Year : 2020

THREE ESSAYS ON OFFSHORING DECISION-MAKING

Weiss Jordi

UNIL | Université de Lausanne

FACULTÉ DES HAUTES ÉTUDES COMMERCIALES

DÉPARTEMENT DES OPÉRATIONS

THREE ESSAYS ON OFFSHORING DECISION-MAKING

THÈSE DE DOCTORAT

présentée à la

Faculté des Hautes Études Commerciales
de l'Université de Lausanne

pour l'obtention du grade de
Docteur ès Sciences en systèmes d'information

par

Jordi WEISS

Directrice de thèse
Prof. Suzanne de Treville

Jury

Prof. Felicitas Morhart, présidente
Prof. Julian Marewski, expert interne
Prof. Mauro Cherubini, expert interne
Prof. Rogelio Oliva, expert externe

LAUSANNE
2020

UNIL | Université de Lausanne

FACULTÉ DES HAUTES ÉTUDES COMMERCIALES

DÉPARTEMENT DES OPÉRATIONS

THREE ESSAYS ON OFFSHORING DECISION-MAKING

THÈSE DE DOCTORAT

présentée à la

Faculté des Hautes Études Commerciales
de l'Université de Lausanne

pour l'obtention du grade de
Docteur ès Sciences en systèmes d'information

par

Jordi WEISS

Directrice de thèse
Prof. Suzanne de Treville

Jury

Prof. Felicitas Morhart, présidente
Prof. Julian Marewski, expert interne
Prof. Mauro Cherubini, expert interne
Prof. Rogelio Oliva, expert externe

LAUSANNE
2020

UNIL | Université de Lausanne
HEC Lausanne
Le Décanat
Bâtiment Internef
CH-1015 Lausanne

IMPRIMATUR

Sans se prononcer sur les opinions de l'auteur, la Faculté des Hautes Etudes Commerciales de l'Université de Lausanne autorise l'impression de la thèse de Monsieur **Jordi WEISS**, titulaire d'un bachelor en Informatique et Mathématiques de l'Université d'Aix-Marseille, d'un bachelor en Droit, Économie, Gestion, mention Gestion de l'Université d'Aix-Marseille, ainsi que d'un master en Management mention Comportement Organisationnel de l'Université de Lausanne, en vue de l'obtention du grade de docteur ès Sciences en Systèmes d'Information.

La thèse est intitulée :

THREE ESSAYS ON OFFSHORING DECISION-MAKING

Lausanne, le 27 novembre 2020

Le doyen

Jean-Philippe Bonardi

HEC Lausanne
Le Décanat
Tél. +41 21 692 33 40 | Fax +41 21 692 33 05
www.hec.unil.ch | hecdoyen@unil.ch

UNIL | Université de Lausanne

Members of the thesis committee

Professor Suzanne de Treville
Swiss Finance Institute Professor of Operations Management, Faculty of Business and Economics, University of Lausanne
Thesis supervisor

Professor Julian Marewski
Professor, Department of Organizational Behavior, Faculty of Business and Economics, University of Lausanne
Internal member of the thesis committee

Professor Mauro Cherubini
Professor, Department of Information Systems, Faculty of Business and Economics, University of Lausanne
Internal member of the thesis committee

Professor Rogelio Oliva
Professor, Robyn L. '89 and Alan B. Roberts '78 Chair in Business at Mays Business School, Texas A&M University
External member of the thesis committee

University of Lausanne
Faculty of Business and Economics

PhD in Information Systems

I hereby certify that I have examined the doctoral thesis of

Jordi WEISS

and have found it to meet the requirements for a doctoral thesis.
All revisions that I or committee members
made during the doctoral colloquium
have been addressed to my entire satisfaction.

Signature: ______________________________ Date: 27.11.2020

Prof. Suzanne DE TREVILLE
Thesis supervisor

University of Lausanne
Faculty of Business and Economics

PhD in Information Systems

I hereby certify that I have examined the doctoral thesis of

Jordi WEISS

and have found it to meet the requirements for a doctoral thesis.
All revisions that I or committee members
made during the doctoral colloquium
have been addressed to my entire satisfaction.

Signature: ______________________ Date: 17.11.2020

Prof. Julian MAREWSKI
Internal member of the doctoral committee

University of Lausanne
Faculty of Business and Economics

PhD in Information Systems

I hereby certify that I have examined the doctoral thesis of

Jordi WEISS

and have found it to meet the requirements for a doctoral thesis.
All revisions that I or committee members
made during the doctoral colloquium
have been addressed to my entire satisfaction.

Signature: ____________ Date: 26/11/2020

Prof. Mauro CHERUBINI
Internal member of the doctoral committee

University of Lausanne
Faculty of Business and Economics

PhD in Information Systems

I hereby certify that I have examined the doctoral thesis of

Jordi WEISS

and have found it to meet the requirements for a doctoral thesis.
All revisions that I or committee members
made during the doctoral colloquium
have been addressed to my entire satisfaction.

