsible for supplying the retailer. Your customer, the retailer, in turn, serves end consumers. You are supplied the cases of beer that you order by the manufacturer.

Each round of the game represents a week. Every week you have to decide: *i*. how much you want to charge your retailer for every case of beer that you deliver to him and *ii*. how many cases of beer you want to order.

You pay £0.50 for every case of beer that you keep in your inventory for one week. You also have to pay £1 for every case of beer requested by your retailer, but which you are not able to supply.

What you will need:

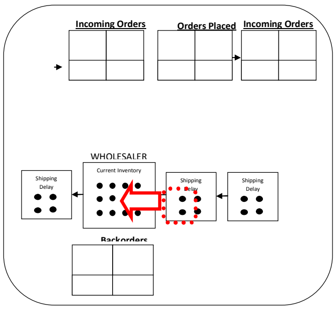
1. ***Your Section of the Game Board***



2. *Your Records sheet*

The Steps of the Game (these steps have to be repeated in *every week*)

Step 1: RECEIVE SHIPMENT



Step 1a

Step 1a: Receive inventory and associated order slip from the first SHIPPING DELAY into your CURRENT INVENTORY.

Step 1b: Find from the associated order slip: *i*. the MANUFACTURER PRICE at the left hand side column and *ii*. the WHOLESALER ORDER QUANTITY received at the right hand side column.

Step 1c: Write in this week's row and column (3) of your records sheet your Delivery Cost, calculated as follows:

Manufacturer Price	Wholesaler Order Qty
£1.5	4

Delivery Cost = WHOLESALER ORDER QUANTITY x MANUFACTURER PRICE

For example for the 1st week you write in the first cell of column (3): 4 x £1.5= £6, as you can see from the slip at the side.

In case you received more than one order slips with the shipments add all corresponding Delivery Costs, where each is calculated according to the above formula.

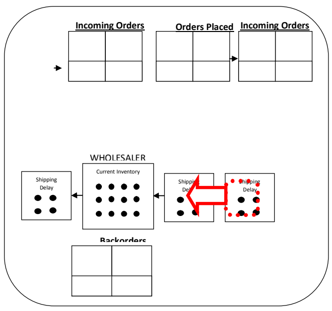
Step 1d: Destroy the incoming order slips associated with the cases of beer that you just received.

Step 1e: Write in this week's row and column (4) of your records sheet the revenues you received from your retailer, as dictated by him.

For example for the 1st week you listen to your retailer saying £8 and you write in the first cell of column (4) £8.

Step 2: ADVANCE SHIPPING DELAYS

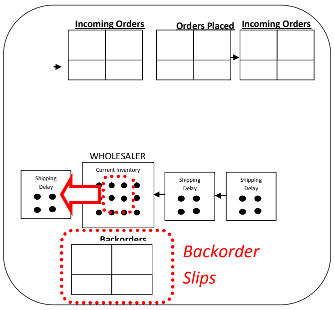
Advance the contents of the second SHIPPING DELAY one position to the left.



Step 2

Step 3: FILL BACKLOG, *if any*, depending on your available inventory.

- *If you don't have any BACKORDER slips, then wait for your partners to complete Step 3, so that you can proceed <u>at the same time with them</u> to Step 4.*



Step 3a

- *For as long as you have BACKORDER slip(s) <u>and</u> available inventory left, perform the following sequence of steps:*

***Step 3a*: Fill as much of your first BACKORDER slip's quantity as you can.**

- If your available inventory entails more cases of beer than your first BACKORDER slip, then move as many cases of beer as written in this BACKORDER slip to the first SHIPPING DELAY to your left.
- If your available inventory entails less cases of beer than your first BACKORDER slip, then move as many cases of beer as you have left in your inventory to the first SHIPPING DELAY to your left.

***Step 3b:* Attach the appropriate BACKORDER slip to the cases of beer you just shipped to your retailer.**

- If you shipped to your retailer all the cases of beer written in the first BACKORDER slip, then attach this BACKORDER slip to the cases of beer you just shipped.

Wholesaler Price	Retailer Order Qty
£2	~~4~~ 1

- If you shipped to your retailer only a part of the quantity written in the first BACKORDER slip, then correct the backorder slip by: *i.* crossing out with your pen its right hand side column (RETAILER ORDER QUANTITY) and *ii.* writing with your pen the exact quantity that you just shipped to your retailer. Attach this backorder slip to the cases of beer you just shipped. At the side you can see an example of a corrected backorder slip, where only 1 out of 4 backlogged cases of beer were shipped to the retailer.

***Step 3c:* Create a new BACKORDER slip.**

- If you attached a *non*-corrected BACKORDER slip to your last shipment, then you should go back to Step 3a, for as long as you have remaining BACKORDER slip(s) <u>and</u> available inventory left.
- If you attached a corrected BACKORDER slip to your last shipment, then complete an empty BACKORDER slip with the quantity that you did not have sufficient inventory to ship and place it <u>as the first</u> of your

BACKORDER slip(s). For the example given above, the new BACKORDER slip should look as is shown at the side. After placing the new BACKORDER slip at the top of all BACKORDER slip(s), you should wait for your partners to complete Step 3, so that you can proceed <u>at the same time with them</u> to Step 4.

Wholesaler Price	Retailer Order Qty
£2	3

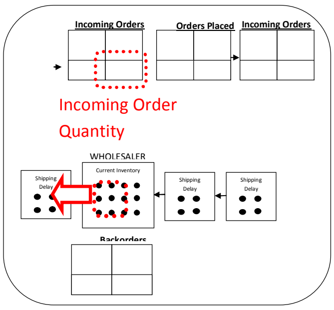
- *When you run out of available inventory or you have satisfied all your* BACKORDER slip(s), *then you should wait for your partners to complete Step 3, so that you can proceed <u>at the same time with them</u> to Step 4.*

Step 4: **FILL INCOMING ORDERS, depending *on your available inventory***

***Step 4a*: Lift incoming order.**

***Step 4b:* Fill as much of the INCOMING ORDER quantity as you can.**

- If your available inventory entails more cases of beer than your INCOMING ORDER, then move as many cases of beer as written in this INCOMING ORDER to the first SHIPPING DELAY to your left.



Step 4b

- If your available inventory entails less cases of beer than your INCOMING ORDER (or is zero), then move as many cases of beer as you have left in your inventory to the first SHIPPING DELAY to your left.

***Step 4c:* Attach the appropriate slip to the cases of beer you just shipped to your retailer.**

- If you shipped to your retailer all the cases of beer written in the INCOMING ORDER, then attach this INCOMING ORDER slip to the cases of beer you just shipped.
- If you shipped to your retailer only a part of the quantity written in the INCOMING ORDER, then correct this slip by: *i.* crossing out with your pen its right hand side column (RETAILER ORDER QUANTITY) and *ii.* writing with your pen the exact quantity that you just shipped to your retailer. Attach this backorder slip to the cases of beer you just shipped. At the side you can see an example of a corrected INCOMING ORDER slip, where only 1 out of 4 ordered cases of beer were shipped to the retailer.

Wholesaler Price	Retailer Order Qty
£2	~~4~~ 1

- If you did not have any inventory left and, thus, did not send anything to your retailer, then place your INCOMING ORDER slip as the last of your BACKORDER SLIP(s), *if any*. Then you should wait for your partners to complete Step 4, so that you can proceed at the same time with them to Step 5.

Step 4d: Create a new BACKORDER slip.

- If you attached a non-corrected INCOMING ORDER slip to your last shipment, then you should wait for your partners to complete Step 4, so that you can proceed at the same time with them to Step 5.
- If you attached a corrected INCOMING ORDER slip to your last shipment, then complete an empty BACKORDER slip with the quantity that you did not have sufficient inventory to ship and place it as the last of your BACKORDER slip(s). For the example given above, the new BACKORDER slip should look like as is shown at the side.

Wholesaler Price	Retailer Order Qty
£2	3

Step 5: COMPLETE RECORDS SHEET WITH INVENTORY OR BACKLOG, if any

- If you have any inventory left, then:

***Step 5a:* Record your inventory.**

Count the number of cases of beer you have left in your inventory and write this number in this week's row and column (1) of your records sheet.

For example for 1st week you write in the first cell of column (1) 12.

- If you have any backorder slips in front of you, then:

Step 5b: Record your backlogged quantity.

Add the quantities included at the right hand side columns of *all* backorder slips you have and write this number in this week's row and column (2) of your records sheet.

- *Please make sure that you either follow Step 5a or Step 5b!*

***Step 6:* Calculate Profits**

***Step 6a:* Calculate this week's profit Profit$_t$.**

$$\text{Profit}_t = \text{Revenues}_t - \text{Acquisition cost}_t - \text{Backlog}_t - \text{Inventory}_t / 2$$

Calculate this week's profit Profit$_t$, according to the above formula, where all elements (t) can be found in this week's row of your records sheet. In greater detail:

Revenues$_t$ in column (4), Production Cost$_t$ in (3), Backlog$_t$ in (2) and Inventory$_t$ in (1).

Step 6b: Calculate the cumulative profit Cumulative Profit$_t$.

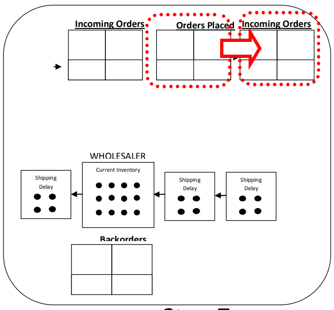
Add to Profit$_t$ the value that can be found in the previous row of column (5) of your records sheet, namely Cumulative Profit$_{t\text{-}1}$, according to the following formula:

$$\text{Cumulative Profit}_t = \text{Profit}_t + \text{Cumulative Profit}_{t-1}$$

Step 6c: Record your cumulative profit.

Write the new cumulative profit in this week's row and column (5) of your records sheet.

Step 7: ADVANCE INCOMING ORDERS



Step 7

Advance order slips from the ORDERS PLACED position to the INCOMING ORDERS position for your manufacturer to be able to see in the next round of the game.

Step 8: DECIDE ON YOUR WHOLESALER PRICE

Step 8a: Decide your wholesaler price.

Decide how much you want to charge your retailer for every case of beer that you deliver to him. Write this number in this week's row and column (6) of your records sheet.

Step 8b: Create a new order slip.

Choose a new (*i.e. empty*) order slip and complete its left hand side column with the price you just wrote in column (6) of your records sheet.

Wholesaler Price	Retailer Order Qty

Step 8c: Pass this order slip on to your retailer.

Step 9: PLACE ORDERS

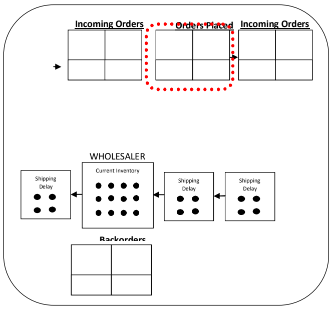
Step 9a: Receive the order slip that your manufacturer is passing on to you.

Step 9b: Decide your order quantity.

Decide how many cases of beer you want to order. Write this number in this week's row and column (7) of your records sheet.

Step 9c: **Complete the order slip with this order quantity.**

Complete the right hand side column of the order slip that you just received from your manufacturer with the value you just wrote in column (7) of your records sheet.



Step 9d

Step 9d: **Place your order.**

Place the above order slip at the appropriate position of your board, as illustrated at the side.

After you have completed Steps 1-9, you should repeat them for the next week, until your facilitator informs you of the last round of the game.

At the end of the game you will be asked to add your end-of-game cumulative profit with all your partners’, in order to calculate the total game profit.

Good Luck!!

WARWICK
BUSINESS SCHOOL

GAME RECORDS (BY WEEK)

POSITION: WHOLESALER **TEAM:**

____

Week	(1) Inventory	(2) Backlog	(3) Delivery Cost	(4) Revenues	(5) Cumulative Profit	(6) Wholesaler Price	(7) Order Quantity
1							
2							
3							
4							
5							
6							
7							
8							
9							
10							
11							
12							
13							
14							
15							
16							
17							
18							
19							
20							
21							
22							
23							
24							
25							
26							
27							
28							
29							
30							

+44 (0)24 7652 4306
+44 (0)24 7652 3719

THE UNIVERSITY OF
WARWICK

The University of Warwick
Coventry CV4 7AL
United Kingdom

WARWICK
BUSINESS SCHOOL

Week	(1) Inventory	(2) Backlog	(3) Delivery Cost	(4) Revenues	(5) Cumulative Profit	(6) Wholesaler Price	(7) Order Quantity
31							
32							
33							
34							
35							
36							
37							
38							
39							
40							
41							
42							
43							
44							
45							
46							
47							
48							
49							
50							

In every week (t) Profit is given by:

$\text{Profit}_t = \text{Revenues}_t - \text{Delivery Cost}_t - \text{Backlog}_t - \text{Inventory}_t / 2$

or

$\text{Profit}_t = \quad \mathbf{(4)} \quad - \quad \mathbf{(3)} \quad - \quad \mathbf{(2)} \quad - \quad \mathbf{(1)} \quad /2$

The corresponding cumulative profit derives as:

$\text{Cumulative Profit}_t = \text{Profit}_t + \text{Cumulative Profit}_{t-1}$.

T +44 (0)24 7652 4306
F +44 (0)24 7652 3719
E enquiries@wbs.ac.uk
W www.wbs.ac.uk

THE UNIVERSITY OF
WARWICK

Warwick Business School
The University of Warwick
Coventry CV4 7AL
United Kingdom

B.3 Manufacturer's Instructions

In today's study you will participate in the "Beer game": a role playing simulation designed to investigate management decision making behaviours. Indeed, you will be working with your partners to help the team to which you have been assigned to make the maximum total, system-wide profits possible. You will participate in the game as the Manufacturer.

The Game Scenario

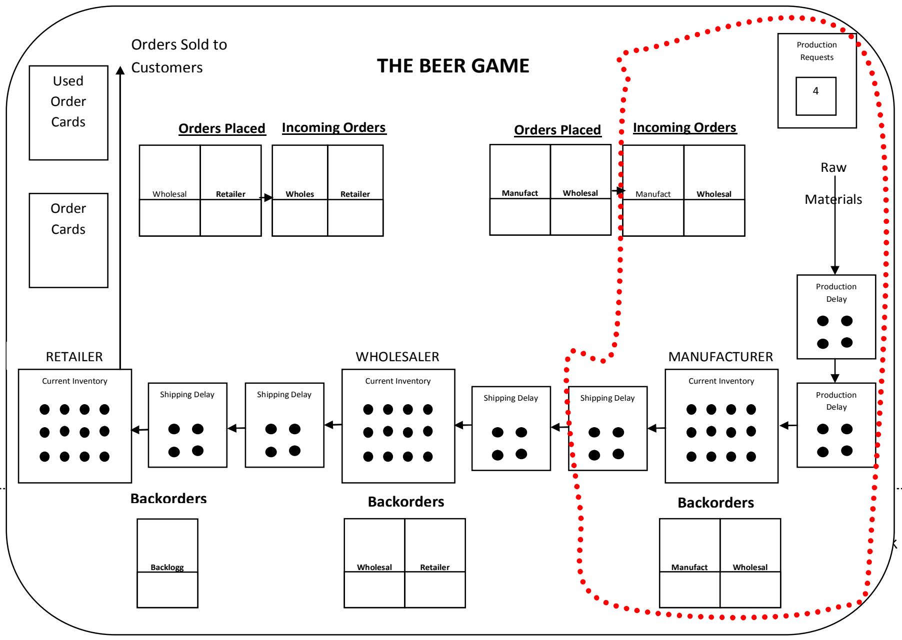
There are three members in each supply chain configuration: a Manufacturer, a Wholesaler and a Retailer. You will be the manufacturer; namely you will be responsible for producing and supplying to the wholesaler the cases of beer that he/she orders. Your customer, the wholesaler, is responsible for supplying the retailer. The retailer, in turn, serves end consumers. You, as the manufacturer, face no capacity constraints and you can assume that you are able to produce as much as you order.

Each round of the game represents a week. Every week you have to decide: *i*. how much you want to charge your wholesaler for every case of beer that you deliver to him and *ii*. how many cases of beer you want to order.

For every case of beer that you produce you pay £0.50. You also pay £0.50 for every case of beer that you keep in your inventory for one week. Last, you pay £1 for every case of beer requested by your wholesaler, but which you are not able to supply.

What you will need:

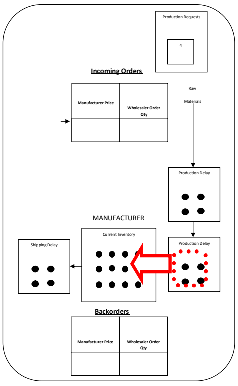
1. ***Your Section of the Game Board***



2. *Your Records sheet*

The Steps of the Game (these steps have to be repeated in *every week*)

***Step 1*: RECEIVE PRODUCED QUANTITY**



Step 1a

Step 1a: Receive inventory from the PRODUCTION DELAY that is the closest to your warehouse into your CURRENT INVENTORY.

Step 1b: Write in this week's row and column (3) of your records sheet your Production Cost, calculated as follows:

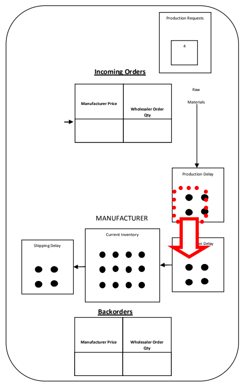
Production Cost = quantity received x manufacturing cost

For example for the 1st week you write in the first cell of column (3): 4 x £0.5= £2.

Step 1c: Write in this week's row and column (4) of your records sheet the revenues you received from your wholesaler, as dictated by him/her.