Signature: ______________________ Date: Nov. 26, 2020

Prof. Rogelio OLIVA
External member of the doctoral committee

Abstract

This thesis studies biases in offshoring decisions and proposes a tool to improve understanding of the value of lead-time. Recent research results show local responsive production reduces mismatch between supply and demand, but this aspect of the cost is often overlooked in offshoring decisions, leading to suboptimal decisions. The tradeoff between lower unit costs and mismatch cost under demand uncertainty as lead-time increases, and the benefits of a local portfolio of products with different demand volatility, make the offshoring decision complex and the optimal solution sometimes counterintuitive. Building on behavioral research, I designed software-based laboratory trials to explore patterns of decisions in an offshoring problem, and a simulation-game to help teach and communicate research insights. In the first paper, I find that participants facing an offshoring problem fail to apply the economically optimal strategy. In the second paper, I find that non-economic factors like peer influence play a role in offshoring decisions. These trials are exploratory in nature and do not provide generalizable results, rather, they are a step towards a better understanding of the fundamental research questions and the conception of experiments. In the third paper, I describe the development and use of a simulation-game to help students, managers and policy makers understand the value of lead-time and volatility portfolio through an active learning approach. My work contributes to the understanding of the impact of bounded rationality in offshoring decisions and proposes a teaching method adapted to the challenges posed by the concepts involved.

Acknowledgements

The last four years have been so intense!

Pursuing a PhD pushes the boundaries of stress, obsessiveness, and doubt. But if you survive that, it is an incredible opportunity to develop yourself, both academically and in so many unsuspected skills. It is the achievement of a whole life of studies, and the springboard toward infinite professional and personal adventures.

It seems I am about to cross the finish line, alive and enriched, and for that I have some people to acknowledge.

First, I want to thank my grandparents Jacques and Eliane, who always supported me in my education, and before that, fueled my curiosity as a child and allowed me to have access to the knowledge of the world, including my first computer and my first travels.

I thank Suzanne for the opportunity to do this PhD. I appreciate the trust and freedom she gave me along with her steady optimism.

Many thanks to Cam for taking care of the department as if we were her family.

I am forever grateful to Annalisa for her support.

Thank you to my friends Bayane, Anita, Maria, Liliane, Cindy, Jenny, Serena, Silvia, Claudia.

Thanks to those who started as coworkers and ended up as friends too: Géraldine, Anaïs, Ksenia, Lory.

The Business and Economics (HEC) faculty of the University of Lausanne provided funding for the compensation of 150 out of the 200 participants in my trial, for a total of 3000 Swiss Francs (Fund N°26056124). The compensation of the remaining 50 participants was self-funded.

Table of contents

1) Synthesis

1.1) Introduction

Recent research results show that local production in high-cost countries can be competitive. Manufacturing of many products that have been offshored over the last decades can and should be made locally, where the products are sold, and not on the other side of the globe.

When taking mismatch costs into account, and with an appropriate product portfolio strategy, there is no need to spread the supply-chains always thinner and to weaken them in the process. Instead, the reactivity of local production offers opportunities in terms of demand fulfillment and product development, as well as important positive social externalities.

In a world where offshoring of most manufactured products has become the norm, these research results are counterintuitive. Moreover, they rely on statistical tools that are not trivial.

At the University of Lausanne, we decided to teach these insights upfront in an introduction course to Operations Management. Over a semester of two hours of weekly classes, we adopt a flipped classroom approach, weekly testing and the use of custom tools and simulation-games to provide students with a toolbox for supply-chain analysis and discussions that foster a deep understanding of local responsive manufacturing.

Once students master the tools and digest the concepts, they often come back with a simple but cornerstone question: Why?

Why do decision-makers keep offshoring their production tools and their knowledge, to countries 10,000 kilometers away? Why complicate the supply-chain to the point that any glitch will disrupt it? Why exploit underpaid workers, occasionally children, when it would be possible to offer jobs to local workforce? Why have garments travel the world in containers with a terrible carbon footprint to save 20% on unit costs, when twice as much is lost in demand mismatch as a result of the lead-time increase caused by this very transportation?

The answer to these fundamental questions is the basis of understanding managers who pursue a policy that is not only not optimal, but harmful. Even a solid idea will not have a real-world impact if it is filtered out by decision-makers, or seen as interesting but not applied.

The key, in my opinion, is the integration of decision-making into economic theory. Economics is not the science of money as the general public often assumes, but the science of human choices and preferences.

The common misconception that managers are rational-decision machines must be debunked, and the human element must be included in the way we conceive, analyze, incentivize and teach management. Results show local manufacturing competitiveness relies on an analysis of demand volatility on one side, and costs on the other — but, in the real world, it is difficult to get a solid grip on these two factors. Theories assume a thorough demand analysis and set parameters. But managers cannot rely on such assumptions. On a daily basis, they deal with messy, and more or less outdated, irrelevant or missing data, oversimplified – when any – demand analysis and a dozen reasons “the model cannot be applied here.” Managers are in an ecosystem of uncertainty, urgency and pressure, each with its own business-specific or company-specific culture and ways of doing things. Of course, each system also has its own performance indicators.

Only when these factors are taken into consideration can we begin to understand why an easy anchor like the unit cost of a product is a go-to decision criterion, while hidden costs like supply and demand mismatch are neglected. Poor decisions are easier to justify when management craves simple indicators and an illusion of rationality amid uncertainty. It is natural, as well, to follow trends set by big name companies. When all the competitors are offshoring, it seems safe to assume they know something, they know better, and someone has found the holy grail of perfect data and did the calculations. Right?