For example for the 1st week you listen to your wholesaler saying £6 and you write in the first cell of column (4) £6.

***Step 2*: ADVANCE PRODUCTION DELAYS**

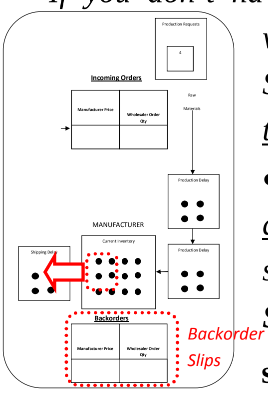


Step 2

Advance the contents of your top PRODUCTION DELAY one position down.

***Step 3:* FILL BACKLOG, *if any*, depending on your available inventory.**

- *If you don't have any BACKORDER slips, then wait for your partners to complete Step 3, so that you can proceed at the same time with them to Step 4.*



Step 3a

- *For as long as you have BACKORDER slip(s) and available inventory left, perform the following sequence of steps:*

***Step 3a*: Fill as much of your first BACKORDER slip's quantity as you can.**

- If your available inventory entails more cases of beer than your first BACKORDER slip, then move as many cases of beer as written in this BACKORDER slip to the first SHIPPING DELAY to your left.
- If your available inventory entails less cases of beer than your first BACKORDER slip, then move as many cases of beer as you have left in your inventory to the first SHIPPING DELAY to your left.

Step 3b: **Attach the appropriate BACKORDER slip to the cases of beer you just shipped to your wholesaler.**

- If you shipped to your wholesaler all the cases of beer written in the first BACKORDER slip, then attach this BACKORDER slip to the cases of beer you just shipped.
- If you shipped to your wholesaler only a part of the quantity written in the first BACKORDER slip, then correct the backorder slip by: *i*. crossing out with your pen its right hand side column (WHOLESALER ORDER QUANTITY) and *ii*. writing with your pen the exact quantity that you just shipped to your wholesaler. Attach this backorder slip to the cases of beer you just shipped. At the side you can see an example of a corrected backorder slip, where only 1 out of 4 backlogged cases of beer were shipped to the wholesaler.

Manufacturer Price	Wholesaler Order Qty
£1.5	~~4~~ 1

Step 3c: **Create a new BACKORDER slip.**

- If you attached a non-corrected BACKORDER slip to your last shipment, then you should go back to Step 3a, for as long as you have remaining BACKORDER slip(s) and available inventory left.
- If you attached a corrected BACKORDER slip to your last shipment, then complete an empty BACKORDER slip with the quantity that you did not have sufficient inventory to ship and place it as the first of your BACKORDER slip(s). For the example given above, the new BACKORDER slip should look like as is shown at the side.

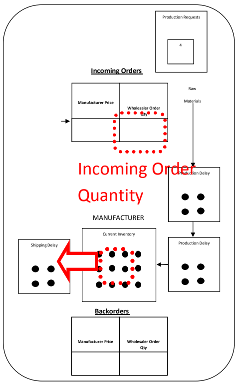
Manufacturer Price	Wholesaler Order Qty
£1.5	3

  After placing the new BACKORDER slip at the top of all BACKORDER slip(s), you should wait for your partners to complete Step 3, so that you can proceed at the same time with them to Step 4.

- *When you run out of available inventory or you have satisfied all your* BACKORDER slip(s), *then you should wait for your partners to* *complete Step 3, so that you can proceed <u>at the same time with them</u> to Step 4.*

Step 4:* FILL INCOMING ORDERS, depending *on your available inventory

***Step 4a*: Lift incoming order.**



Step 4b

***Step 4b:* Fill as much of the INCOMING ORDER quantity as you can.**

- If your available inventory entails more cases of beer than your INCOMING ORDER, then move as many cases of beer as written in this INCOMING ORDER to the first SHIPPING DELAY to your left.
- If your available inventory entails less cases of beer than your INCOMING ORDER (or is zero), then move as many cases of beer as you have left in your inventory to the first SHIPPING DELAY to your left.

***Step 4c:* Attach the appropriate slip to the cases of beer you just shipped to your wholesaler.**

- If you shipped to your wholesaler all the cases of beer written in the INCOMING ORDER, then attach this INCOMING ORDER slip to the cases of beer you just shipped.
- If you shipped to your wholesaler only a part of the quantity written in the INCOMING ORDER, then correct this slip by: *i*. crossing out with your pen its right hand side column (WHOLESALER ORDER QUANTITY) and *ii*. writing with your pen the exact quantity that you just shipped to your wholesaler. Attach this backorder slip to the cases of beer you just shipped. At the side you can see an example of a corrected INCOMING ORDER slip, where only 1 out of 4 ordered cases of beer were shipped to the wholesaler.

Manufacturer Price	Wholesaler Order Qty
£1.5	~~4~~ 1

- If you did not have any inventory left and, for this reason, did not send anything to your wholesaler, then place your INCOMING ORDER slip as <u>the last</u> of your BACKORDER SLIP(s), *if any*. Then, you should wait for your partners to complete Step 4, so that you can proceed <u>at the same time with them</u> to Step 5.

***Step 4d:* Create a new BACKORDER slip.**

- If you attached a non-corrected INCOMING ORDER slip to your last shipment, then you should wait for your partners to complete Step 4, so that you can proceed at the same time with them to Step 5.

Manufacturer Price	Wholesaler Order Qty
£1.5	3

- If you attached a corrected INCOMING ORDER slip to your last shipment, then complete an empty BACKORDER slip with the quantity that you did not have sufficient inventory to ship and place it at the section of your board BACKORDER slip(s). For the example given above, the new BACKORDER slip should look like as is shown at the side.

Step 5: COMPLETE RECORDS SHEET WITH INVENTORY OR BACKLOG, if any

- If you have any inventory left, then:

***Step 5a:* Record your inventory.**

Count the number of cases of beer you have left in your inventory and write this number in this week's row and column (1) of your records sheet.
For example for the 1st week you write in the first cell of column (1) 12.

- If you have any backorder slips in front of you, then:

Step 5b: Record your backlogged quantity.

Add the quantities included at the right hand side columns of *all* backorder slips you have and write this number in this week's row and column (2) of your records sheet.

- *Please make sure that you either follow Step 5a or Step 5b!*

***Step 6:* Calculate Profits**

***Step 6a:* Calculate this week's profit Profit$_t$.**

Calculate this week's profit Profit$_t$, according to the following formula, where all elements (t) can be found in this week's row of your records sheet. In greater detail:
Revenues$_t$ in column (4), Production Cost$_t$ in (3), Backlog$_t$ in (2) and Inventory$_t$ in (1).

$$\boxed{\text{Profit}_t = \text{Revenues}_t - \text{Production Cost}_t - \text{Backlog}_t - \text{Inventory}_t / 2}$$

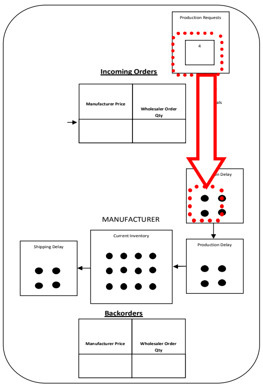
***Step 6b:* Calculate the cumulative profit Cumulative Profit$_t$.**

Add to Profit$_t$ the value that can be found in the previous row of column (5) of your records sheet, namely Cumulative Profit$_{t\text{-}1}$ (acc. to the following formula).

$$\text{Cumulative Profit}_t = \text{Profit}_t + \text{Cumulative Profit}_{t\text{-}1}$$

***Step 6c:* Record your cumulative profit.**

Write the new cumulative profit in this week's row and column (5) of your records sheet.



***Step 7:* BREW**

Introduce production requests from last week into the first PRODUCTION DELAY square.

Step 7

***Step 8:* DECIDE ON YOUR MANUFACTURER PRICE**

***Step 8a:* Decide your manufacturer price.**

Decide how much you want to charge your wholesaler for every case of beer that you deliver. Write this number in this week's row and column (6) of your records sheet.

***Step 8b:* Create a new order slip.**

Choose a new (*i.e. empty*) order slip and complete its left hand side column with the price you just wrote in column (6) of your records sheet.

Manufactu rer Price	**Wholesaler Order Qty**

***Step 8c:* Pass this order slip on to your wholesaler.**

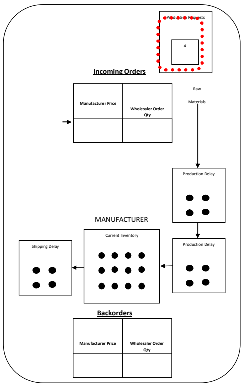
Step 9: **PLACE PRODUCTION REQUESTS**

Step 9a: **Decide your order quantity.**

Decide how many cases of beer you want to order. Write this number in this week's row and column (7) of your records sheet.

Step 9b: **Create a new PRODUCTION REQUESTS slip.**

Choose a new (*i.e. empty*) PRODUCTION REQUESTS slip and complete it with the value you just wrote in column (7) of your records sheet.



Step 9c

Step 9c: **Place your production requests.**

Place the above PRODUCTION REQUESTS slip at the appropriate position of your board, as illustrated at the side.

After you have completed Steps 1-9, you should repeat them for the next week, until your facilitator informs you of the last round of the game.

At the end of the game you will be asked to add your end-of-game cumulative profit with all your partners', in order to calculate the total game profit.

Good Luck!!

WARWICK
BUSINESS SCHOOL

GAME RECORDS (BY WEEK)

POSITION: RETAILER **TEAM:**

____

Week	(1) Inventory	(2) Backlog	(3) Delivery Cost	(4) Revenues	(5) Cumulative Profit	(6) Order Quantity
1						
2						
3						
4						
5						
6						
7						
8						
9						
10						
11						
12						
13						
14						
15						
16						
17						
18						
19						
20						
21						
22						
23						
24						
25						
26						
27						
28						
29						
30						

T +44 (0)24 7652 4306
F +44 (0)24 7652 3719

THE UNIVERSITY OF
WARWICK

The University of Warwick
Coventry CV4 7AL
United Kingdom

WARWICK
BUSINESS SCHOOL

Week	(1) Inventory	(2) Backlog	(3) Delivery Cost	(4) Revenues	(5) Cumulative Profit	(6) Order Quantity
31						
32						
33						
34						
35						
36						
37						
38						
39						
40						
41						
42						
43						
44						
45						
46						
47						
48						
49						
50						

In every week (t) Profit is given by:

$\text{Profit}_t = \text{Revenues}_t - \text{Delivery Cost}_t - \text{Backlog}_t - \text{Inventory}_t / 2$

or

$\text{Profit}_t = \quad \textbf{(4)} \quad - \quad \textbf{(3)} \quad - \quad \textbf{(2)} \quad - \quad \textbf{(1)} \quad /2$

The corresponding cumulative profit derives as:

$\text{Cumulative Profit}_t = \text{Profit}_t + \text{Cumulative Profit}_{t-1}$.

+44 (0)24 7652 4306
+44 (0)24 7652 3719
enquiries@wbs.ac.uk
www.wbs.ac.uk

THE UNIVERSITY OF
WARWICK

Warwick Business School
The University of Warwick
Coventry CV4 7AL
United Kingdom

WARWICK
BUSINESS SCHOOL

TOTAL GAME PROFIT

TEAM: _______________

POSITION	CUMULATIVE PROFIT
Retailer	
Wholesaler	
Manufacturer	

TOTAL PROFIT: _______________

T +44 (0)24 7652 4306
F +44 (0)24 7652 3719
E enquiries@wbs.ac.uk
W www.wbs.ac.uk

THE UNIVERSITY OF WARWICK

Warwick Business School
The University of Warwick
Coventry CV4 7AL
United Kingdom

B.4 *The team optimal solution* of the *Contract Beer Distribution Game*

It follows from relation (6.9) that the prices $wP_i(t)$ that echelon managers charge to their respective customers do not have any impact at all on the aggregate supply chain profits. From (6.9) it also becomes evident that total supply chain profits $P_C(t)$ are maximized when all echelon managers take up ordering policies that simultaneously: *i*. maximize the retailer's revenues $R_1(t)$; *ii*. minimize the manufacturer's production cost $SC_N(t)$; and *iii*. minimize the aggregate inventory costs $IC_C(t) = \sum_{i=1}^{N} IC_i(t)$. The objective of minimizing total inventory costs is studied first, while later on it is demonstrated that the policies that minimize total inventory costs $IC_C(t)$ also comply with the dual objective of minimizing the factory's production cost $SC_N(t)$ and maximizing the retailer's revenues $R_1(t)$.

To this end, it is first explained why the *Contract Beer Distribution Game*'s total inventory cost model is equivalent to Chen's (1999) team model. According to (6.5) the total supply chain inventory holding and backorder cost is given by:

$$IC_C(t) = \sum_{i=1}^{N} [h_i \cdot [IN_i(t)]^+ + b_i \cdot [IN_i(t)]^-] = \sum_{i=1}^{N} [h_i \cdot A + b_i \cdot B] \tag{B.4.1}$$

In order to establish the connections with Chen's (1999) existing multi-echelon inventory model and, thus, be able to make the required comparisons, the following additional definitions are required:

For any two periods t_1 and t_2 with $t_1 < t_2$ the interval $[t_{1,}t_2]$ signifies periods t_1, ..., t_2; while $(t_{1,}t_2]$ $t_1 + 1$, ..., t_2; and $[t_{1,}t_2)$ t_1, ..., $t_2 + 1$. For example, $D(t_{1,}t_2]$ denotes the total customer demand between periods $t_1 + 1$ and t_2.

Any echelon's i installation stock $IS_i(t)$ consists of its net inventory and its outstanding orders, namely orders processed by the upstream supplier, shipments in transit from the upstream supplier and orders backlogged at the upstream supplier. Its evolution over time is completely independent of shipments received and is, therefore, given by:

$$IS_i(t_2) = IS_i(t_1) + oQ_i(t_1, t_2] - oQ_i(t_1 - l_{i-1}, t_2 - l_{i-1}] \text{ for } 1 < i \leq N \qquad \text{(B.4.2a)}$$

$$IS_1(t_2) = IS_1(t_1) + oQ_1(t_1, t_2] - D[t_1, t_2) \qquad \text{(B.4.2b)}$$

Any echelon's i effective echelon inventory position $IP_i(t)$ consists of its effective installation stock at the beginning of period t (namely the part of its installation stock that excludes the shipments that do not get to i after the total required lead-time M_i; that is the upstream supplier's backlog at the time of receipt of i's order $-IN_{i+1}(t + l_i)$, if any) and the installation stocks at all downstream sites in an appropriately time-shifted manner that accommodates the relevant information delays:

$$IP_i(t) \stackrel{\text{def}}{=} IN_i(t) + S_{i+1}(t - L_i, t + l_i] + IS_{i-1}(t - l_{i-1}) + \cdots \qquad \text{(B.4.3)}$$
$$+ IS_1(t - l_{i-1} - \cdots - l_1)$$

Any echelon's i echelon inventory level $IL_i(t)$ consists of its on-hand inventory plus the installation stock of all its successor stages, again in the appropriate time-shifted way:

$$IL_i(t) \stackrel{\text{def}}{=} IN_i(t) + IS_{i-1}(t - l_{i-1}) + \cdots + IS_1(t - l_{i-1} - \cdots - l_1) \qquad \text{(B.4.4)}$$

Since in the *Contract Beer Distribution Game* only quantities that are physically kept in a site's warehouse incur inventory holding charges (and not the quantities that are backlogged, as in Chen's model) only positive inventories are included in expression A of (B.4.1). In addition, each site is only charged for its own warehouse's inventories (and not the quantities in transit to or backlogged from its downstream customers); while, in addition, no echelon incremental holding costs apply. For these three reasons, Chen's (1999) $IL_i(t)$ requirement in expression *A* of (B.4.1) (as given by (B.4.4)) gets simplified in our case to $IN_i(t)$ (given by (6.4)). The same also holds for Chen's $IL_1(t)$ expression in *B* of (B.4.1) that gets simplified to $IN_i(t)$ in our case. At this point it needs to be clarified that it is because all sites *i* incur linear backlog penalties b_i that they are all included in *B* (and not only the retailer, as in Chen's case).

Now that it has been demonstrated why Chen's formulation of total inventory holding and backorder costs and (B.4.1) are equivalent, it is also determined whether Chen's optimality conditions hold in the case of the *Contract Beer Distribution Game*. Chen (1999) relies on three optimality conditions to apply Chen and Zheng's (1994) procedure to identify and simplify Clark and Scarf 's (1960) and Federgruen and Zipkin's (1984) optimum ordering policies. Although there is no reason for these optimality conditions not to hold in the *Contract Beer Distribution Game*'s case, the formal proof is outlined in the paragraphs that follow.