All these factors encourage myopic strategies, that step by step, one local optimization after the other, have made an overcomplicated system, overextended to the point of dislocation, look like an optimal solution, when it is, in fact, generating weaknesses, costs and risks. These cost-minimizing strategies are based on models that artificially reduce uncertainties to risks, and usually reduce risks to convenient normal distributions. Unsurprisingly, their outputs look good on paper but offer no robustness to real-life challenges. The goal is to train students, future managers, to avoid these pitfalls, deal with uncertainty and have a positive impact on companies and society.

In this thesis, I explore the offshoring decisions through the lens of behavioral science. Based on the literature on heuristics and biases, I designed laboratory trials to highlight the dimensions involved in offshoring decisions: do people try to optimize profit? Are they able to compute the optimal solution to a problem involving costs and demand volatility? Do such affect factors as social externalities and peer influence have an impact on these decisions?

Also, to facilitate teaching and communication of the research insights on local manufacturing competitiveness, I developed a simulation-game that helps students, managers and policy makers understand the value of reducing lead-time.

My thesis is articulated around three papers.

The first paper looks at a software-based trial I designed presenting a choice between local production, with high costs but known demand, and offshoring, with lower costs but high demand uncertainty. Based on previous studies in quantitative finance and the Cost Differential Frontier tool developed at University of Lausanne, I created two scenarios challenging 100 participants to make a profit-optimizing decision. The main research question is: Are participants able to formulate a rational solution for a complex problem involving cost of uncertainty and volatility? And if not, can we identify biases in their decision-making? The results show a misuse of heuristics leading to suboptimal decisions and highlight the potential usefulness of decision tools to help decision-makers evaluate the value of responsiveness when facing demand uncertainty.

In the second paper, I describe extending the software-based task to explore the impact of non-economic factors, like peer influence – the modification of one's attitudes, values or behaviors to follow or conform to those of an influencing group or individual – and framing – the modification of the perceived value of alternatives by highlighting different features – on decision-making. The laboratory trial is designed as an application of the classic heuristics and biases experiments to a specific business case. With 100 new participants in two new conditions, and using the results of the previous paper as a baseline, I seek to answer the question: Can non-economic factors influence a managerial decision? Results show an impact of peer-influence on the decision of participants, while the framing of the offshoring choice as a social decision rather than a business decision fails to show a significant effect.

This experimental work aims at opening a new decision space beyond the classic Newsvendor problem. Although a formal theoretical frame is lacking at this stage of the research, the trials highlight the existence of behavioral effects that can inform the development of teaching and decision-helping tools.

In the third paper I present the Lead-Time Manager, a simulation-game I developed at the University of Lausanne on the topic of lead-time, demand volatility and offshoring decision-making. I detail the scenario, underlying model, and interface of the simulation-game, as well as its integration in an Operations Manager course and the way it helps acquiring complex and counter-intuitive notions. Finally, I share some insights from this experience that may inform the development of similar game-simulations in a teaching and research communication context. The Lead-Time Manager is an answer to the need for decision-helping tools highlighted in the first two papers.

I consider my research to be at the intersection of three different fields: lead-time in Operations Management, heuristics and biases in Behavioral Economics, and simulation-game design in Active Learning education approach.

I examine an Operations problem – offshoring – through the lens of heuristics and biases and propose a solution in the form of an Active Learning tool. The literature on the value of lead-time was the starting point of my research and is the theme of both my laboratory trials and the simulation-game I developed. The literature on heuristics and biases shaped my approach to the Operations problem and informed the design of my software-based tasks. The literature on Active Learning opened a solution space and informed my development of the Lead-Time Manager simulation-game, which is a contribution to this field.

According to Hevner et al. (2004, p. 76), Information Systems is the confluence of behavioral science and design science, to “extend the boundaries of human problem solving and organizational capabilities by providing intellectual as well as computational tools.” In that spirit, my thesis contributes to the understanding of how offshoring decisions are made, the limit of the rationality in the process and how we can help managers and future managers make better, more informed decisions with the help of such hand-on tools as simulation-games that make abstract insights more accessible.

To help contextualize the papers, I start with a literature review on each of these three topics presenting the ideas that influenced my research.

1.2) Valuing Lead-Time

1.2.1) Decision Lead-Time

The starting point of my thesis was the research of de Treville on the value of lead-time. The base assumption is a classic Operations Management case in which a company selling manufactured goods must decide how to produce them. Demand and/or product development occur in one location. The company can produce close to its market and/or development center, which we define as local production; or it can produce farther away, often at a lower cost. Such distant producers are often offshore, so we will refer throughout this thesis to a choice between local and offshore production. A local production allows for responsiveness, potentially on-demand production, but incurs higher costs because of the salary standards of the "high-cost countries." An offshore supplier can provide lower costs per unit, but implies a long decision lead-time, defined as the time between commitment to a production/order decision and observation of the actual demand. A decision lead-time of zero would mean producing on demand, instead, the offshore supplier requires orders to be passed weeks to months before the demand is known, which implies a level of uncertainty.

Back in 2004, de Treville, Shapiro and Hameri (2004) studied the case of a paper production company that was struggling with its supply-chain performance, experiencing both inventory surplus for some products and shortage of other custom products required by increasingly demanding customers. The analysis showed that improving the information flow from market to upstream actors, a typical reflex in this situation, fails to solve the problem if the lead-time is not reduced. In this first study, the idea of supplier distance was not yet present, and the lead-time reduction was achieved by changing production cycles, reducing lot sizes, and generally reorganizing the capacity to aim for flexibility.