The definition of installation stocks $IS_i(t)$, as given in (B.4.2) is first considered. If echelon *i* places an order to its upstream supplier *i*+1 at time period *t*, then this order will be received by *i*+1 at *t*+l_i. Two different cases can be distinguished. First, the case that *i*+1 has at time period *t*+l_i sufficient inventory to fully satisfy *i*'s newly received order (namely $IN_{i+1}(t+l_i) \geq oQ_i(t)$). In this case, *i*'s outstanding orders at time period *t* become simply the shipments that *i* receives from *i*+1 between the time of delivery of the last shipment (this shipment was still in transit to *i* at *t*), *i.e*. *t*-L_i, and the time that this new order will be received by supplier i+1, *i.e.* t+l_i. Therefore: $IS_i(t) = IN_i(t) + S_{i+1}(t - L_i, t + l_i]$. Second, the case that i+1 does not have sufficient inventory at time t+l_i to fully satisfy i's newly received order (namely $IN_{i+1}(t + l_i) < oQ_i(t)$). In this case, i's outstanding orders at time period t include, except for the shipments that i receives from i+1 in the appropriate time interval, i+1's backlog at that time, namely $-IN_{i+1}(t + l_i)$. Therefore: $IS_i(t) = IN_i(t) + S_{i+1}(t - L_i, t + l_i] - IN_{i+1}(t + l_i)$. Combining the two above cases:

$$IS_i(t) = IN_i(t) + S_{i+1}(t - L_i, t + l_i] - \min\{0, IN_{i+1}(t + l_i)\}$$

which in turn leads to:

$$IN_i(t) + S_{i+1}(t - L_i, t + l_i] \le IS_i(t) + IN_{i+1}(t + l_i) \text{ for } i=1,\dots,N$$

By adding the quantities $IS_{i-1}(t - l_{i-1}) + \cdots + IS_1(t - l_{i-1} - \cdots - l_1)$ in both sides of the above equation, according to (B.4.3) and (B.4.4), the following relation is obtained:

$$IP_i(t) \le IL_{i+1}(t + l_i) \text{ for } i=1,\dots,N \tag{B.4.5}$$

(B.4.5) represents Chen's (1999) first optimality condition.

Attention is now turned to the definition of echelon inventory level $IL_i(t)$, as given by (B.4.4). By shifting the echelon inventory level $IL_i(t)$ by i's total lead-time M_i (B.4.4) becomes:

$$\begin{aligned} IL_i(t + M_i) = IN_i(t + M_i) + IS_{i-1}(t + M_i - l_{i-1}) + \cdots \\ + IS_1(t + M_i - l_{i-1} - \cdots - l_1) \end{aligned} \tag{B.4.6}$$

By incorporating the inventory balance equations (6.4) and installation stock balance equations (B.4.2), (B.4.6) becomes:

$$
\begin{aligned}
IL_i(t+M_i) = IN_i(t) &+ S_{i+1}(t-L_i, t+l_i] \\
&- oQ_{i-1}(t-l_{i-1}, t+M_i-l_{i-1}] + IS_{i-1}(t-l_{i-1}) \\
&+ oQ_{i-1}(t-l_{i-1}, t+M_i-l_{i-1}] \\
&- oQ_{i-2}(t-l_{i-1}-l_{i-2}, t+M_i-l_{i-1}-l_{i-2}] + \cdots \\
&+ IS_1(t-l_{i-1}-\cdots-l_1) \\
&+ oQ_1(t-l_{i-1}-\ldots-l_1, t+M_i-l_{i-1}-\cdots-l_1] - D[t \\
&- l_{i-1}-\cdots-l_1, t+M_i-l_{i-1}-\cdots-l_1)
\end{aligned}
$$

According to (B.4.3) the above gets transformed to:

$$IL_i(t+M_i) = IP_i(t) - D[t-l_{i-1}-\cdots-l_1, t+M_i-l_{i-1}-\cdots-l_1) \qquad \text{(B.4.7)}$$

(B.4.7) reflects Chen's (1999) second optimality condition.

Chen's third optimality concerns echelon inventory levels taken at the beginning of period $t+M_i$, namely before customer demand arises. If exactly the same procedure as above is followed with time periods shifted before occurrence of customer demand, it can also be proven that Chen's third optimality holds. This straightforward proof is here omitted for reasons of brevity.

This completes the proof that all Chen's optimality conditions hold in the *Contract Beer Distribution Game* case.

In summary, it has so far been proven that the two formulations of total inventory and backorder costs, that is the one provided by Chen (1999) and (6.10) are equivalent. In addition, it has been formally proven that all Chen's optimality conditions hold in the *Contract Beer Distribution Game* model. For these reasons, Chen's approach to estimate the *team* optimal solution could also be adapted in the case of the *Contract Beer Distribution Game*. The following functions are first recursively defined for each site i=1,…,N:

$$G_i(y) \stackrel{\text{def}}{=} E\{h_i(y - D[t - \mathcal{L}_i, t - \mathcal{L}_i + M_i]) + b_i(y - D[t - \mathcal{L}_i, t - \mathcal{L}_i + M_i])^-\} \quad \text{(B.4.8)}$$

Clearly, $G_i(y)$ is convex and has a finite minimum point, which is denoted by Y_i.

Therefore, the optimal policy that achieves the lower bound on the long-run average value of total inventory and backlog costs according to (6.10) is one where each echelon manager orders to keep his/her installation stock at the constant level Z_i^*, i=1,…,N, where $Z_i^* = Y_i$. Hence, the precise decision rule that each echelon manager i needs to follow to attain this minimum total cost is easy to implement: as soon as local installation stock reaches the optimal target level Z_i^*, echelon i needs to place an order of size equal to the last received order.

In summary, it has so far been proven that if all echelon managers i placed orders to maintain their respective optimal target levels Z_i^*, namely according to (6.10), then the minimum total inventory holding and backlog cost $IC_O(t) = \min\{IC_O(t)\}$ would be attained. From (6.1b) it can be recognised that if this policy is followed by the manufacturer, then the manufacturer's objective to minimize the production cost for the period $SC_N(t)$ would not be contradicted. According to (6.9), the only thing that still needs to be proven that if the retailer follows the optimal ordering policy that is given by relation (6.10), then his/her maximum revenues $R_1^*(t)$ would be attained.

To this end, three distinct cases can be can identified: *a*). In case the retailer does not hold any inventory at all at time period *t*, namely $IN_1(t-1) + S_2(t - L_1) \leq 0$, the retailer receives zero revenues: $R_1(t) = 0$; *b*). In case the retailer holds positive inventory, but strictly less than period's *t* demand, namely $0 < IN_1(t-1) + S_2(t - L_1) < D(t)$, then the retailer receives revenues $R_1(t) = p \cdot IN_1(t-1) + S_2(t - L_1)$, according to (6.2b); *c*). In case the retailer holds inventory that is higher in quantity than period's t demand, namely $IN_1(t-1) + S_2(t-L_1) \geq D(t)$, the retailer receives revenues $R_1(t) = p \cdot D(t)$, according to (6.2b). By comparing these three cases, it is recognised that in the first two cases the retailer has lost the opportunity to satisfy some, or any, of the customer demand, which has in turn caused him/her some loss of potential revenues. For this reason, in order to earn maximum revenues $R_1^*(t)$, the retailer needs to keep sufficient inventory in his/her warehouse to suit the third case. Nevertheless, keeping too much inventory in the retailer's warehouse would unnecessarily increase his/her own inventory holding costs and, thus, the entire supply chain's inventory costs. This comes into conflict with the first stated objective. On the contrary, constantly maintaining the optimal target level S_1^*, according to Chen (1999), would ensure that the retailer holds sufficient inventory to minimize the retailer's own backlogs, which means satisfy customer demand as much as possible. But this also maximizes the retailer's revenues $R_1(t)$, without compromising minimisation of total inventory and backlog costs.

This proof explains why in case all echelon managers i=1,...,N behaved as a perfectly rational team and placed orders to their upstream suppliers of size $oQ_i(t)$ that maintained their respective optimal target levels Z_i^*, then the *first-best case* maximum profit $P_O^*(t)$, as given by (6.9), would be attained.

WARWICK BUSINESS SCHOOL

B.5 ***The individual optimal solution*** **of the** ***Contract Beer Distribution Game***

It is assumed that each upstream supplier *i*+1 is perfectly reliable; namely, each supplier i+1 always has ample stock to ship all the quantity that was requested $M_i = l_i + L_i$ periods ago, that is $oQ_i(t - M_i)$. Under this hypothetical scenario, the inventory of each echelon i increases by the exact order quantities that echelon manager *i* placed M_i time periods before, that is irrespectively of the shipments that were actually received from the upstream supplier *i*+1. In addition, the inventory of echelon *i* decreases by the quantities that are requested by the downstream customer i-1. Following this, each echelon manager *i* always incurs the shipment (or production) cost that corresponds to his/her own ordered quantities M_i time periods ago, namely $SC_i(t) = wP_{i+1}(t - M_i) \cdot oQ_i(t - M_i)$.

First, the problem that the retailer (*i*=1) is facing is considered. The retailer needs to determine the order quantity $q_1 := oQ_1(t)$ that will maximize his/her expected net profit, which is: $\widehat{P}_1 = E\{R_1(t) - SC_1(t)$ -$IC_1(t)\}$. Since the retailer's revenues depend on his/her inventory availability and customer demand, it is easily derived that $R_1(t) = p \cdot min\{IN_1(t), D(t)\}$, while the retailer's inventory holding and backorder cost is, according to relation (6.5): $IC_i(t) = h_1 \cdot [IN_1(t)]^+ + b_1 \cdot [IN_1(t)]^-$. Therefore:

$$\widehat{P}_1 = E\{p \cdot min\{IN_1(t), D(t)\} - w_2 \cdot q_1(t - M_1) - h_1 \cdot [IN_1(t)]^+ - b_1 \cdot [IN_1(t)]^-\}$$

It follows that the retailer's expected net profit can be calculated from (6.19):

+44 (0)24 7652 4306
+44 (0)24 7652 3719
enquiries@wbs.ac.uk
www.wbs.ac.uk

THE UNIVERSITY OF WARWICK

Warwick Business School
The University of Warwick
Coventry CV4 7AL
United Kingdom

$$\widehat{P}_1(q_1) = p \cdot \int_0^{q_1} u\, f(u)du + p \cdot \int_{q_1}^{\infty} q_1\, f(u)du - w_2 \cdot q_1(t - M_1) - h_1 \cdot \int_0^{q_1} (q_1 - u)\, f^{M_1+1}(u)du - b_1 \cdot \int_{q_1}^{\infty} (u - q_1)\, f^{M_1+1}(u)du \qquad \text{(B.5.1)}$$

The perfectly rational retailer always *obeys dominance*, namely chooses the strategy that generates the highest profit and eliminates all other possible options that would produce lower expected profits. In order, thus, to maximize the expected value of his/her own profit $\widehat{P_1}$, among all available policies, the retailer is assumed to prefer a base stock policy (Chen, 1999; Cachon and Netessine, 2004; Su, 2008). Hence, the retailer's problem gets simplified to identifying the *order-up-to level* z_1^* that would maximize his/her respective individual profit, as is given by (6.19), namely:

$$\widehat{P}_1(z_1) = p \cdot \int_0^{z_1} u\, f(u)du + p \cdot \int_{z_1}^{\infty} z_1\, f(u)du - w_2 \cdot q_1(t - M_1) - h_1 \cdot \int_0^{z_1} (z_1 - u)\, f^{M_1+1}(u)du - b_1 \cdot \int_{z_1}^{\infty} (u - z_1)\, f^{M_1+1}(u)du \qquad \text{(B.5.2)}$$

It is easy to verify that (B.5.2) is concave and, hence, one can easily determine the best z_1^* from the first order newsvendor-type condition $\frac{d\widehat{P_1}\,(z_1)}{dz_1} = 0$:

$$p \cdot F(z_1^*) + (h_1 + b_1) \cdot F^{M_1+1}(z_1^*) = b_1 + p \qquad \text{(B.5.3)}$$

where f reflects the cumulative distribution function of customer demand and f^{M_1} represents the cumulative distribution function of the customer demand that has occurred over the last M_1 periods.

Next, the problem that an echelon manager *i*>1 is facing is considered. Echelon manager i needs to determine the prices $w_i = wP_i(t)$ and order quantities $q_i = oQ_i(t)$ that would maximize his/her respective profits $\widehat{P}_i = E\{R_i(t) - SC_i(t)\ \text{-}IC_i(t)\}$, where his/her respective revenues are given by

$R_i(t) = SC_{i-1}(t) = wP_i(t - M_{i-1}) \cdot oQ_{i-1}(t - M_{i-1})$, acquisition costs by $SC_i(t) = wP_{i+1}(t - M_i) \cdot oQ_i(t - M_i)$ and inventory holding costs by $IC_i(t) = h_1 \cdot [IN_1(t)]^+ + b_1 \cdot [IN_1(t)]^-$. It is evident that *i*''s decisions in time period *t* affect his/her net profit in time period t+M_i. But under study here is the expected value of net profit $\widehat{P}_i(t + M_i)$, so it would not make any difference if its projection after M_i periods is used instead:

$$\widehat{P}_i(w_i, q_i) = w_i \cdot \int_0^{q_i} u\, f_i(u)\mathrm{d}u + w_i \cdot \int_{q_i}^{\infty} q_i\, f_i(u)\mathrm{d}u - w_{i+1} \cdot q_i - h_i \cdot \int_0^{q_i}(z_i - u)\, f_i^{M_i}(u)\mathrm{d}u - b_i \cdot \int_{q_i}^{\infty}(u - q_i)\, f_i^{M_i}(u)\mathrm{d}u \ \text{ for } 1 < i \leq N$$

A perfectly rational echelon manager always *obeys dominance,* namely chooses the strategy that generates the highest profit and eliminates all other possible options that would produce lower expected profits. In order, thus, to maximize this expected value $\widehat{P}_i(w_i, q_i)$, echelon manager *i* is assumed to prefer a base stock policy, like the retailer (Chen, 1999; Cachon and Netessine, 2004; Su, 2008). Hence, echelon manager's *i* problem gets simplified to identifying the prices w_i^* and *order-up-to level* z_i^* that would maximize his/her respective individual profit, as is given by (B.5.4):

$$\widehat{P}_i(w_i, q_i) = w_i \cdot \int_0^{z_i} u\, f_i(u)\mathrm{d}u + w_i \cdot \int_{z_i}^{\infty} s_i\, f_i(u)\mathrm{d}u - w_{i+1} \cdot q_i - h_i \cdot \int_0^{z_i}(z_i - u)\, f_i^{M_i}(u)\mathrm{d}u - b_i \cdot \int_{z_i}^{\infty}(u - z_i)\, f_i^{M_i}(u)\mathrm{d}u \ \text{ for } 1 < i \leq N \quad \text{(B.5.4)}$$

where f_i reflects the probability density function of the demand that partner *i* faces (from the incoming from *i-1* order) and $f_i^{M_i}$ the probability density function of the demand that partner *i* faces over the last M_i periods.

Application of the Leibnitz's rule about differentiation under the integral sign (Flanders, 1973) for the derivatives of first order provides (B.5.5a) and (B.5.5b):

$$\frac{\partial \hat{P}_i(w_i,z_i)}{\partial w_i} = 0 \Rightarrow \int_0^{s_i} u f_i(u)du + \int_{z_i}^{\infty} z_i f_i(u)du = 0 \quad \text{for } 1 < i \leq N \tag{B.5.5a}$$

$$\frac{\partial \hat{P}_i(w_i,z_i)}{\partial z_i} = 0 \Rightarrow w_i \cdot F_i(z_i^*) + (h_i + b_i) \cdot F_i^{M_i}(z_i^*) = b_i + w_i \text{ for } 1 < i \leq N \tag{B5.5b}$$

where F_i reflects the cumulative distribution function of the demand that echelon manager *i* faces (incoming from *i-1*) and $F_i^{M_i}$ the cumulative distribution function of the demand that echelon manager *i* faces over the last M_i periods.

In order to establish whether the expected net profit of echelon manager is concave and, thus, there is a unique maximum, the second order derivative of (B.5.4) needs to be calculated, according to Leibnitz's rule. To this end, following the rule of differentiation under the integral sign (Flanders, 1973) the derivative of (6.23) is used: $\frac{\partial^2 \hat{P}_i(w_i,z_i)}{\partial {w_i}^2} = F_i(z_i^*) > 0$, which is strictly higher than 1 for *i*>1. Thus, there is a price w_i that would maximize *i*'s expected value of net profit.

Equations (B.5.5a) and (B.5.5b) combined offer the set of conditions that every echelon manager's price w_i and quantity q_i decisions (for *i*>1) should satisfy, in order to maximize his/her respective expected value of net profit.

Appendix C

The *Contract Beer Distribution Game* –

The experiments

C.1 Details about the Gaming Sessions

Sample

Volunteers were recruited from a pool of 2009 Warwick Business School students (MSc in Management, MSc in Management Science and Operational Research and MSc in Business Analytics and Consulting). There were in total 12 volunteers who registered their interest to participate in the study. Based on this level of interest, four were asked to play the role of the manufacturer (*i.e.* S_{MAN} = 4), denoted as MAN_0 to MAN_3, four the role of the wholesaler (*i.e.* S_{WHL} = 4), denoted as WHL_0 to WHL_3, and four the role of the retailer (*i.e.* S_{RET} = 4), denoted as RET_0 to RET_3. The participants were randomly assigned to each of the 12 totally available subject codes.

Computer Interface

The first three participants who were invited to the laboratory played the *Contract Beer Distribution Game* facing each other over the board. All other participants were asked to record their decisions in computerized simulation games of the *Contract Beer Distribution Game* with three serial echelons (Steckel *et al*, 2004). They worked with a computer interface that simulated the interacting partners' responses. This computer interface has been adapted from the ABS model of the *Contract Beer Distribution Game* that has been developed at the end of *Stage 1* (*i.e. Outcome 1*).

Written instructions on the required task were distributed to all participants well in advance of their allocated session so that they could get familiar with the task and the available software as quickly as possible. The instructions informed them that the product under study was beer and that it faced stochastic customer demand.

In greater detail, although they were made aware that each round's demand was independent of any previous round's, they were not informed about the exact type of distribution that customer demand followed. The main reason was to remain consistent with Sterman's (1989, 1992) original *Beer Distribution Game*'s set-up. The participants were also instructed to make decisions that, to their best knowledge, would make the entire aggregate channel as highly profitable as possible. But in order to reflect real supply chain interactions as accurately as possible, participants were not provided information about the aggregate channel profit that was realised at the end of each round.