The geographical aspect surfaced a few years later (de Treville & Trigeorgis, 2010). The authors noted that many supply-chains have become so extended and lean, to profit from the lowest possible unit costs, that they have also become extremely fragile. Any unexpected event, a change in demand or an issue in the supply-chain, can have catastrophic consequences on the whole operation. They presented the possibility of bringing the production close to the market as a financial option. Much like an insurance policy, this is a cost to pay in exchange for the right to postpone the production decision until more is known about the demand.

1.2.2) Cost Differential Frontier

In 2014, de Treville, Schuerhoff et al. (2014) formalized the idea and developed a model, based on real-options theory, that gives a monetary value to lead-time reduction. The inputs of the model are basic and refer to the classic Newsvendor model (Arrow, Harris & Marschak, 1951): distribution of the demand, price, cost, and salvage value of the product.

The output of the model is the price premium that the company should rationally be willing to pay to reduce or eliminate the decision lead-time, thereby reducing exposure to demand volatility. This postponement of the time when the production decision must be made is achieved by producing as close as possible to the market.

Demand uncertainty leads to mismatch costs – storage/disposal of surplus inventory, or sales missed because of shortages – and investing in lead-time reduction is a way to decrease the mismatch. The model evaluates the point of equilibrium that optimizes profit.

An online calculator (http://cdf-oplab.unil.ch) is freely available and expresses the output either in terms of Cost Differential – how much cheaper unit costs should the offshore supplier offer to be interesting despite mismatch – or Cost Premium as shown in figure 1.1 – what unit costs increase should a company be willing to incur to reduce its lead-time.

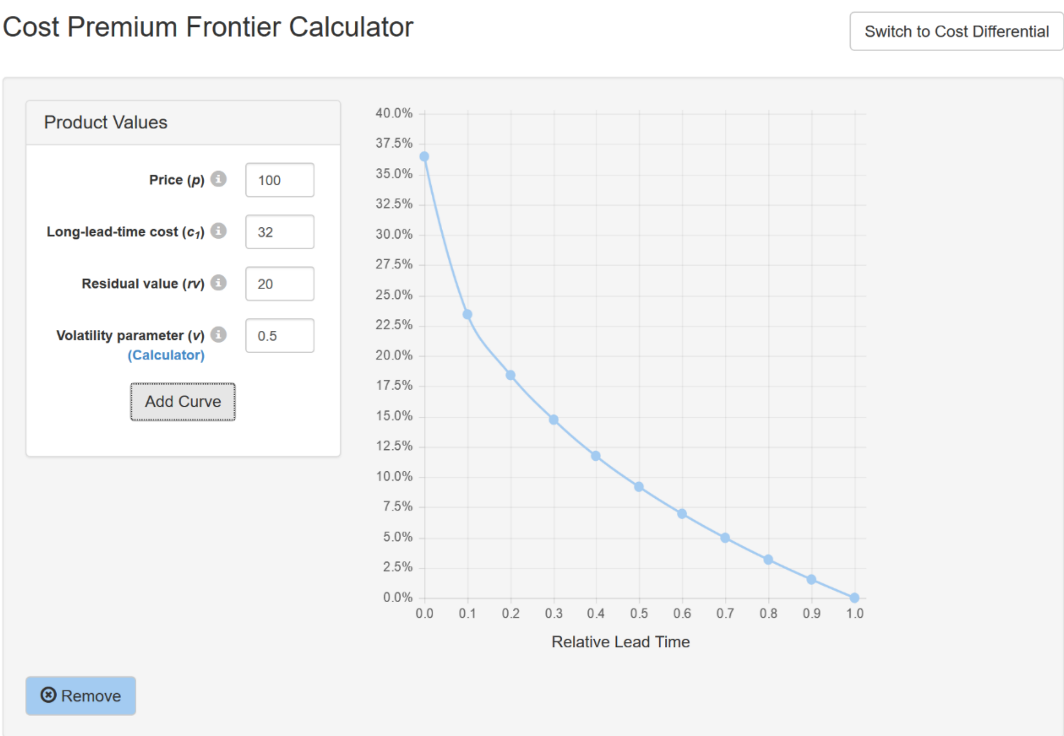

Figure 1.1: The Cost Premium Frontier calculator developed by de Treville, Schuerhoff et al. (2014) expresses in a straightforward way the value of lead time reduction, in terms of a premium that a company should be willing to pay in order to reduce the mismatch between supply and demand.

The authors noted that, contrary to common usage, a lognormal distribution is a better fit for modeling demand than a normal one as it includes the possibility of big demand peaks. Such peaks are critical to consider as they can be both a source of great mismatch between offer and demand, or a source of profit if operations are designed for responsiveness to demand surge. It also allows for the representation of demand distribution with coefficients of variation larger than 0.33 without generating aberrant negative demand on the left side of the distribution. The intuition behind the model is that as demand volatility increases, the risk of mismatch between production and demand increases, too, giving more value to the option of producing locally.

In a subsequent study, de Treville, Bicer et al. (2014) applied the model at three companies in vastly different industries – a carmaker, a food and beverages company, and a pharmaceutical firm – and got feedback from practice, showing the model is simple enough to be usable in a real-life environment. The lack of accurate historical data did not prevent the authors from estimating the volatility of demand, as they developed different estimation methods that can rely on managers' knowledge and intuition about demand peaks, intensity and frequency. The results showed that the value of lead-time was consistently underestimated in companies, mainly because managers overlooked demand volatility, or oversimplified it by looking at sales data instead of investigating actual demand.