The instructions that were distributed to the subjects who played the role of the retailer are presented in Appendix C.2, while the instructions that were distributed to the subjects who played the role of the wholesaler and manufacturer are attached in Appendix C.3 and C.4 respectively. Apart from written instructions, the participants could address questions both before the start of the session and during its course. The game could not be re-started, once it had began.

Customer Demand

The retailers were presented with a customer demand that followed the step-up function of Sterman's (1989, 1992) original *Beer Distribution Game*: namely, it amounted to 4 cases of beer for the first 4 periods, subsequently (*i.e*. at time period 5) it increased to 8 cases of beer and thereafter remained fixed at 8 cases of beer (Kaminsky and Simchi-Levi, 1998; Kimbrough *et al*, 2002; Hieber and Hartel, 2003; Nienhaus *et al*, 2006; Steckel *et al*, 2004). The main reason that the human retailers were not presented with the customer demand that is discussed in *Chapter 6* (*i.e*. normal distribution truncated at zero with μ=5 and σ = 2) is to simplify all participants' decision task as much as possible and protect them from the complications that might be inherent with continuous demand distributions (Bearden and Rapoport, 2005). The reader should, nevertheless, be reminded at this point that the ABS model of the *Contract Beer Distribution Game* that has been used to infer all conclusions is built on the assumption of the truncated at zero normal distribution, because this more closely reflects reality, especially in cases where limited information about the distribution of customer demand is available (Gallego and Moon, 1993; Son and Sheu, 2008; Ho *et al*, 2009). The last point noteworthy of further attention is that only the participants who were asked to act as the retailer were presented with information about true customer demand. The reasons that the participants who played all other roles did not have access to this information were two-fold: *first*, customer demand did not have any impact on their respective profits, according to the corresponding relations of type (6.6); s*econd*, this choice was consistent with Sterman's (1989, 1992) original *Beer Distribution Game* set-up.

Duration of Sessions

The total duration of each session was restricted to 2 hours, so that the subjects would maintain their level of interest and concentration over the course of the game. In order to give participants some time to get used to their new roles, the first 10 rounds were used as trial periods. The participants were informed in advance about the fact that these rounds were only meant for their practice and would not count towards the final outcome (*i.e*. 'dry-run' periods: Friedman and Sunder, 1994, pg. 78). In total, each game ran for N=90 consecutive rounds for each participant (that is, including the trial periods), but the participants were not aware of the exact session's duration, so that end-of-game effects could be eliminated (Croson and Donohue, 2003; Steckel *et al*, 2004; Croson and Donohue, 2005; 2006; Wu and Katok, 2006; Croson *et al*, 2007). In order to comply with the minimum sample size requirements and ensure sufficient statistical power, more than 10 samples for each *decision attribute* were collected (Weisberg, 2005; Hair *et al*, 2006), namely 7x10 for price decisions and 8x10 for order quantity decisions, as given by relations (7.1) and (7.2) respectively. Each gaming session was followed by debriefing and a post-game interview. This interview was of open form; its main aim was to strongly encourage participants to express in words their feelings and thoughts over the course of the game, as well as explain their underlying mental decision making process. Appendix C.5 provides an illustrative example of what constituted the basis of the conversation that took place. The list of questions that is therein presented is by no means exhaustive, but only serves for illustrative purposes.

Financial Incentives

The participants were not offered any financial incentives because there was no budget available to this end. Nevertheless, it remains unclear whether providing financial incentives would have a significant impact on the inferred decision making strategies (Smith and Walker, 1993; Camerer and Hogarth, 1999; Croson, 2002).

Interacting Partners

The previous laboratory investigations of the *Beer Distribution Game*, as reviewed in *Sub-section 2.2.2*, force subjects to play interactively either with each other (Croson and Donohue, 2003; Steckel *et al*, 2004; Croson and Donohue, 2005; Croson and Donohue, 2006; Nienhaus *et al*, 2006; Wu and Katok, 2006;

Croson *et al*, 2007) or with automated responses that simulate all the other roles (Kaminsky and Simchi-Levi, 1998; Hieber and Hartel, 2003). Nevertheless, the common drawback of these approaches is that participants are asked to interact with exactly one set of pre-allocated partners whose responses could be either pre-determined (*i.e*. interact with a predetermined sequence of decisions) or specified live, that is during the course of the game (*i.e*. interact with a person or a predetermined model). But people might adopt completely different strategies, when they are given different stimuli. Following this, the main idea is to extend as much as possible the range of responses that are presented to each human subject, so that their adopted strategies would depend as little as possible on their pre-allocated partners. In order to overcome this same problem, in the case of the *Newsvendor Problem* setting all participants were presented with exactly the same series of scenarios that entailed all possible partners' responses, with exactly the same order (*s. Sub-section 4.3.2*). The reason that this approach could not be applied in the case of the *Contract Beer Distribution Game* setting is that the setting is a lot more complicated and, so, the full range of all possible human *reaction*s could not be predicted with certainty.

That is why an alternative approach is used for the *Contract Beer Distribution Game*. In order to improve the accuracy of subjects' deduced decision making strategies, each subject needs to be assigned to more than one interaction (or else treatment factor combinations or else 'supply chain configurations'). However, participants could not be asked to visit the laboratory more than once and also could not be asked to participate in sessions that would exceed the limit of 2 hours. Otherwise, their levels of interest and concentration might decline (Camerer, 1995; Duffy, 2006). The result is that a dual objective has to be satisfied: participants need to be allocated to multiple supply chain configurations, yet within a single and limited in duration session. This is accomplished by asking participants to interact with the ABS version of the *Contract Beer Distribution Game*, where the two remaining roles' responses are simulated according to their respective fitted decision models $f_i^{wP(t)}$ and $f_i^{oQ(t)}$. In this way, all human participants could be assigned to any number of interactions between the decision models $f_i^{wP(t)}$ and $f_i^{oQ(t)}$that had already been inferred, and to interact with any number of such models that had previously been inferred.

Following this, the remaining questions are two-fold: *first*, which were the specific *supply chain configurations* to which each human subject was assigned and *second*, which was the order by which the different participants were invited to the laboratory. Answers to both of these questions were provided by the experimental design named 'Latin Hypercube Design' (McKay *et al*, 1979). Table C.1.1 outlines the gaming sessions that were conducted, according to the *Latin Hypercube Experimental Design* of k=3 treatment factors (*i.e*. *MAN*, *WHL*, *RET*) at s=4 levels each. More details on the exact way that this experimental protocol derived from the above *Latin Hypercube Design* (4^2, *3*) are provided in Appendix C.6.

The grey shaded row in Table C.1.1 (*i.e*. *Session No*. *1*) that is separated from the remaining rows with a dashed line represents the "base" session that was required to let the iteration between gaming sessions and inference of decision making strategies begin. To this end, one decision model needed to be deduced for each available role: one for the manufacturer (MAN_0), one for the wholesaler (WHL_0) and one for the retailer (RET_0). This is why the subjects who had been randomly assigned to the subject codes MAN_0, WHL_0 and RET_0 were asked to participate in the study first. Since there were no pre-deduced decision models for these subjects to interact with, they were asked to play with each other interactively over the board. Once the decisions of MAN_0, WHL_0 and RET_0 were recorded, the adequate combinations of decision models that would determine their corresponding $f_i^{wP(t)}$ and $f_i^{oQ(t)}$, according to types (7.1) and (7.2), were inferred. The exact approach that was used to this end is discussed in some detail in *Sub-section 7.3.3*.

Table C.1.1: The Experimental Protocol

Session No.	***Participant*** (*i.e.* Decision Making Strategy –ies- to be determined)	***Supply Chain Configuration*** (*i.e.* Known Decision Making Strategies)
1	$\boldsymbol{MAN_0, WHL_0, RET_0}$	---
2	$\boldsymbol{WHL_2}$	MAN_0, RET_0
3	$\boldsymbol{RET_3}$	WHL_2, MAN_0
4	$\boldsymbol{RET_1}$	MAN_0,WHL_2 MAN_0,WHL_0
5	$\boldsymbol{MAN_1}$	WHL_2, RET_1
6	$\boldsymbol{WHL_3}$	MAN_0, RET_0 MAN_1, RET_0 MAN_1,RET_1
7	$\boldsymbol{WHL_1}$	MAN_1,RET_0
8	$\boldsymbol{RET_2}$	MAN_1, WHL_0
9	$\boldsymbol{MAN_2}$	WHL_1, RET_2 WHL_1, RET_0 WHL_0, RET_3
10	$\boldsymbol{MAN_3}$	WHL_1, RET_2 WHL_0, RET_1 WHL_0, RET_3

The participants who had been assigned to all the other subject codes were asked to interact with the computer interfaces that have been described in an earlier paragraph of this sub-section. Table C.1.1 also denotes that in the second gaming session (*i.e Session No. 2*) the decisions of the participant, who had been assigned the code WHL_2, were recorded. This participant was asked to interact with the fitted decision models of MAN_0 and RET_0. The result of this second gaming session was that the decision models $f_i^{wP(t)}$ and $f_i^{oQ(t)}$ that corresponded to WHL_2 could be inferred. Subsequently, in the third gaming session (*i.e Session No. 3*) the decisions of the participant, who had been assigned the code RET_3, were recorded. This participant was in turn asked to interact with the the fitted decision models of MAN_0 and WHL_2. Following this third session, the decision model $f_i^{oQ(t)}$ that corresponded to RET_3 was deduced.

In the next, fourth, gaming session (*i.e Session No. 4*) the decisions of the participant, who had been assigned the code RET_1, were recorded. This participant was asked to interact with two different *supply chain configurations*: namely, the MAN_0 and WHL_2 interaction and the MAN_0 and WHL_0 interaction. The only difference between this gaming session that comprised of two different *supply chain configurations* and the previous gaming sessions that only included one *supply chain configuration* was that the sample size of total observations (N=90) was equally split over the two *supply chain configurations* that were under study, with 5 trial periods applied at the beginning of each. At each beginning, the participants were informed that they would be interacting with a different set of partners and the game was restarted. The remaining gaming sessions (*Sessions No. 5 - 10)* proceeded in exactly the same way.

Table C.1.1 indicates how 50% of the gaming session that were performed consisted of multiple supply chain configurations. Since the experimental protocol that was followed derived from the Latin Hypercube Experimental Design, it satisfied the first objective that was set: namely, allocate participants to multiple supply chain configurations. Furthermore, Table C.1.1 demonstrates how 17 different supply chain configurations were possible within, in total, 10 gaming sessions. This was accomplished by running multiple supply chain configurations within a single gaming session. In this way, no human subjects were asked to participate in more than one gaming sessions. Because of the way that the sampling observations were split over the different supply chain configurations that were explored in each gaming session, the session durations were also even. The result was that the second objective that was required from the experimental protocol was also successfully addressed.

C.2 Debriefing and End-of-Game interview

We would like to take this opportunity to warmly thank you for having taken the time to participate in the “Beer Game”. Without your help this research would not have been possible.

Now that the game has ended it is time for you to think about your feelings at the course of the game:

- How did you feel (*i.e*. calm, collected, in control or perhaps frazzled, frustrated or at the mercy of events)?
- What did you think about your automated partners (did you think they showed great skill, they had your best interests at heart, or they fouled up)?
- Was there any special factor that caused any great difficulties to your decision making?
- Was there any factor that you considered highly significant to your decisions?
- Did you find any shortcut that was of any help to your decision making process?
- Did you feel that you could effectively use your prices to control the incoming order quantities that you received from your customer?
- Was there any additional piece of information that you found missing from the game set-up?

A general observation that has been made from the “Beer Game” is that irrespectively of your aforementioned feelings, performance of teams is always poor: Even though people from diverse backgrounds may play, similar patterns always occur. What is even more important, no way has yet been established to teach and help participants to learn to do better. The ultimate reason is that it is the structure of our management processes that creates their decision making behaviour.

If any of the above learning outcomes are of particular interest to you or you have any ideas about ways to improve the “Beer Game" supply chain, plz. do not hesitate to contact us. We are looking forward to hearing from you and discussing the above issues in greater detail.

Sincerely thanking you again,

On behalf of the research team:

Stavrianna Dimitriou

Doctoral Researcher

T +44 (0)24 7652 4306
F +44 (0)24 7652 3719
E enquiries@wbs.ac.uk
W www.wbs.ac.uk

Warwick Business School
The University of Warwick
Coventry CV4 7AL
United Kingdom

Research Supervisors:

***Prof*. Stewart Robinson**
Professor of Operational Research
Associate Dean for Specialist Masters Programmes
Author of the book: “Simulation - The Practice of Model Development and Use” by John Wiley and Sons (2003)

***Dr*. Kathy Kotiadis**
Assistant Professor of Operational Research

C.3 Retailer's Instructions

In today's study you will participate in the "Beer game": a role playing simulation designed to investigate management decision making behaviours. There is no beer in the beer game and the game does not promote drinking. Indeed, you will be working with your partners to help the team to which you have been assigned to make the maximum total, system-wide profits possible. You will participate in the game as the Retailer.

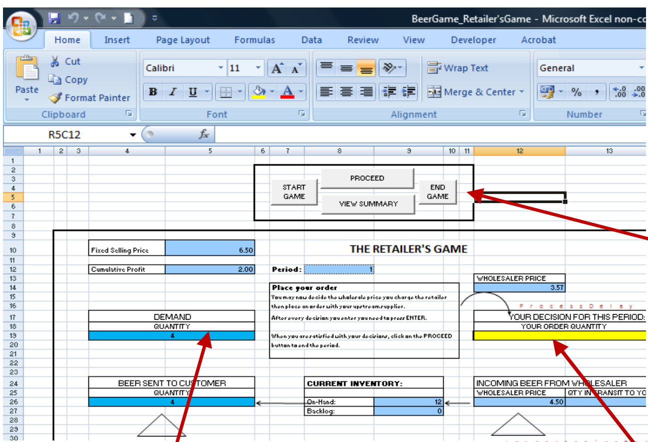
The Game Scenario

There are three members in each supply chain configuration: a Manufacturer, a Wholesaler and a Retailer. You will be the retailer; namely you will be responsible for serving end consumers. You are supplied the cases of beer that you order by the wholesaler, who is, in turn, supplied by the manufacturer.

Each round of the game represents a week. Any week's demand is completely independent of the demand of any earlier week. Every week you have to decide: how many cases of beer you want to order.

You pay £0.50 for every case of beer that you keep in your inventory for one week. You also have to pay £1 for every case of beer demanded by your customers, but which you are not able to provide (Backlog cost). You receive £6.5 for every case of beer that you sell to your customers (This is your selling price).

Your Computer Screen



The Control Panel

1. Click on START GAME to start the game.
2. After you have entered your decisions for each round of the game, click on PROCEED.
3. In case you wish to view a summary of all previous periods' results, click on VIEW SUMMARY.
4. To finish the game click on END GAME.

Previous Round's Outcome

You are given the information from the previous period's outcome in the blue cells.

Your decision

You need to enter your decision for every round of the game in the yellow cell.

Instructions of the Game

***Step 1*: **Click on START GAME

For every round of the game (until your facilitator informs you of the end of the game) repeat the following sequence of steps:

Step 2: Observe any of the information that is given to you in the blue coloured cells that you feel is relevant to the decisions you have to make:

Cumulative Profit: The total profit you have realised until this round of the game (in £'s). It includes: *i*. the earnings you just received from your customer, *ii*. the cost you have to pay to your wholesaler for the shipment you just received, *iii*. your weekly inventory cost and *iv*. your weekly backlog cost. All weekly profits are aggregated to give the cumulative profit.

Wholesaler Price: The price that your wholesaler is currently charging you for every case of beer that he/she delivers to you.

Previous Period's Order Quantity: The order quantity that you placed in last period to your wholesaler.

Incoming Beer from Wholesaler – This is the shipment that you now received from your wholesaler. He/she had shipped this quantity two weeks earlier.

Wholesaler Price: The price that you had agreed to pay your wholesaler for every case of beer that was delivered to you.

Quantity In Transit: The quantity of incoming beer (in cases of beer) that is currently in transit to your warehouse.

On-Hand Current Inventory: The number of cases of beer that you currently have available in your warehouse.

Backlog: The number of cases of beer requested by your customer but you did not have sufficient inventory left to deliver.

Beer Sent to Retailer - This is the shipment that you just sent to your customer. He/She will be able to receive this shipment two weeks later.

Quantity: The number of cases of beer that you have now shipped to your customer.

Demand– This is the demand that you are now facing.

Quantity: The number of cases of beer that you now have to ship to your customer.

Step 3: Decide your order quantity (yellow coloured cell). Press ENTER.

Step 4: Click on PROCEED.

Step 5: Repeat the above sequence of steps for the next round of the game.

If, at any point during the game, you wish to view a summary of the results acquired, then you should click on VIEW SUMMARY.

When your facilitator informs you of the end of the game, then you should make your decisions for the last round of the game and click on END GAME.

Your facilitator will be constantly with you to guide you and assist you in any questions you might have. Plz. do not hesitate to ask any clarification you might feel you need!

Good Luck!!

C.4 Wholesaler's Instructions

In today's study you will participate in the "Beer game": a role playing simulation designed to investigate management decision making behaviours. There is no beer in the beer game and the game does not promote drinking. Indeed, you will be working with your partners to help the team to which you have been assigned to make the maximum total, system-wide profits possible. You will participate in the game as the Wholesaler.

The Game Scenario

There are three members in each supply chain configuration: a Manufacturer, a Wholesaler and a Retailer. You will be the wholesaler; namely you will be responsible for supplying the retailer. Your customer, the retailer, in turn, serves end consumers. You are supplied the cases of beer that you order by the manufacturer.

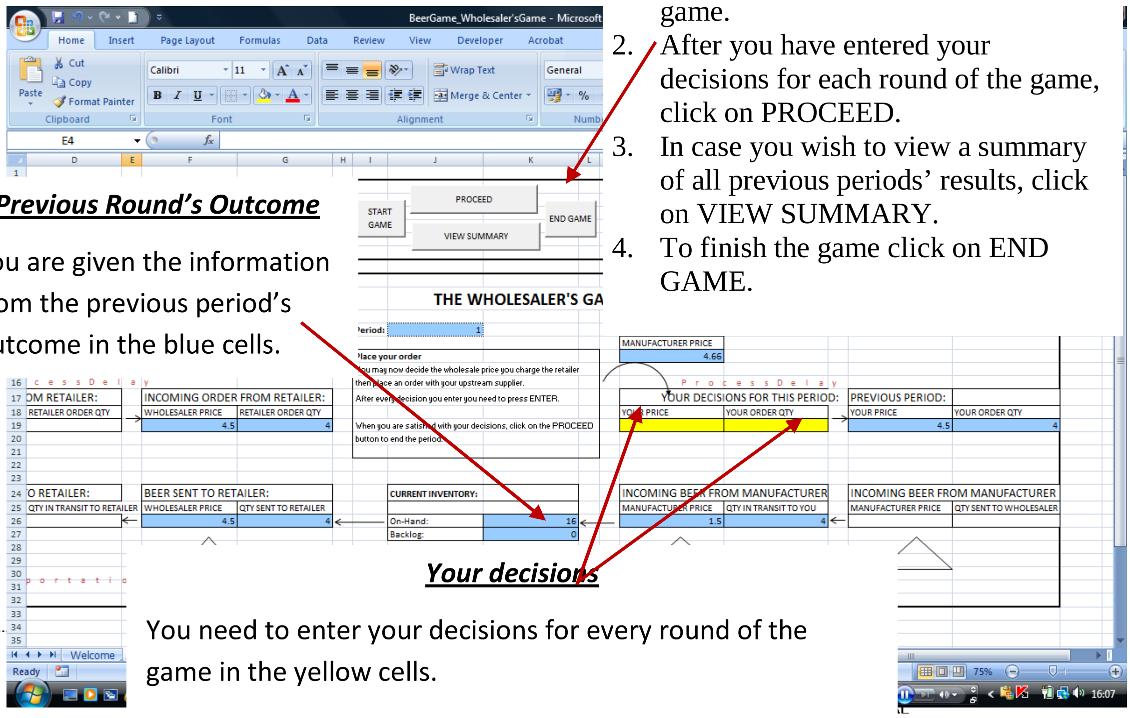
Each round of the game represents a week. Every week you have to decide: *i*. how much you want to charge your retailer for every case of beer that you deliver to him and *ii*. how many cases of beer you want to order.

You pay £0.50 for every case of beer that you keep in your inventory for one week. You also have to pay £1 for every case of beer requested by your retailer, but which you are not able to supply.

Your Computer Screen

The Control Panel

1. Click on START GAME to start the game.
2. After you have entered your decisions for each round of the game, click on PROCEED.
3. In case you wish to view a summary of all previous periods' results, click on VIEW SUMMARY.
4. To finish the game click on END GAME.



Previous Round's Outcome

You are given the information from the previous period's outcome in the blue cells.

Your decisions

You need to enter your decisions for every round of the game in the yellow cells.

Instructions of the Game

***Step 1*:** Click on START GAME

For every round of the game (until your facilitator informs you of the end of the game) repeat the following sequence of steps:

Step 2: *Observe any of the information that is given to you in the blue coloured cells that you feel is relevant to the decisions you have to make:*

Cumulative Profit: The total profit you have realised until this round of the game (in £'s). It includes: *i.* the earnings you just received from your retailer, *ii.* the cost you have to pay to your manufacturer for the shipment you just received, *iii.* your weekly inventory cost and *iv.* your weekly backlog cost. All weekly profits are aggregated to give the cumulative profit.

Manufacturer Price: The price that your manufacturer is currently charging you for every case of beer that he/she delivers to you.

Previous Period's Price: The price that you decided in last period to charge your retailer.

Previous Period's Order Quantity: The order quantity that you placed in last period to your manufacturer.

Incoming Beer from Manufacturer – This is the shipment that you now received from your manufacturer. He/She had shipped this quantity two weeks earlier.

Manufacturer Price: The price that you had agreed to pay your manufacturer for every case of beer that was delivered to you.

Quantity In Transit: The quantity of incoming beer (in cases of beer) that is currently in transit to your warehouse.

On-Hand Current Inventory: The number of cases of beer that you currently have available in your warehouse.

Backlog: The number of cases of beer requested by your retailer but you did not have sufficient inventory left to deliver.

Beer Sent to Retailer - This is the shipment that you now sent to your retailer. He/she will be able to receive this shipment two weeks later.

Wholesaler Price: The price you had agreed with your retailer to be paid for every case of beer that you would deliver to him.

Retailer Order Quantity: The number of cases of beer that you have now shipped to your retailer.

Incoming Order from Retailer – This is the order that you now received from your retailer. He/She had placed this order one week earlier.

Wholesaler Price: The price you had agreed with your retailer to be paid for every case of beer that you would deliver to him.

Retailer Order Quantity: The number of cases of beer that you now have to ship to the retailer.

***Step 3*:** Decide your wholesaler price (first yellow coloured cell). Press ENTER.

***Step 4*:** Decide your order quantity (second yellow coloured cell). Press ENTER.

***Step 5*:** Click on PROCEED.

Step 6: Repeat the above sequence of steps for the next round of the game.

If, at any point during the game, you wish to view a summary of the results acquired, then you should click on VIEW SUMMARY.

When your facilitator informs you of the end of the game, then you should make your decisions for the last round of the game and click on END GAME.

Your facilitator will be constantly with you to guide you and assist you in any questions you might have. Plz. do not hesitate to ask any clarification you might feel you need!

Good Luck!!

C.5 Manufacturer's Instructions

In today's study you will participate in the "Beer game": a role playing simulation designed to investigate management decision making behaviours. There is no beer in the beer game and the game does not promote drinking. Indeed, you will be working with your partners to help the team to which you have been assigned to make the maximum total, system-wide profits possible. You will participate in the game as the Manufacturer.

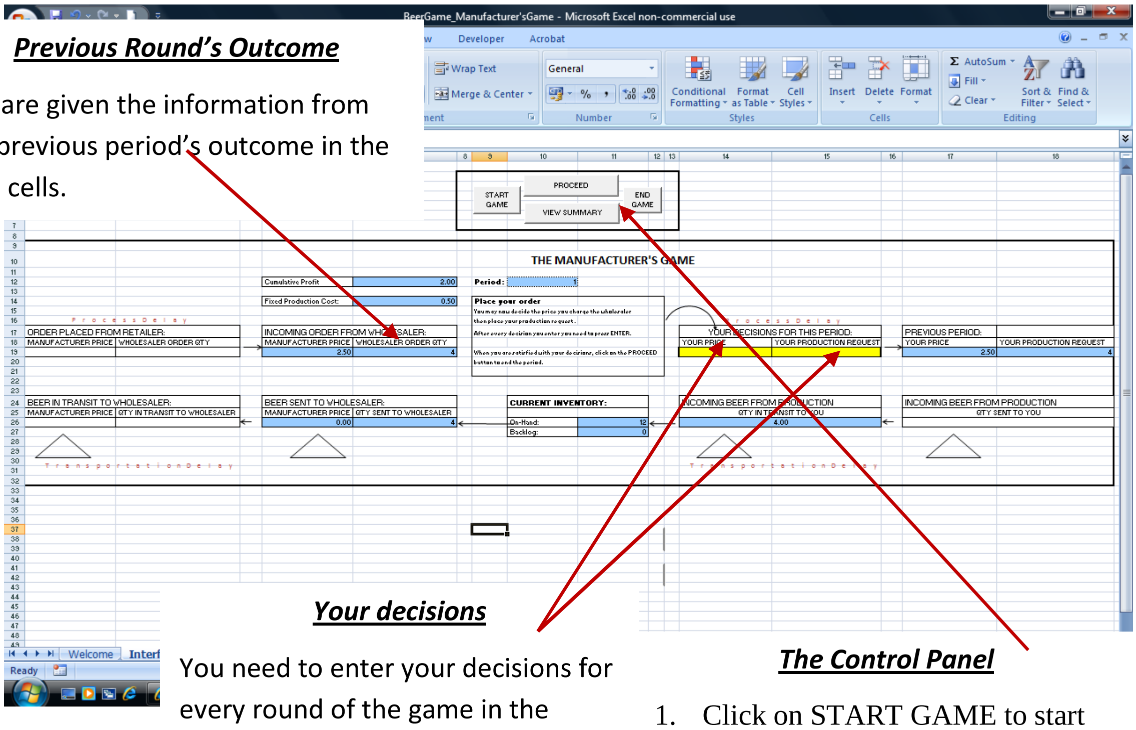
The Game Scenario

There are three members in each supply chain configuration: a Manufacturer, a Wholesaler and a Retailer. You will be the manufacturer; namely you will be responsible for producing and supplying to the wholesaler the cases of beer that he/she orders. Your customer, the wholesaler, is responsible for supplying the retailer. You, as the manufacturer, face no capacity constraints and you can assume that you are able to produce as much as you order.

Each round of the game represents a week. Every week you have to decide: *i*. how much you want to charge your wholesaler for every case of beer that you deliver to him and *ii*. how many cases of beer you want to order.

For every case of beer that you produce you pay £0.50 (fixed production cost). You also pay £0.50 for every case of beer that you keep in your inventory for one week. Last, you pay £1 for every case of beer requested by your wholesaler, but which you are not able to supply (demand in backlog).

Your Computer Screen



Previous Round's Outcome

You are given the information from the previous period's outcome in the blue cells.

Your decisions

You need to enter your decisions for every round of the game in the yellow cells.

The Control Panel

1. Click on START GAME to start the game.
2. After you have entered your decisions for each round of the game, click on PROCEED.
3. In case you wish to view a summary of all previous periods' results, click on VIEW SUMMARY.
4. To finish the game click on END GAME.

Instructions of the Game

Step 1: Click on START GAME

For every round of the game (until your facilitator informs you of the end of the game) repeat the following sequence of steps:

Step 2**:** Observe any of the information that is given to you in the blue coloured cells that you feel is relevant to the decisions you have to make:

Cumulative Profit: The total profit you have realised until this round of the game (in £'s). It includes: *i*. the earnings you just received from your wholesaler, *ii*. the cost you have to incur for producing your requested cases of beer, *iii*. your weekly inventory cost and *iv*. your weekly backlog cost. All weekly profits are aggregated to give the cumulative profit.

Fixed Production Cost: The fixed production cost you have to incur for every case of beer that you produce.

Previous Period's Price: The price that you decided in last period to charge your wholesaler.

Previous Period's Production Request: The production request that you placed in last period.

Incoming Beer from Production – This is the batch that you now received from production. You had placed a production request for this particular order three weeks ago.

Quantity In Transit: The quantity of incoming beer (in cases of beer) that is currently in transit to your warehouse.

On-Hand Current Inventory: The number of cases of beer that you currently have available in your warehouse.

Backlog: The number of cases of beer requested by your wholesaler but you did not have sufficient inventory left to deliver.

Beer Sent to Retailer - This is the shipment that you now sent to your wholesaler. He/she will be able to receive this shipment two weeks later.

Wholesaler Price: The price you had agreed with your retailer to be paid for every case of beer that you would deliver to him.

Retailer Order Quantity: The number of cases of beer that you have now shipped to your retailer.

Incoming Order from Wholesaler – This is the order that you now received from your wholesaler. He/she had placed this order one week earlier.

Manufacturer Price: The price you had agreed with your wholesaler to be paid for every case of beer that you would deliver to him.

Wholesaler Order Quantity: The number of cases of beer that you now have to ship to the wholesaler.

***Step 3*:** Decide your manufacturer price (first yellow coloured cell). Press ENTER.

***Step 4*:** Decide your production request (second yellow coloured cell). Press ENTER.

***Step 5*:** Click on PROCEED.

Step 6: Repeat the above sequence of steps for the next round of the game.

If, at any point during the game, you wish to view a summary of the results acquired, then you should click on VIEW SUMMARY.

When your facilitator informs you of the end of the game, then you should make your decisions for the last round of the game and click on END GAME.

Your facilitator will be constantly with you to guide you and assist you in any questions you might have. Plz. do not hesitate to ask any clarification you might feel you need!

Good Luck!

C.6 Details about the Experimental Protocol

The *Latin Hypercube Design* (LHD) was specifically developed by McKay *et al*. (1979) to sample responses not osnly on the edges of the hypercube of the area created by all possible combinations of input factors, but also in its interior. It is a type of stratified sampling, where each level of an input factor appears exactly once and each possible factor level combination has an equal probability of occurrence (Mason *et al*, 2003; Fang *et al*, 2006; Kleijnen, 2008).We explain our reasoning for choosing LHD to base the experimental protocol in the paragraphs that follow.

Since we were interested in assigning subjects to multiple configurations, we sought for an experimental design that would sample on the widest range of possible factor levels (*i.e*. space filling property: Santner *et al*, 2003; Kleijnen *et al*, 2005). Hence, among all evaluation criteria of experimental designs suggested by Kleijnen *et al*. (2005) space filling revealed as the most important for our purposes. From the variety of designs that was applicable to our needs, as proposed by Sanchez and Lucas (2002), Kleijnen *et al*. (2005) and Sanchez (2005a), LHD was specifically designed to address space filling. Hence, it derived as the best suited, mostly for the three following reasons: a). it forced minimal assumptions on response surfaces; b). it enabled efficient sampling over a wide range of possible input factor levels and c). it ignored interaction and quadratic terms (of the factor levels) that were outside of the interests of our study.

We now describe the steps that we had to follow to construct the Latin Hypercube Sample for k treatment factors at s levels each (Santner *et al*, 2003; Fang *et al*, 2006; Kleijnen, 2008).

Step 1: *Take k independent permutations of integers 1,...,s* $\pi_j(1), \dots, \pi_j(s)$ *for j=1,..., k.*

Step 2.1**:** Take *k* independent permutations of integers 1,..., *s* $\pi_j(1), \dots, \pi_j(s)$ for *j*=1,..., *k*.

Step 2.2**:** Pair these *k* independent permutations with the previous *k* permutations to create *s* pairs of factor levels.

Step 3.1**:** Take *k* independent permutations of integers 1,..., *s* $\pi_j(1), \dots, \pi_j(s)$ for *j*=1,..., *k*.

Step 3.2**:** Combine these *k* independent permutations with the previous *s* pairs of factor levels to create s^2 triplets of factor levels.

This algorithm clearly explains why it dictated the need for s^2=16 design points or supply chain configurations for *k* factors at *s* levels each. This is why it is denoted as *LHD*(s^2, *k*).

By using the spreadsheet of Sanchez (2005b), based on Cioppa and Lucas' (2007) recommendations, we composed the list of 16 design points (D.P.) presented in Table C.6.1 that follows. At this point we would like to remind the reader that the following 16 supply chain configurations were conducted <u>in addition to</u> and <u>following</u> the initial BASE configuration (MAN_0, WHL_0, RET_0), in which all participants were asked to play the game over the board. This is why this BASE session is illustrated within a row, separated with a dashed line from the remaining rows of Table C.6.1. The design points (D.P.) that are listed in Table C.6.1 satisfied all the above specifications of *LHD*(s^2, *k*).

Table C.6.1: The Design Points of the Experimental Design $LHD(s^2, k)$

D.P.	***MAN***	***WHL***	***RET***
0	MAN_o	WHL_0	RET_o
1	MAN_o	WHL_2	RET_o
2	MAN_o	WHL_2	RET_3
3	MAN_o	WHL_2	RET_1
4	MAN_o	WHL_0	RET_1
5	MAN_1	WHL_2	RET_1
6	MAN_o	WHL_3	RET_o
7	MAN_1	WHL_3	RET_o
8	MAN_1	WHL_3	RET_1
9	MAN_1	WHL_1	RET_o
10	MAN_1	WHL_0	RET_2
11	MAN_2	WHL_1	RET_2
12	MAN_2	WHL_1	RET_o
13	MAN_2	WHL_0	RET_3
14	MAN_3	WHL_1	RET_2
15	MAN_3	WHL_0	RET_1
16	MAN_3	WHL_0	RET_3

Each supply chain configuration was conducted in the exact order that Table C.6.1 presents. Each new participant was each time asked to make decisions on behalf of the only unknown factor level. For example, following the BASE session and after the decision making strategies of MAN_0, WHL_0 and RET_0 had been deduced, WHL_2 came to the laboratory to play the role of the wholesaler. The participant who had been randomly assigned the role of WHL_2 was asked to interact with the supply chain configuration MAN_0, RET_0, because these were the only manufacturer and retailer decision making strategies that had been determined so far. The design point 2 of our experimental design forced the supply chain configuration MAN_0, WHL_2, RET_3. From the above combination of factor levels the only unknown corresponded to the role of the retailer (RET_3). For this reason, the participant who was randomly assigned the role of RET_3 was asked to interact with the supply chain configuration MAN_0, WHL_2. We proceeded in exactly the same way. Table C.6.2 outlines the gaming sessions that were conducted, along with the corresponding supply chain configurations.