Furthermore, the model considers only mismatches arising from demand-volatility exposure. The examples presented by de Treville, Bicer et al. (2014) further included mismatches arising from use of tenders and from high fill-rate requirements. Similarly, de Treville, Schuerhoff et al. (2014) showed that the Cost Differential Frontier model assuming lognormally distributed demand produced lower results than those calculated under assumptions of heavy-tailed demand, or of a stochastic instantaneous volatility. Thus, these two papers imply that, in most cases, it is safe to assume that the lognormal-based Cost Differential Frontier model represents a lower bound for the true cost differential or cost premium frontier.

Biçer, Hagspiel and de Treville (2018) extended the model with the approach of "jumps" in demand knowledge, suggesting that as time passes and selling time gets closer, the uncertainty about demand does not necessarily decrease linearly or exponentially, but can suddenly change significantly as the result of events or new information, such as the result of a tender. They showed that approximating the forecast-evolution process by a constant instantaneous volatility process was acceptable when jumps are expected to decrease median demand, but that incorporating the jumps into the model made an important difference when a jump was expected to increase median demand – a demand peak, for example.

1.2.3) Volatility Portfolio

Building on the Cost Differential Frontier model, de Treville, Catani and Saarinen (2017) argued that what is needed for competitiveness in high-cost countries is a volatility portfolio. They distinguished between two types of products. Products A are premium products with high margins and high demand volatility, while products C are basic products with low margins and low demand volatility, but they are both made by the same company using similar tools and skills. The model would attribute a high cost premium to product A and advise for local production, while it would attribute a low cost premium to product C and one could think it would better to make it offshore with a long lead-time and at the lowest possible cost. The authors proposed instead that production can be organized in the high-cost country in a way that creates a synergy between both types of products. To be responsive and capitalize on its market proximity, the factory needs to work with a capacity buffer, a capability for production that allows to respond to peak demands of product A. The capacity buffer is necessary but will not always be used – when the demand for product A is low. The authors suggest the best way to use this available capacity is to have an additional, complementary product, with lesser time constraints, that can be produced to stock instead of leaving the capacity idle when it is not used to make product A. These are the characteristics of product C.

Making both products A and C in the same factory in a high-cost country is a way to balance capacity utilization by playing on their complementarity. The authors propose that the cost of the capacity buffer should be considered as an option cost assigned to product A. Therefore product C, which would result in a deficit if fully costed, becomes profitable if fixed costs – including labor – are paid by product A, which allows a manufacturer to be competitive in a high-cost country with a standard product at a low price point.

The results of this research align with the growing awareness about reshoring, the opposite movement of offshoring: bringing back activities to the area they were originally located. Politics and society in general have started to understand the critical importance of having manufacturing activities in developed countries, in terms of jobs and innovation – both of which follow production as exemplified by the fact that 71% of U.S. patents come from manufacturing (Autor et al., 2016) – but also in terms of sustainability, social well-being and strategic reactivity in case of crisis.

It is important to note that the reshoring process must be accompanied by a general rethinking of the company's operations strategy to be successful. A flexible approach to production is necessary to leverage the lead-time reduction and convert it into responsiveness.

A common mistake observed in high-cost countries manufacturing is over-specialized automation and extreme, lean manufacturing. When pushed too far, this strategy creates constraints that reduce responsiveness. A production line that is designed to be the most efficient at making a specific product will be difficult to reconfigure to make another product, or simply to tweak to make variations of the base product, making it unable to leverage the proximity to market – to propose customized products, for example. Instead, companies should capitalize on skilled workers and the right level of automation to maximize responsiveness.

A promising implementation of a responsive manufacturing organization is Seru, a Japanese name used to designate a set of cellular-manufacturing principles. Instead of using highly specialized production lines, Seru principles recommend creating versatile cells, with multi-purpose tools and skilled workers, that are easy to adapt to different jobs. Yin et al. (2017) described the advantages and successful implementation of Seru at Sony and Canon.

Unlike lean manufacturing, the goal of Seru is not to maximize utilization and efficiency, but to foster adaptability and ability to innovate. A consequence is that cycle times, which define the average duration of the task each worker performs in the chain, and indirectly the share of the total work each worker accomplishes, are substantially longer in a Seru setting. Where a chain worker might have a single 5-second task – like gluing the screen of a smartphone in place – repeated for 10 hours daily, a Seru worker is able to perform a larger share of the manufacturing process of the same product. Skilled workers, along with the ability to constantly construct and disassemble cells based on orders that are received, is an example of how an on-demand local production can be implemented.

In this thesis I use simulation-based trials to explore how these insights are incorporated into decision-making and explore the use of a simulation-game to facilitate their transmission to decision-makers.