Table C.6.2: The Experimental Protocol

Session No.	**D.P.** (*s*. Table C.5.1)	***Supply Chain Configuration*** (*i.e*. Known Decision Making Strategies)	***Participant*** (*i.e*. Decision Making Strategy –ies- to be determined)
1	0	---	MAN_0, WHL_0, RET_0
2	1	MAN_o, RET_o	WHL_2
3	2	MAN_o, WHL_2	RET_3
4	3	MAN_o, WHL_2	RET_1
	4	MAN_o, WHL_0	
5	5	WHL_2, RET_1	MAN_1
6	6	MAN_o, RET_0	WHL_3
	7	MAN_1, RET_0	
	8	MAN_1, RET_1	
7	9	MAN_1, RET_0	WHL_1
8	10	MAN_1,WHL_0	RET_2
9	11	WHL_1, RET_2	MAN_2
	12	WHL_1, RET_0	
	13	WHL_0, RET_3	
10	14	WHL_1, RET_2	MAN_2
	15	WHL_0, RET_1	
	16	WHL_0, RET_3	

It is clear from Table C.6.2 that by conducting 10 gaming sessions and, therefore, asking each subject to participate only once, we managed to sample 17 different supply chain configurations. Nevertheless, according to the experimental protocol applied, not all participants needed to participate in multiple supply chain configurations; approximately only 50% did: namely, the ones who participated to sessions 4, 6, 9 and 10. There was no other difference between these sessions and the remaining 5 sessions (2, 3, 5, 7 and 8) apart from the fact that the overall duration of the game (in rounds or time periods) was split over the total number of supply chain configurations, so that the total duration of the session (in actual minutes) would not be significantly different across different configurations. The reason for this specification was that all subjects would remain equally concentrated and interested over the course of the session. In this regard, the total duration of all sessions was kept to about 2 hours, including debriefing and brief interview with each participant at the end. Participants were kindly asked not to share any of this information with other students that would subsequently participate in the study.

In summary, by iterating between: (*i*) recording participants' decisions; (*ii*) deducing decision models; and (*iii*) using the decision models for subsequent gaming sessions, this approach has three main advantages over the usual, sequential approaches:

- it eliminates the risk of deducing decision making strategies that are overly sensitive to specific role allocation and supply chain configurations;
- it reduces the time requirements of each experimental session, because decision making delays from different players do not accumulate (*i.e*. each subject played the *Contract Beer Distribution Game* on his/her own pace without any effect on other players' decisions);
- it enables gradually building of and, therefore, assuring the validity of the inferred decision models. The exact approach that was followed to validate the inferred decision models and assure that they closely followed the decisions that were truly observed during the course of the simulation game is described in *Sub-section 7.3.3* that discusses the inferred decision models.

C.7 Testing the Assumptions of Multiple Linear Regression

The paragraphs that follow discuss the elaborate tests that were conducted to test whether all dependent and independent variables of relations (7.5) and (7.6) satisfied the linearity, normality, and homo-skedasticity requirements of multiple linear regression (Weisberg, 2005; Hair *et al*, 2006; Fox, 2008). The corresponding scatterplot matrices were only used as a first indicator to this end. Figure C.7.1 illustratively presents the scatterplot matrix of $i_s = MAN_0$ dependent (*i.e. decision variable*) and independent (*i.e. decision attributes*) variables, following relations (7.5) and (7.6) above, as recorded in the *Gaming Session No. 1* of Table 7.8. This particular example is only presented for illustration purposes, while exactly the same testing procedure was also applied to all remaining subjects' datasets of decisions. But since the scatterplot matrix of Figure C.7.1 is unclear and, therefore, hard to be distinguished, for clarity reasons the scatterplots of the dependent variable $\langle oQ(t)\rangle_{MAN_0}$ with the independent variables $< wP_i(t-1) >_{MAN_0}$ and $< \sum_{j=1}^{t} P_i(j) >_{MAN_0}$ are also attached in Figures C.7.2 and C.7.3 that follow. In the paragraphs that follow the scatterplot matrix of Figure C.7.1 and the separate sceatteplots of Figures C.7.2 and C.7.3 are discussed.

a) *Linearity:* The 1st column of Figure's C.7.1 scatterplot matrix reveals the existence of a potentially non-linear relationship between any change in the *decision variable* price $\langle wP(t)\rangle_{MAN_0}$and the *decision attributes*: previous order quantity $oQ_i(t-1)$; shipment in transit $S_{i+1}(t-L_i+1)$; incoming order quantity $oQ_{i-1}(t-l_{i-1})$ and cumulative profit $\sum_{j=1}^{t} P_i(j)$.

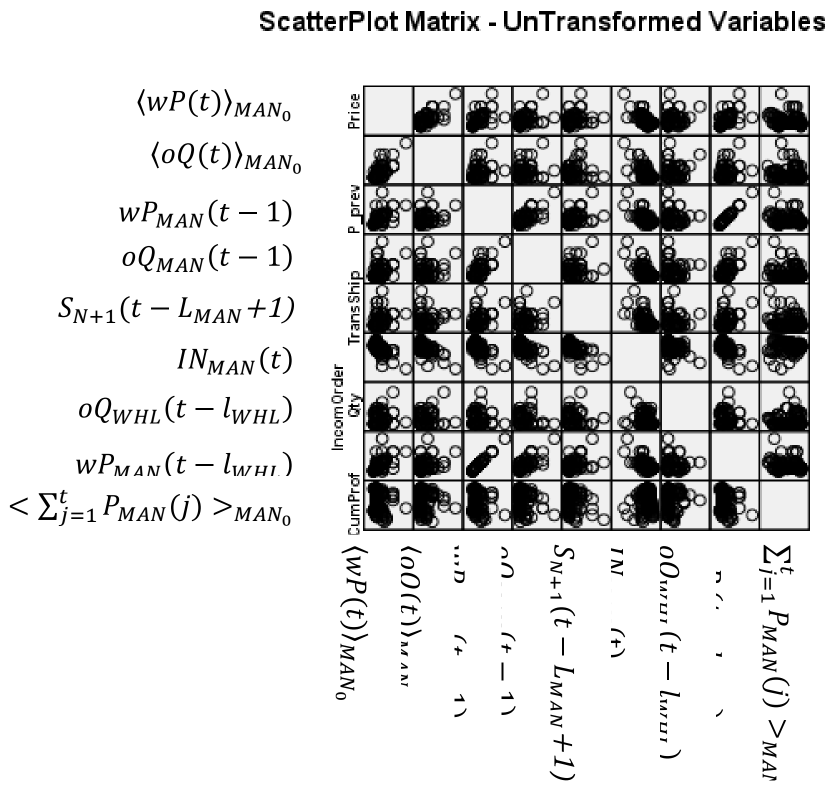


Figure C.7.1: Scatterplot Matrix of MAN_0 dependent and independent variables

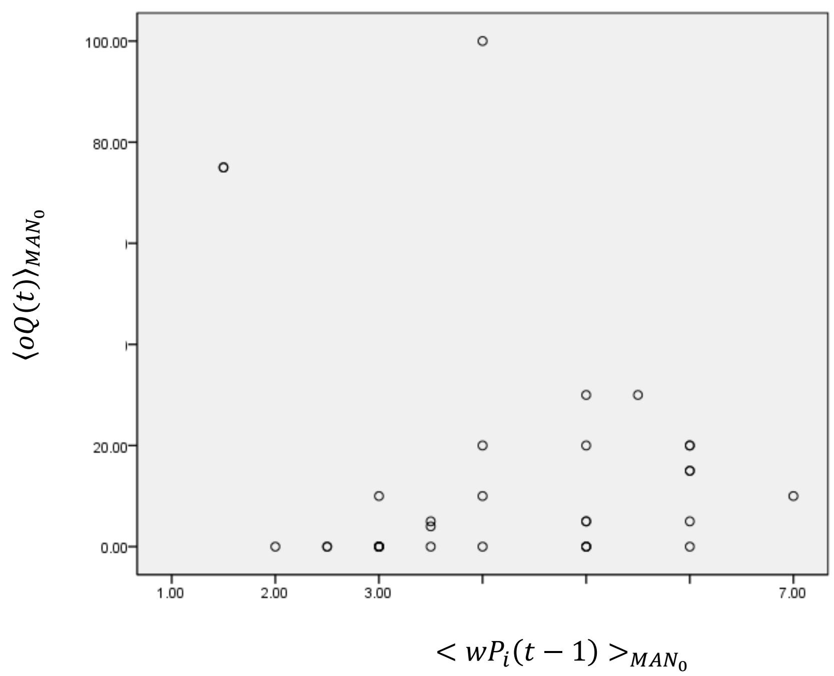


Figure C.7.2: Scatterplot of $\langle \boldsymbol{oQ(t)}\rangle_{\boldsymbol{MAN_0}}$ with $< wP_{\boldsymbol{i}}(\boldsymbol{t}-\boldsymbol{1}) >_{\boldsymbol{MAN_0}}$

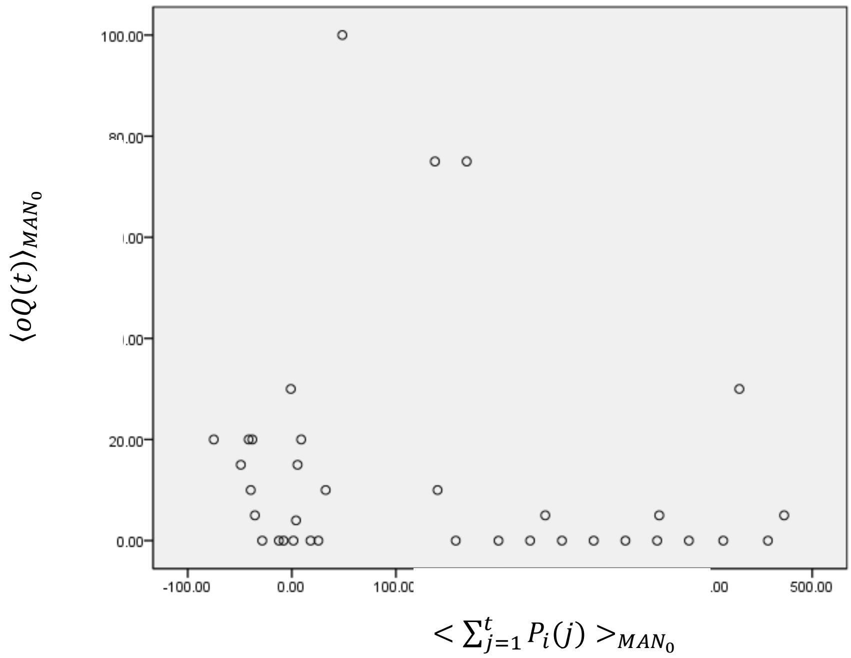


Figure C.7.3: Scatterplot of $\langle \boldsymbol{oQ(t)} \rangle_{\boldsymbol{MAN_0}}$ with $< \sum_{j=1}^{t} \boldsymbol{P_i(j)} >_{\boldsymbol{MAN_0}}$

The second column of Figure's C.7.1 scatterplot matrix demonstrates a non-strictly linear relationship between the *decision variable* quantity $\langle oQ(t) \rangle_{MAN_0}$ and the *decision attributes*: previous order $oQ_i(t-1)$ and cumulative profit $\sum_{j=1}^{t} P_i(j)$. Figure C.7.2 more clearly establishes that there was a linear relationship between $\langle oQ(t) \rangle_{MAN_0}$ and $< wP_i(t-1) >_{MAN_0}$, while the relationship between $\langle oQ(t) \rangle_{MAN_0}$ and $\sum_{j=1}^{t} P_i(j)$ might indeed not be linear, according to Figure C.7.3. In order to additionally confirm that all other relationships between dependent and independent variables were strictly linear, partial regression plots were additionally resorted to. Figure C.7.4 indicatively presents the partial regression plot of $\langle wP(t) \rangle_{MAN_0}$ with $\sum_{j=1}^{t} P_i(j)$. The red line going through the centre of the points slopes up, based on that the regression coefficient of $\sum_{j=1}^{t} P_i(j)$ is positive. Since in Figure C.7.4 no clear curvi-linear pattern of residuals could be observed, testimony for a non-linear relationship between $\langle wP(t)\rangle_{MAN_0}$ and $\sum_{j=1}^{t} P_i(j)$ could not be further supported. Exactly the same procedure was repeated for all remaining pairs of dependent and independent variables; in this way the existence of non-linear relationships between the charged price $\langle wP(t)\rangle_{MAN_0}$ and the shipment in transit $S_{i+1}(t - L_i + 1)$ was established.

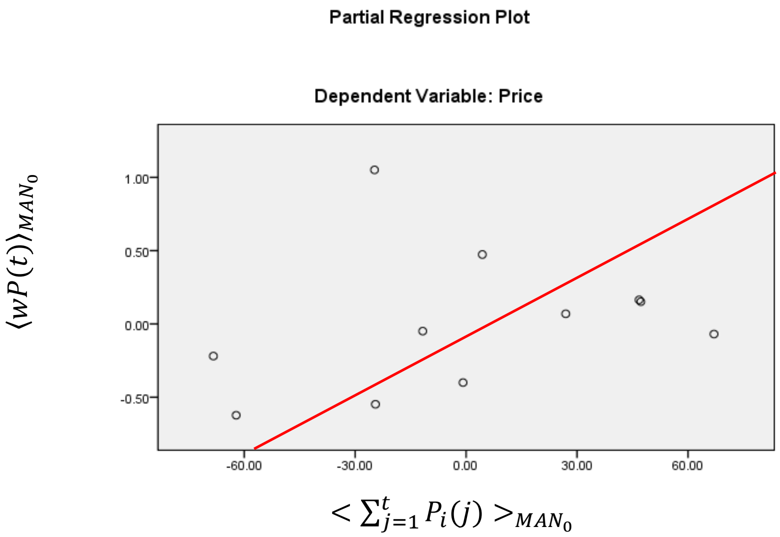


Figure C.7.4: Partial Regression Plot of $\langle \boldsymbol{wP(t)}\rangle_{\boldsymbol{MAN_0}}$ with $< \sum_{j=1}^{t} \boldsymbol{P_i(j)} >_{\boldsymbol{MAN_0}}$

b) *Normality:* Normality was visually inspected via normal histograms and normal probability plots. Figure C.7.5 indicatively presents the normal histogram of the residuals of $\langle wP(t)\rangle_{MAN_0}$. Since this normal histogram appeared ill formed, the normal probability plots were additionally required.

Figure C.7.6 indicatively presents the quantile-quantile (*Q-Q*) plot of MAN_0 's quantity decisions $\langle oQ(t)\rangle_{MAN_0}$ that plots the quantiles from $\langle oQ(t)\rangle_{MAN_0}$ data set statistics against "expected" quantiles from standard normal distribution (Thode, 2002). The systematic deviations of the data from linearity indicates that

MAN_0 's quantity decisions were not normally distributed. This was further supported by the Kolmogorov-Smirnov test result, which compares the $\langle oQ(t) \rangle_{MAN_0}$ dataset with the normal distribution (with mean: 13.543; standard deviation: 23.700), as presented in Table C.6.1. According to the largest absolute difference between the empirical observation of $\langle oQ(t) \rangle_{MAN_0}$ and the theoretical value of the tested normal distribution (0.284), the Kolmogorov-Smirnov test statistic was calculated equal to 1.679, which exceeded the 5% significance level critical value of 0.895 (Thode, 2002), which indicated departure from normality (p>0.07).

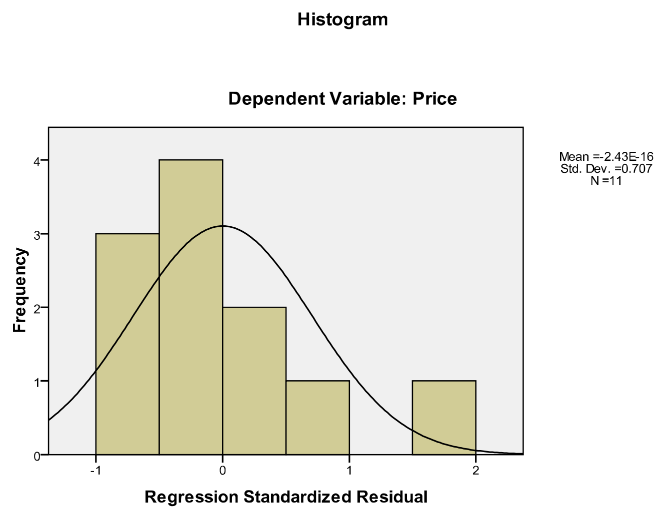


Figure C.7.5: Normal Histogram of $\langle \boldsymbol{wP(t)} \rangle_{\boldsymbol{MAN_0}}$

The same conclusion could also be drawn from the Darling-Anderson test, which is generally considered as more reliable, due to its higher power, as it places more weight on the tails of the distribution (Robinson, 2007). Its results are presented in Figure C.7.7 that follows.

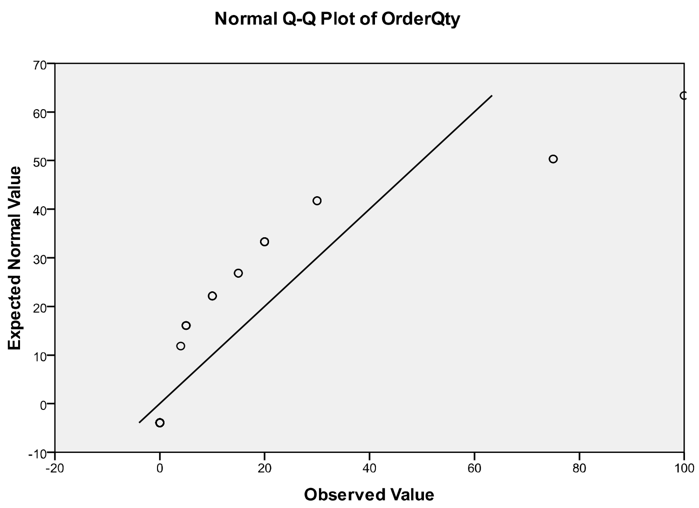


Figure C.7.6: *Quantile-Quantile* (*Q-Q*) plot of $\langle \boldsymbol{oQ(t)} \rangle_{\boldsymbol{MAN_0}}$

Table C.7.1: One-Sample Kolmogorov-Smirnov Test for $\langle oQ(t) \rangle_{MAN_0}$

Characteristics of $\langle \boldsymbol{oQ(t)} \rangle_{\boldsymbol{MAN_0}}$ dataset		
Normal Parameters	Mean	13.543
	Std. Deviation	23.700
Most Extreme Differences	Absolute	0.284
	Positive	0.250
	Negative	-0.284
Kolmogorov-Smirnov Z		1.679
Asymp. Sig. (2-tailed)		.007

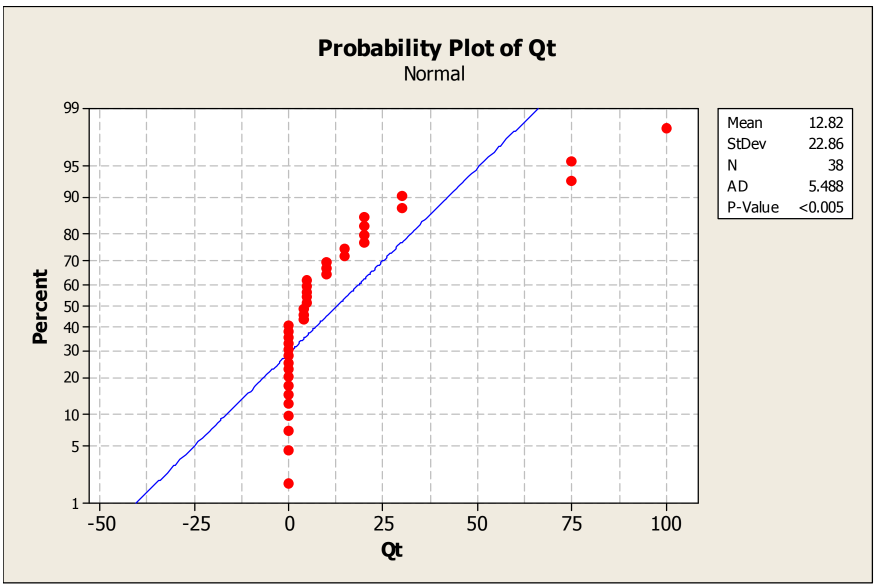


Figure C.7.7: The Darling-Anderson Test for Normality of $\langle \boldsymbol{oQ(t)} \rangle_{\boldsymbol{MAN_0}}$

Figure C.7.7 additionally justifies why the hypothesis that $\langle oQ(t)\rangle_{MAN_0}$followed the normal distribution was rejected (at the 0.5% significance level). A further indication of non-normality could also be provided by Figure's C.7.1 scatterplot matrix, according to which a high concentration of $\langle oQ(t)\rangle_{MAN_0}$ values at zero is evident. In greater detail, the distribution of $\langle oQ(t)\rangle_{MAN_0}$ decisions took strictly non-negative values: namely, it was continuous on the positive integers, but exhibited an added mass at the value of zero. Therefore, it seemed to follow, instead of the normal distribution, a type of mixed compound Poisson distribution (Poisson sum of gamma distributions), which belonged to the exponential family of distributions (Fox, 2008). But this distribution with the added mass at the value of zero more closely resembled to the actual mental decision making process that participants described in the post-game interviews that they went through in order to make their respective order quantity decisions: namely, they first decided whether they wished to place an order; and second, they determined their preferred exact order quantity, that is *provided* they wished to place a non-zero order. Similar conclusions could be drawn for all participants' order quantity decisions $\langle oQ(t)\rangle_{i_s}$.

c) *Homo-skedasticity*: Figure C.7.8 illustrates the plot of $\langle wP(t)\rangle_{MAN_0}$studentized residuals against the predicted dependent values. This plot's graphical comparison with the null plot, illustrated in red colour, demonstrates that the dispersion of $\langle wP(t)\rangle_{MAN_0}$variances is unequal. The lack of a sufficient number of unique spread/level pairs to conduct the Levene test (Levene, 1960) is another strong indication of the hetero-skedasticity that was inherent in the data set of $\langle wP(t)\rangle_{MAN_0}$, which, nevertheless, did not come as a surprise, given the previously identified non-normality of at least one of the independent variables. The same procedure was also followed for all independent variables of MAN_0's $f_{MAN_0}^{oQ(t)}$decision model of type (7.6), namely $wP_i(t-1)$, $wP_i(t), wP_{i+1}(\mathrm{t}), oQ_i(t-1)$, $S_{i+1}(t-L_i+1)$,$oQ_{i-1}(t-l_{i-1}), wP_{\mathrm{i}}(t-l_{i-1}), IN_i(\mathrm{t}), \sum_{j=1}^{t} P_i(j)$ and heteroskedasticity was additionally established for a number of these variables.

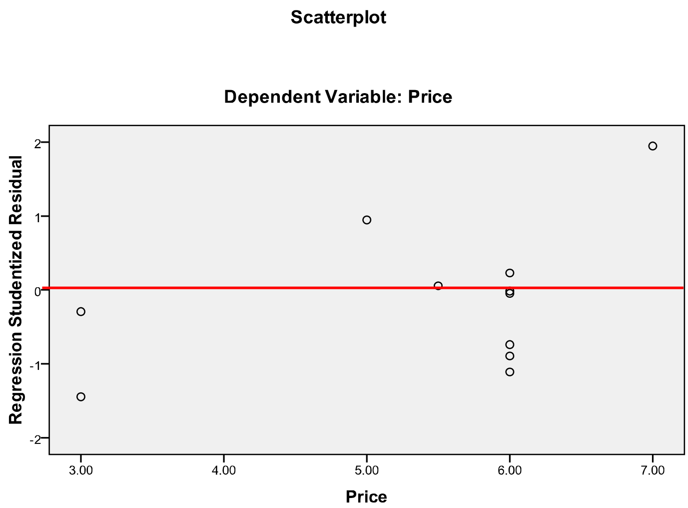


Figure C.7.8: Residual Plot of $\langle \boldsymbol{wP(t)} \rangle_{\boldsymbol{MAN_0}}$

In summary, by following the testing procedure that has been in some detail described in the preceding paragraphs, departures from *linearity*, *normality* and *homo-skedasticity* have been confirmed for some of the dependent and independent variables. For this reason, the simple linear regression models of types (7.3) and (7.4) could not be considered as adequate to portray participants' price and order quantity decisions, respectively (Weisberg, 2005; Hair *et al*, 2006; Fox, 2008). Appropriate modifications of them needed to be instead applied.

To this end, the following two remedies are put in force. The *first* remedy is that the participants' order quantity decisions are viewed as two distinct decisions: (*i*) whether they wish to place a strictly positive order and, provided that they do, (*ii*) exactly to how much would this order quantity amount to. This remedy addresses the non-normality of the order quantity decisions $\langle oQ(t)\rangle_{i_s}$ of most human participants, namely the added mass at the value of zero that most participants' order quantity decisions have. The *second* remedy is that appropriate transformations are enforced to the values of the *decision attributes* that violate normality. In this way, non-linearity and hetero-skedasticity are additionally accounted for (Weisberg, 2005; Hair et al, 2006).

For illustration purposes the transformations that have been applied to i_s=*MAN*$_0$ *decision attribute*s are subsequently presented. The improvements in normality, linearity and homo-skedasticity that are offered by these transformations over the untransformed decision models of i_s=*MAN*$_0$ according to relations (7.3) and (7.4) are subsequently discussed.

$$\varphi_{MAN_0}\left\{\lambda_{oQ_3(t-1)}^{MAN_0}, oQ_3(t-1)\right\} = \frac{[oQ_3(t-1)+1]^{-2}-1}{(-2)}$$

$$\varphi_{MAN_0}\left\{\lambda_{oQ_3(t-L_3+1)}^{MAN_0}, oQ_3(t-L_3+1)\right\}$$
$$= \frac{[oQ_3(t-L_3+1)+1]^{-2}-1}{(-2)}$$

$$\varphi_{MAN_0}\left\{\lambda_{oQ_2(t-l_2)}^{F_3}, oQ_2(t-l_2)\right\} = \frac{[oQ_2(t-l_2)+1]^{-2}-1}{(-2)}$$

$$\varphi_{MAN_3}\left\{\lambda_{IN_3(t)}^{MAN_0}, IN_3(t)\right\}$$
$$= \begin{cases} \dfrac{[IN_3(t)+1]^{-2}-1}{(-2)}, & if\ IN_3(t) \geq 0 \\ -\left[\dfrac{(-IN_3(t)+1)^{-0.5}-1}{(-0.5)}\right], & if\ IN_3(t) < 0 \end{cases}$$

$$\varphi_{MAN_3}\left\{\lambda_{CP(t)}^{MAN_0}, \sum_{j=1}^{t} P_i(j)\right\}$$
$$= \begin{cases} \dfrac{\left[\sum_{j=1}^{t} P_3(j)\ +1\right]^{-2}-1}{(-2)}, & if\ \sum_{j=1}^{t} P_3(j)\ \geq 0 \\ -\left[\dfrac{\left(-\sum_{j=1}^{t} P_3(j)\ +1\right)^{-0.5}-1}{(-0.5)}\right], & if\ \sum_{j=1}^{t} P_3(j)\ < 0 \end{cases}$$

Figure C.7.9 presents the scatterplot of MAN_0 dependent and independent variables, after the aforementioned Yeo-Johnson (2000) have been applied. For reasons of greater clarity, Figure C.7.10 presents the scatterplot of $\langle oQ(t)\rangle_{MAN_0}$with the transformation of $< \sum_{j=1}^{t} P_i(j) >_{MAN_0}$.

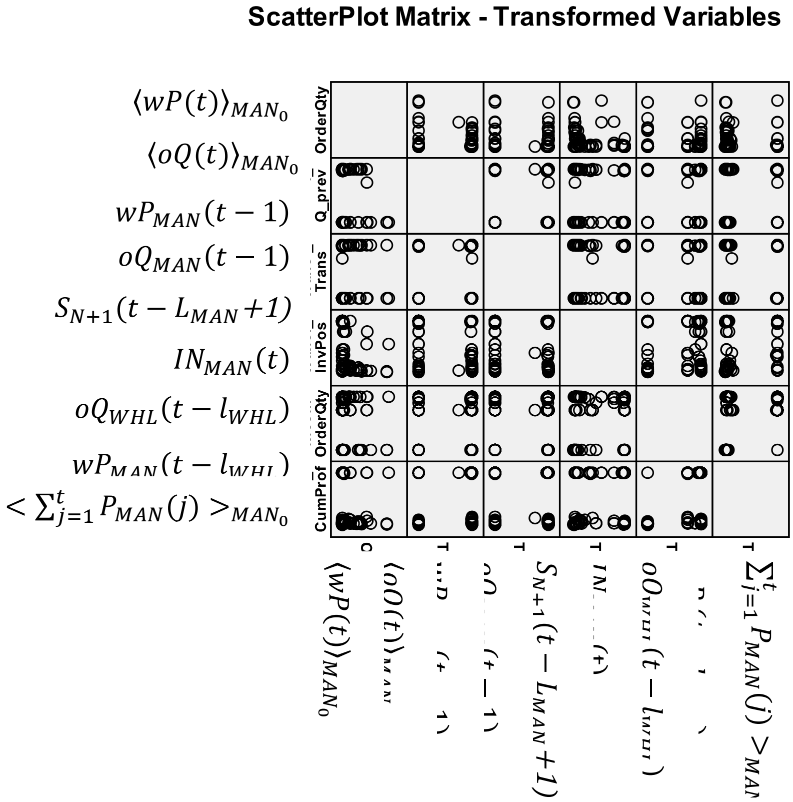


Figure C.7.9: Scatterplot Matrix of MAN_0 dependent and independent variables

In this regard, the visual comparison of Figure C.7.10 with Figure C.7.3 can clearly demonstrate how the above Yeo-Johnson (2000) transformations offered satisfying remedies to the linearity, normality and homo-skedasticity requirements of multiple linear regression.

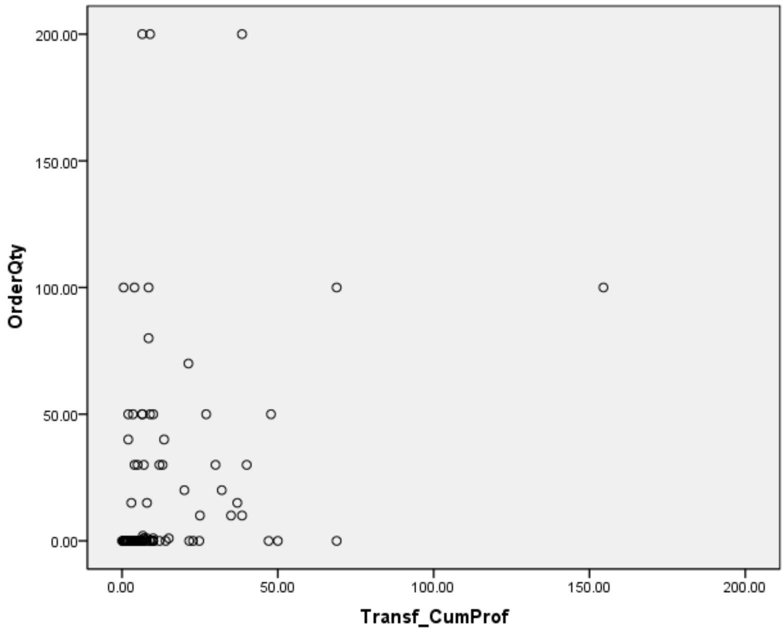


Figure C.7.10: Scatterplot of $\langle oQ(t)\rangle_{MAN_0}$ with transformed dataset of $< \sum_{j=1}^{t} P_i(j) >_{MAN_0}$

C.8 Details about Generalised Linear Models

Generalized Linear Models (GLMs), originally formulated by Nelder and Wedderburn (1972) to synthesize and extend linear, logistic and Poisson regression under a single framework, consist of three components (McCulloch *et al*, 2008; Fox, 2008):

- The conditional distribution of the dependent variable, given the values of the independent variables,
- The linear predictor of all independent variables' pre-specified transformations and
- The link function that transforms the expectation of the dependent variable to the linear predictor.

Hence, transforming the simple linear regression models of type (7.3) and (7.4) to the corresponding GLMs would involve three distinct steps: First, we would have to choose the appropriate distribution of the dependent variables (*i.e*. some sort of mixed compound Poisson distribution, which with appropriate algebraic manipulation would be transformed to the common linear-exponential form of the exponential family of distributions); based on this, we would select the appropriate link function for different participants' decision making strategies (*i.e*. according to their recorded decisions the log, invese, inverse square, square root etc. might for example derive as appropriate) and last, we would determine the exact set of independent variables that should be included in the model (*i.e*. we would choose from the list of *decision attribute*s specified in relations (7.3) and (7.4) the corresponding sub-set of the ones that are statistically significant. The first step would serve to address the normality and homoskedasticity violations of our participants' decision making models, while the second would address the linearity violation.

The appropriate modifications that have been developed to adapt GLMs to the correlation requirements of time-series data (e.g. Kedem and Fokianos, 2002) turn GLMs particularly attractive for our research purposes. In addition, GLMs have already been extensively applied in previous experimental research that is relevant to our study (but is not solely restricted to the behavioural dimension of the Beer Distribution Game). For example, Lurie and Swaminathan (2009) directly applied GLMs to their experimentally collected data for the Newsvendor Problem, while a number of other papers (i.e. Bostian et al, 2008; Su, 2008; Ho *et al*, 2009) concentrated on the behavioural models that they proposed to predict human order quantity decisions in a variety of different settings (*i.e.* the Newsvendor problem, the Beer Distribution Game and the Newsvendor problem with competing retailers) and only resorted to experimentally collected data to support the validity of these behavioural models.

Yet, we identified three main limitations with the application of GLMs to determine participants' i_s decision making strategies for price $\langle wP(t)\rangle_{i_s}$ and quantity $\langle oQ(t)\rangle_{i_s}$). First, in GLMs the equivalent to regression coefficients $a_k^{i_s}$ and $\beta_k^{i_s}$ of relations (7.5) and (7.6) are included in the linear predictor, which is in turn mirrored to the expectation of the dependent variable via the link function. Hence, the associations and inter-connections of *decision attribute*s and *decision variable*s become very complicated and, thus, hard to interpret. It is for this reason that GLMs could not be easily used to draw insights on the importance weights that different participants assigned to their *decision attribute*s for each decision they made. But the ultimate purpose of our study is to systematically explore the effect of different decision makers' individual preferences, priorities and cognitive limitations on overall supply chain performance, which pre-assumes deep understanding and classification of participants' overall adopted decision making strategies. This is the second reason why we decided to seek for an alternative way to model participants' respective decision making strategies. Third, the post-game interviews we had with participants revealed a more detailed picture of the mental decision making process that most subjects undertook to complete their required decision tasks: As already discussed, most subjects first decided whether they wished to place an order; and second, they specified their preferred order quantity, that is provided they wished to place an order. GLMs failed to approximate these distinct decision making steps of participants.