1.3) Human Decision-Making

1.3.1) Bounded Rationality

A second field of literature that was foundational to my research revolves around decision-making, heuristics and biases. Behavioral factors have long been neglected in the field of economics. One of the pioneers is Herbert Simon, who introduced the idea of bounded rationality (Simon, 1955), stating that contrary to what has been assumed in most if not all economics theory, individuals are not maximizing their utility in their choices. Individuals have neither the computational power nor the full understanding of their environment and options necessary for such optimization. Assuming – or making the simplification – that they do is a significant flaw for any subsequent theory. Instead, Simon (1956) coins the term satisficing to refer to the individual's quest for outcomes that "permit satisfaction at some specified level" (p. 136) of a given goal, rather than the pursuit of an absolute optimal outcome that – if it even exists – would require to invest in the search a quantity of resources that exceeds what the individual can afford or is willing to invest.

In his Nobel Prize lecture, Simon (1979) strongly encouraged research in decision-making to go beyond the classic and outdated theory of rational agents. He proposed what a bounded rationality decision model could look like: "One procedure already mentioned is to look for satisfactory choices instead of optimal ones. Another is to replace abstract, global goals with tangible subgoals, whose achievement can be observed and measured. A third is to divide up the decision-making task among many specialists" (p. 501). Simon regretted that instead of rebuilding their models, the classical theorists had chosen to patch them with such artifices as Statistical Decision Theory and Game Theory.

1.3.2) Heuristics and Biases

Starting in the 1970s, the heuristics-and-biases program led by Kahneman and Tversky considerably developed the theory around bounded rationality decision-making, via experiences highlighting biases that can be linked to heuristics. Heuristics are defined as rules of thumbs, unconscious mental strategies to simplify our decision-making. They are recognized as useful, very often necessary, but rely on cognitive processes that can lead to systematic and, in some cases severe, errors.

In their 1974 paper (Tversky & Kahneman, 1974), they identified three main categories of heuristics: Representativeness, Availability and Anchoring. They proposed multiple experiments specifically designed to provoke mistakes by playing on the way each heuristic treats and simplifies information in the mind of the subject. They suggested that these mistakes, the biases, cannot easily be corrected and are robust to motivation, concentration, and even expertise on the topic.

In a following work, Kahneman and Tversky (1984) insisted the invariance criterion of rational choice theory – same conditions should always lead to the same decisions – is not valid in real-life decisions. The normative properties of dominance, invariance, transitivity, and substitution that are set as basis of rational decision by von Neumann and Morgenstern (1947) are regularly violated by human decision-makers.

Kahneman and Tversky cited the well-known and widely reproduced prospect theory in which people tend to display risk aversion in the domain of gains and risk seeking in the domain of losses. They designed an experiment in which two options proposed to the decision-making subject are framed either as potential gains or potential losses. In this – farseeing – "Asian disease problem," preferences between two disease-control programs were found to be reversed depending on whether the programs were presented in terms of deaths or lives saved, despite the fact outcomes were mathematically the same in both conditions.

Kahneman (2003) later connected the work on heuristics to the dual-process theory. Dual-process theory (Chaiken & Trope, 1999) proposes a two-system view of decision-making. System 1, or intuition, is fast, effortless, and automatic. System 2, or reasoning, is slower, effortful and conscious. System 1 is always active, producing intuitive judgements, that System 2 can either endorse without modification, adjust, correct or override. It can happen that no intuitive response comes to mind, in which case System 2 is directly activated. Becoming aware of potential biases can lead a decision-maker to rely more on System 2, but corrections are not straightforward and can be either insufficient or excessive.

Kahneman argued this framework implies accessibility is paramount, as thoughts and impressions that are easily accessible – easy to think about – can influence the System 1 initial judgement, and potentially the final decision, if not corrected efficiently by System 2. The same information can lead to different decisions depending on how a problem is framed to foster accessibility of a different idea.

In this theory, the source of biases is a failure of System 2 in identifying and correcting a System 1 mistake. Hilbert (2012) suggested that in addition – or possibly on a deeper level – many biases can be explained by the noisiness of our memory. The lack of fidelity in the storage of input evidence and retrieval for output estimate, is an “almost mechanical flaw” (p. 234).

Kahneman and Frederick (2002) unified the original three groups of heuristics via the hypothesis that they all share a fundamental mechanism called attribute substitution: “When confronted with a difficult question people often answer an easier one instead, usually without being aware of the substitution” (p. 53). This idea echoes what Simon (1979) described as a procedure to “replace abstract, global goals with tangible subgoals” (p. 501).

Adopting attribute substitution as a root of heuristics function led the authors to replace the Anchoring class of heuristics – that did not work this way – with a more general Affect heuristic, suggesting we unconsciously attribute an affective value to every proposition, which can be used to make a decision for lack of a better criterion. The new definition of heuristic led the authors to argue that their use is widespread in diverse cases of decision-making, and not limited to decisions involving uncertainty.

Kahneman and Frederick (2002) also suggested factors that are susceptible to reduce biases, like statistical knowledge, intelligence attention and easily cognitively treatable format of information and attention. However, they insisted on the general robustness of biases, grounded in the imperfect functioning of System 1 and System 2.

Kahneman and Tversky have a clinical and neutral approach to heuristics and biases, even though their experiments are oriented toward the points of failure that are biases. More recently, authors like Gigerenzer and Klein have brought a new approach to the study of decision-making, one that fully embraces the use of heuristics and does not necessarily consider it as a degraded process compared to a rational ideal.

1.3.3) Fast and Frugal Heuristics

Starting in the 1990s, the fast-and-frugal heuristics program led by Gigerenzer challenged the heuristics-and-biases research strategy. A deep controversy exists between the two research programs about the goals pursued in human decision-making study, the adopted frameworks, and the nature of biases.

Gigerenzer (1996) articulates his assertion that the heuristics-and-biases program fell short of its goal of understanding human cognitive processes around two main criticisms. First, the heuristics proposed are too vague, and do not result neither in testable models, nor in specifications of the conditions in which each heuristic is active. Second, the observed deviations from optimality are based on narrow and artificial rationality norms, that do not acknowledge the context of the decision and sometimes treat single-events with tools aimed at mathematical probabilities.

While the heuristics-and-biases program focuses on demonstrating cognitive fallacies at an abstract level and consider biases as a price to pay when using heuristics, the fast-and-frugal heuristics program investigates human decisions in their context, and aims at understanding why, how and in what environment can specific heuristics be performant and resources efficient. While Kahneman (2003) insists on the robustness of biases, Gigerenzer (1991) shows that the problem structure is paramount and that some biases can simply be eliminated through attention.

The dual-process theory is also subject to controversy, both about its intrinsic assumption that intuitive judgments are generally less accurate than consciously reasoned judgements, and about its very relevance as a theoretical framework. Keren and Schul (2009) argue that the definition of the two processes are not rigorous and not empirically valid, as the criteria that are supposed to distinguish between system 1 and system 2 – such as the speed of processing or level of awareness – form a continuum rather than a dichotomy, opening the door to an arbitrary number of systems depending only on how the bounds are set. Kruglanski and Gigerenzer (2011) propose a unified theory of judgment based on the idea that both systems are in fact rule-based, that these rules are common, selected according to individual's attention capacity, processing motivation and perceived fit with the problem, among a set of options constrained by the task features and the individual memory.

Gigerenzer and his ABC research group (1999) approach heuristics as a toolbox. We constantly face choices in an environment where information is incomplete, missing, overabundant, noisy, ambiguous or erroneous, and our own computing power is limited, as is the time we have to make decisions. Therefore, what we need are processes that are fast and frugal – in terms of amount of input and computation requirements – and the use of heuristics is rational in the way that it responds to this need.

Heuristics allows us to direct information search, decide when to stop the search, and select among the options available with our limited abilities, knowledge and time.

The success of the use of heuristics depends on our ability to pick the right one in the toolbox for the right task. Matching the right heuristic with the right decision, to take advantage of the structure of information at hand, is what the authors call “Ecological Rationality.” In a specific environment, the right heuristic can outperform a complex rational decision process while being significantly more efficient in terms of resources utilization.

Marewski, Gaissmaier and Gigerenzer (2010) add to the idea that complex problems require simple decision processes through the angle of robustness. While a very sophisticated decision model would beat a simpler one at fitting past data, when this historical data is not all meaningful for the current decision, or mixed with irrelevant noise, overfit will decrease the model's generalizability to new problems. Counterintuitively, the less precise prediction of the simpler model ends up being more accurate than the artificial convolutions of the complex model. The authors note that noisiness in the input and feedback information of our decisions is all the more prominent that we live in an ever more complex world of uncertainty.

The distinction between risk and uncertainty is fundamental in the ecological rationality framework and the discussion about relevance and performance of heuristics. In a situation of risk, possible outcomes, as well as their respective probability, are known, which opens the possibility of mathematical optimization (Knight, 1921). In a situation of uncertainty "not all alternatives, consequences, and probabilities are known" (Hafenbrädl et al., 2016, p. 217) to the decision maker, which makes mathematical optimization unfeasible (Mousavi & Gigerenzer, 2017). Mousavi and Gigerenzer (2014, p. 1671) argue that in situations of uncertainty, using a heuristic with the best possible "functional matches between cognition and environment" is the best course of action, not just a degraded backup strategy. Gigerenzer et al. (1999) propose a classification of heuristics based on types of application:

- Ignorance-based heuristics, a less-is-more approach in which the subject knows very little about the problem and focuses on searching for recognizable features.
- One-Reason heuristics, a simplification process of the problem to one of its dimensions, of which the Take-the-best heuristic is a well-known example.
- Elimination heuristics, to select between options or categories using one cue at a time.
- Satisficing, setting a level of aspiration and committing to select the first option that satisfies it, is useful when options are not all on the table at the same time and may become unavailable as time advances.

Gigerenzer and his ABC research group presented a collection of examples, from animal behavior to human romantic partner selection and stock-market investment, and their experiments showed impressive performances from the simple heuristics. In many cases, decision-makers can take advantage of the structure of information of their environment to generate options, stop the search, analyze the options and select a satisfying one, all of that in a short time and at a low cognitive cost. But the research program also investigates when and why heuristics sometimes let us down.

Gigerenzer (2003) explored real-life examples illustrating how the human difficulties in dealing with uncertainty can lead to misguided choices, by obfuscating the relevant representation of information that would allow an ecologically rational reasoning. He cited innumeracy, the “inability to reason about uncertainties and risk” (p. 24), as a critical source of errors in a wide range of decisions, including public policies, medical treatment decisions and criminal investigation.

Innumeracy casts a light on the relevance of the fast-and-frugal heuristics programs in education. Gigerenzer (2003) suggests part of the problem is that mathematical education focuses mainly on algebra, geometry and calculus: tools for working with certainties. Statistics are taught – at best – as formulas and procedures, but students are never given the opportunity to understand them on a deeper level, to recognize uncertainty in daily events, to estimate degrees of risks and to turn data into manageable and intuition-compatible representations.