For the above three reasons we sought for an alternative way to model participants' i_s decision making strategies for price $\langle wP(t)\rangle_{i_s}$ and quantity $\langle oQ(t)\rangle_{i_s}$); one that would more naturally follow the mental decision making steps of participants and simultaneously address the violations that disqualified us from using the linear relations in (7.5) and (7.6) (*i.e.* linearity, normality and homoskedasticity).

C.9 Details about Participants'Decision Models

We can clearly see from Table 7.8 that all human retailers (RET_0 - RET_3) took considerably into account the currently charged price $wP_W(t)$ for their decision to place a non-zero order or not. RET_0, RET_2, RET_3 also significantly considered the previously ordered quantity $oQ_R(t-1)$. RET_1 preferred to instead rely on the shipment in transit towards his warehouse $S_{WHL}(t-L_{RET}+1)$, which the other three retailers (RET_0, RET_2, RET_3) almost ignored. This supports that RET_0, RET_2 and RET_3 correctly perceived their previous order quantities as a more reliable indicator of their outstanding orders than the shipments in transit. Last but not least, all human retailers (RET_0 - RET_3) only marginally considered their current inventory positions $IN_{RET}(t)$ and cumulatively realized profits $\sum_{j=1}^{t} P_{RET}(j)$ in their decisions to place an order or not. Overall, the logistic regression models that were fitted to human retailers' decisions to place an order with their upstream wholesaler explained more than 60% of the total variation existent in their recorded decisions (according to Nagelkerke R^2) and satisfied the *by chance accuracy criterion*.

Based on the above observations, we can characterise RET_0, RET_2 and RET_3 as 'price and cost sensitive', since they significantly considered for their decisions both the price charged to them and their previous order placement decision, which is an indicator of inventory holding and backlog costs. RET_1 derived as more highly 'price sensitive', because she only let the currently charged price to play a significant role in her decision to place an order.

We can clearly see from Table 7.9 that all human retailers (RET_0 - RET_3) significantly considered the currently charged price $wP_W(t)$ for their exact order quantity decision. On the contrary, RET_0 - RET_3 marginally considered their previous order quantities $oQ_R(t-1)$. RET_0 - RET_3 almost ignored the shipments in transit from the wholesaler $S_W(t-L_R+1)$.

This ignorance provided further evidence in support of retailers RET_0, RET_2, RET_3 accurate perception of outstanding orders. As far as current inventory position $IN_R(t)$ is concerned, RET_0 considered it significant, while RET_1 and RET_3 only marginally considered it. Finally, as for the cumulative realized profit $\sum_{j=1}^{t} P_R(j)$, RET_0 and RET_3 ignored it, while RET_1 and RET_2 significantly considered it for their order quantity decisions.

Overall, the regression models that we fitted to each human retailer's order quantity decisions are statistically significant at the 10% significance level and explain more than 70% of the total variation that existed in their recorded decisions (*adj*.R^2). At this point we find worthwhile to explain that since our ultimate objective was to attain the highest adjusted coefficients of determination *adj*.R^2, we kept in the fitted regression models some of the *decision attribute*s that derived as statistically in-significant, yet of considerable magnitude (*e.g*. RET_2's current inventory position $IN_{RET}(t)$).

In summary, we can characterize RET_0 as 'price conscious' because he only let the currently charged wholesaler price to affect to a significant degree his exact order quantity decision: he considerably took into account neither his current inventory position nor his realized profit. As for RET_1, she revealed as 'price and profit conscious', as she reserved considerable attention to both the currently charged price and her realized profit. As for RET_3, he exhibited exactly the complementary strategy, since he was significantly influenced by both the currently charged price and his current inventory position. It was for this reason that we labelled RET_3 as 'price and cost conscious'. Finally, RET_2 revealed as 'price and cost and profit conscious', because the wholesale price, his current inventory position and his realized profit all factors combined, determined to a significant degree his quantity decision.

We now try to shed some more light on all our human retailers' decision making strategies: RET_0 initially considered both the price currently charged to him by his wholesaler and his previous order placement decision as to whether he preferred to place a non-zero order or not (*i.e.* 'price and cost sensitive'); while once he had decided to place an order, he exclusively considered price as to how much did he wish to order (*i.e.* 'price conscious'). RET_1 appeared overly sensitive to profit, as price can be considered as an additional indicator of profit-to-be realized: not only did she exclusively consider the wholesaler price in her decision to place an order or not (*i.e.* 'price sensitive'), but she also let only this price and her cumulatively realized profit majorly affect her exact order quantity (*i.e* 'price and profit conscious'). RET_2 adapted a more thoroughly balanced strategy by considering both price and cost in his initial order placement decision (*i.e.* 'combined price and cost sensitive') and bearing in mind all three categories of factors combined in his exact quantity decision, namely price, cost and profit (*i.e.* 'price and cost and profit conscious'). RET_3's rationale was somewhat similar, as profit would simply originate from the combination of the newly charged price and the total costs incurred. It was most probably for this reason that RET_3 took into account price and cost in his initial order placement decision (*i.e.* 'combined price and cost sensitive'), as well as his subsequent exact order quantity decision (*i.e.* 'price and cost conscious').

It is evident from Table 7.9 that all human wholesalers (WHL_0 - WHL_3) took considerably into account relevant prices for every new price decision they made; namely, they accounted for the price currently charged to them $wP_{MAN}(t)$ and/or their own charged price that is attached to their incoming orders $wP_{WHL}(t - l_{RET})$. WHL_0 - WHL_3 also chose to take into consideration among the information that was available to them some indication of how much inventory / backlog they had: WHL_0 chose her previous order quantity $oQ_{WHL}(t-1)$; WHL_2 the shipment in transit to his warehouse $S_{MAN}(t - L_{WHL} + 1)$ and his incoming order quantity $oQ_{RET}(t - l_{RET})$, in increasing order of importance. WHL_1 preferred instead to assign significant priority directly to her inventory availability $IN_{WHL}(t)$; while WHL_3 strived for an almost equivalent consideration of the shipment in transit to his warehouse $S_{MAN}(t - L_{WHL} + 1)$, his available inventory $IN_{WHL}(t)$ and his cumulative realized profit $\sum_{j=1}^{t} P_{WHL}(j)$. Overall the regression models that we fitted to each human wholesaler's pricing decisions are statistically significant at the 10% significance level and explain more than 65% of the total variation that exists in their recorded decisions (*adj*.R^2).

In summary, all wholesalers WHL_0 - WHL_3 appeared to manipulate their prices in a way that would mostly benefit their own respective profits. For WHL_3 profits were a significant factor; as for total incurred costs, WHL_3 perceived them as majorly determined by his current inventory position and the shipment to be received. Therefore, WHL_3's pricing strategy derived almost as a *reaction* to profits and inventories, enabling us to characterize him as 'profit and current availability reactive'. As for the remaining three wholesalers, WHL_0 – WHL_2 perceived profits as majorly determined by prices and costs by the aforementioned indications of inventory availability.

Hence, in what concerns pricing decisions, WHL_2 could be easily characterized as 'price and future availability reactive'; WHL_1 as 'price and present availability reactive' and WHL_0 as 'price and past order reactive'. This WHL_0's strategy can be justified by her assumption that her previous order quantity will soon be delivered by her upstream wholesaler. The latter, however, might not happen, in case a stock-out at the wholesaler's site occurs. This WHL_0's pre-supposition demonstrates her limited apprehension of the complicated phenomenon taking place, which, nevertheless, might at least partially be explained by the relatively limited duration of her gaming session. The other three wholesalers' pricing strategies support their effective use of prices as a mechanism that can control new order quantities, based on their own inventory availabilities.

We can clearly see from Table 7.10 that all human wholesalers (WHL_0 - WHL_3) significantly considered both the prices charged to them by their upstream manufacturers $wP_{MAN}(t)$ and their own current prices $wP_{WHL}(t)$ in order to decide to place a non-zero order; the only exception was WHL_1 who almost ignored her own price and significantly relied only on the manufacturer's current price. Since wholesalers WHL_0 - WHL_3 treated prices as a sufficient measure of realized profits, they almost ignored their cumulative profits $\sum_{\boldsymbol{j=1}}^{\boldsymbol{t}} P_{WHL}(j)$ in their order placement decisions. In addition, wholesalers WHL_0 - WHL_3 took considerably into account some indication of inventory availability: WHL_1 its simplest form, which is the present inventory position $IN_{WHL}(t)$; while the other three wholesalers its future situation. In this regard, WHL_3 only accounted for his own previous order quantity $oQ_{WHL}(t-1)$, in opposition to WHL_0 and WHL_2, who correctly realized that their future inventory would be given by their own previous order quantity $oQ_{WHL}(t-1)$, combined with their newly received from the retailer order quantity $oQ_{RET}(t-l_{RET})$. WHL_3's possible underlying reasoning might be that he would prefer to avoid placing a new order, whenever he had placed a new order in the preceding period.

In summary, in what concerns order placement decisions, we can characterize WHL_0 and WHL_2 as 'price and future availability sensitive', WHL_1 as 'price and present availability sensitive' and WHL_3 as 'price and part future availability sensitive'. Overall, all human wholesalers' fitted logistic regression models explained more than 60% of the total variation inherent in their respective datasets (according to Nagelkerke R^2) and satisfied the by chance accuracy criterion.

Table 7.10 clearly indicates that all human wholesalers (WHL_0 - WHL_3) also accounted for some measure of profitability and inventory availability in their exact order quantity decisions. WHL_0 was the exception: she completely ignored her inventory availability and resorted to a more degree to the price charged to her by her upstream supplier $wP_{MAN}(t)$ and to a lesser degree to her cumulatively realized profit $\sum_{j=1}^{t} P_{WHL}(j)$. The other three wholesalers WHL_1 – WHL_3 relied to the same objective to some measure of price (*i.e.* previous own price $wP_{WHL}(t-1$ for WHL_1; current own price $wPWHLt$ for WHL_2; a combination of present prices for WHL_3: own $wP_{WHL}(t)$ and manufacturer's $wP_{MAN}(t)$) and some of inventory availability (*i.e.* shipment in transit from manufacturer $S_{MAN}(t-LWHL+1$ for WHL_1; incoming from retailer order quantity $oQRETt-lRET$ for WHL_2; a combination of shipment in transit from manufacturer $S_{MAN}(t-LWHL+1$ and current inventory position $INWHLt$ for WHL_3.

For this reason, in respect to order quantity decisions, we could characterize WHL_1 as 'price and future availability conscious', where future availability was mostly regarded as soon to be received shipments. We could also characterize WHL_2 as 'price and current availability conscious', where current availability was mostly assessed via the just received order quantity. WHL_3 derived as 'price and present and future availability conscious': he directly associated his current availability with his current inventory position; while he regarded future availability in terms of shipments in transit towards his warehouse. As for WHL_0, she followed a completely different order quantity strategy: since the price charged by her supplier can be treated as an additional indicator of her own profit-to-be realized, she resulted as mostly 'profit conscious'. Overall, the wholesalers' quantity decision models are statistically significant at the 10% significance level and explain more than 60% of the recorded dataset's total variation ($adj.R^2$).

Combining the wholesalers' order placement and quantity decisions, it is very interesting to observe that all human wholesalers exhibited complementary strategies in these two distinct decisions, as if they tried to incorporate as much of the available information as possible. Namely, although WHL_0 considered her future availability in her order placement decision (*i.e*. 'price and future availability sensitive'), once she had decided to place an order, she was only concerned about her profitability (*i.e*. 'profit conscious'). WHL_1 considered current availability in her order placement decision (*i.e*. 'price and present availability sensitive'), yet future availability in her exact quantity decision (*i.e*. 'price and future availability conscious'). WHL_2 adopted the completely opposite strategy: he accounted for his future availability in his order placement decision (*i.e*. 'price and future availability sensitive'), but for his current availability in his exact quantity decision (*i.e*. 'price and present availability conscious'). WHL_3

prioritized, in addition to price, past orders in his order placement decision (*i.e.* 'price and part future availability sensitive') and present and future availability in his exact quantity decision (*i.e.* 'price and present and future availability conscious').

We can clearly observe from Table 7.12 that our participant MAN_3 simplified his pricing task by constantly charging a fixed price of 3 *m.u.* throughout the entire gaming session. As for the remaining human manufacturers (MAN_0 - MAN_2), in order to determine their new prices, they significantly relied on the incoming order price $wP_{MAN}(t - l_{WHL})$ they charged l_{WHL} periods ago. Nevertheless, it was only MAN_2 who managed to successfully associate this past price with her incoming order quantity $oQ_{WHL}(t - l_{WHL})$; F_1 associated it with his own previous order quantity $oQ_{MAN}(t - 1)$; while MAN_0 completely ignored all indicators of inventory availability and/or previous ordering behavior that was available to him (*i.e.* previous order quantity $oQ_{MAN}(t - 1)$, shipment in transit $oQ_{MAN}(t - L_{WHL} - 1)$, incoming order quantity $oQ_{WHL}(t - l_{WHL})$, inventory position $IN_{MAN}(t)$). In addition to incoming order price $wP_{MAN}(t - l_{WHL})$ and previous order quantity $oQ_{MAN}(t - 1)$ in decreasing order of importance, MAN_1 marginally considered his cumulatively realized profit $\sum_{j=1}^{t} P_{MAN}(j)$. Overall, the pricing models that were fitted to human manufacturers MAN_0 - MAN_2 are statistically significant at the 10% significance level and explain more than 70% of the total variation existent in their respective original datasets (*adj.*R^2).

In summary, MAN_0's pricing strategy mostly depended on the price attached to his incoming order, turning him, thus, to 'incoming order price reactive'. MAN_1 paid significant attention to his past order quantity and incoming order price. For this reason, we could characterize him as 'past order and incoming price reactive'. Following the same rationale, MAN_2 was viewed as 'incoming order and price reactive'; while, finally MAN_3, as already recognized, adapted a 'fixed pricing' strategy.

Table 7.13 presents our human manufacturers' respective order placement decisions. The price-relevant *decision attribute*s (*i.e.* $wP_{MAN}(t-1)$, $wP_{MAN}(t)$) were not applicable to MAN_3's case, because he set prices to the fixed value of 3 *m.u.*. All other manufacturers MAN_0 - MAN_2 considered their previous price $wP_{MAN}(t-1)$ unimportant on whether they should now place a new order or not; MAN_0 and MAN_2, on the contrary, assigned great importance to their currently decided price $wP_{MAN}(t)$ for their new order placement decision. In addition, MAN_2 considered her cumulatively realized profit $\sum_{j=1}^{t} P_{MAN}(j)$, but she, like MAN_0, completely ignored all indicators of inventory availability and/or previous ordering behavior that was available to her. The latter were, in contrast, considered of utmost importance to MAN_3, who appeared to endeavour to compensate for his lack of consideration of prices by taking into account all other *decision attribute* (*i.e.* previous order $oQ_{MAN}(t-1)$; shipment in transit $oQ_{MAN}(t-L_{WHL}-1)$; inventory position $IN_{MAN}(t)$). Among inventory availability measures, MAN_1 limited his attention to present inventory position.

Based on the above observations, we characterized MAN_0 as 'price sensitive', MAN_1 as 'present availability sensitive', MAN_2 as 'price and profit sensitive' and, finally, MAN_3 as 'profit and present and future availability sensitive'. In summary, all logistic regression models that we fitted to human manufacturers' order placement decisions explained more than 65% of the total variation and complied with the by *chance accuracy criterion*.

Table 7.14 outlines the decision models that we deduced that our participants followed to determine the exact quantities of their production requests, that is provided they desired to place a new production request. It becomes evident from Table 7.14 that all human manufacturers MAN_0 – MAN_3 considered at least one indicator of price or profit and at least one of inventory availability in their respective quantity decisions. The only exception was MAN_3 who systematically ignored all measures of price and profit. MAN_0 accurately associated his previous price $wP_{MAN}(t-1)$ with the quantity that he is now requesting and, thus, prioritized it, while MAN_2 failed to make this connection and, hence, prioritized her current price $wP_{MAN}(t)$ instead. Nevertheless, current price could successfully be considered as an indicator of MAN_2 's future incoming order quantities and, therefore, MAN_2 's higher preference of it could reveal as a successful strategy. MAN_1 considered his cumulatively realized profit $\sum_{j=1}^{t} P_{MAN}(j)$ as more significant and, therefore, resorted to it to make a quantity decision. Among the available inventory-related measures, all human manufacturers MAN_0 – MAN_3 assigned high significance to their respective current inventory position $IN_{MAN}(t)$, F_0 and MAN_3 to their corresponding previous order quantities $oQ_{MAN}(t-1)$ and MAN_1 to the just received order's quantity $oQ_{WHL}(t-l_{WHL})$. It is very interesting that none of our participants perceived the shipment in transit $\mathrm{oQ_{MAN}(t-L_{MAN}-1)}$ of relevance to their quantity decisions, most probably because they had accurately perceived the assumed perfect reliability of their production facility.

The above observations guided us to characterize MAN_0 's quantity strategy as 'past price and present availability conscious', MAN_1 's as 'profit and present and future availability conscious', MAN_2 's as 'present price and present availability conscious'; MAN_3 's as 'present and part future availability conscious'. Overall, the regression models that we fitted to our manufacturers' quantity decisions are significant at the 10% significance level and explained more than the 60% observed variation (*adj*. R^2).

Last but not least, we find it very interesting to highlight that only MAN_0 appeared to adapt a strategy similar to wholesalers' tactic to incorporate as much of the available information as possible. In this regard, MAN_0 overall considered past and present prices and present inventory availability while determining new production requests. As for the remaining three manufacturers MAN_1 – MAN_3, they systematically preferred one of the available *decision attribute*s over all others: MAN_2 price, while MAN_1 and MAN_3 present inventory availability.