I consider this last aspect about representation of information critical, and in my opinion, it is underlying in all the literature about heuristics. The benefit of heuristics is to allow the human mind to get a workable representation of information.

1.3.4) Experts’ Sources of Power

Klein (2001) also studied the way people make decisions in real settings under time and resources constraints. The Naturalistic Decision-Making framework seeks to answer: What are people doing when they are not using deductive logical thinking, analysis of probabilities and statistical methods?

Klein shares a lot with Gigerenzer: the importance of the environment and its idiosyncratic structure, the idea of satisficing, the very positive view of the use of heuristics and the consideration of biases as a minor issue compared to the benefits. He called the naturalistic decision-making methods “sources of power” and highlighted their use by experts in various domains like firefighters, pilots, military leaders, nurses.

His hypothesis is that while beginners might want to use a more classical and rationally structured decision process, experts have developed skills that allow then to use efficient heuristics and make better decisions with fewer resources. They do not become better at using a heavy formal process, instead they develop ad-hoc processes based on efficient heuristics. The experts interviewed by Klein often do not feel like they are considering options, or even like they are making decisions, they feel like the best course of action comes to mind intuitively and automatically.

To illustrate it with an evocative example: professional tennis players are so good at returning a tennis ball not because they are better than average people at computing the mathematical function of the trajectory of the ball, but because they developed excellent and efficient intuitive processes.

This finding is counterintuitive as we might expect beginners to jump on the first option they can think of, when it is, in fact, experts who can generate a single course of action that will work, while novices need to compare different approaches.

Becoming an expert requires the development of perceptual skills linked to the decision environment. Accumulating experience, although it is not sufficient – the process to turn experience into a big-picture vision is not widely agreed upon – is necessary, and Klein suggests that simulations are a valuable training tool, as they give easy, on-demand access to various meaningful situations that would otherwise take years to encounter and digested into expertise, they can speed up the training.

Klein (2001) identified three main “sources of power”:

- Intuition, the non-conscious perception or recognition a pattern or situation is not right, without necessarily being able to precisely define the problem.
- Mental simulation, the ability to create a mental representation of a solution and assess if it could work, or what would go wrong, then jump to the next idea, until satisficing.
- Stories, to make sense of what led to the current situation and what can possibly happen next.

The author argued human decision-making is fundamentally a satisficing – as opposed to optimizing – process. We do not filter through all possible options but merely channel from one opportunity to another, sometimes even considering only one option. The goals are not fixed from the beginning of the decision process, but are rather refined or redefined along the way. Just like in Gigerenzer’s (1999) view, the context and previous experiences of the decision-maker are paramount in selecting an accurate strategy.

Klein defines a bad decision as one for which we not only regret the outcome, but also, and more importantly, the process. In the Naturalistic Decision-Making framework, mistakes do not come from biases in the way we think, but rather from a lack of expertise or a faulty design of the problem that does not allow it to be correctly understood, coming back to the importance of information representation.

1.3.5) Managerial and Entrepreneurial Decision-Making

Armed with this theoretical basis on heuristics and biases, I searched for literature about the application of heuristics and biases in the management field in general and in offshoring decisions in particular.

Entrepreneurs are often singled out as a subject for managerial decision-making studies, as they face many choices, and are “more susceptible to the use of decision-making biases and heuristics than managers in large organizations” (Buzenitz & Barney, 1997, p. 9).

According to the authors, the difference between entrepreneurs and managers is not about demographic, personal or psychological differences, but in the decision-making process they use. Much like the ecological rationality in the work of Gigerenzer, using heuristics is what allows them to thrive in an environment that would otherwise be overwhelming, and in which “the window of opportunity would often be gone by the time all the necessary information became available for more rational decision-making” (p. 10).

Baron (1998) concurred that the key to entrepreneurs’ decision-making is not personal characteristics, as entrepreneurs are not different from the average person from a personality point of view, but the cognitive processes they use: “How, in the terms of cognitive psychology, they attempt to make sense of the complex world around them” (p. 277). Entrepreneurs do not have a greater willingness to take risks, or more optimism. Rather, they work in an environment where they are prone to more uncertainty, pressure, information overload, and are therefore in a position to often use heuristics in their decision-making processes, and consequently be subject to more biases. The author listed five examples of biases – counterfactual thinking, affect infusion, attributional style, planning fallacy, self-justification – and designated them as the source of wrong decisions, rather than personality traits like overconfidence. The good news, according to Baron, is that thinking patterns are easier to change than traits.

Forbes (2005) studied the overconfidence bias and compared how it affected company-founder entrepreneurs compared to non-founder managers. He defined overconfidence as “the degree to which people do not know what they do not know” (p. 626). The author discovered founders are indeed more overconfident that non-founders, but also that age, low organizational decision structure and presence of external investors reduce the degree of overconfidence exhibited by decision-makers, while overall self-confidence does not have an impact. His conclusion is in line with Baron (1998): Individual personalities of entrepreneurs are not homogenous and are not the main explaining factor of their decision-making. Rather, cognitive processes – both from self-selection for the job and as a consequence of the environment of such job – play a major role.

Simon et al. (2000) stated it is a paradox that entrepreneurs are willing to take the high risk of starting businesses if they do not have a risk-seeking personality. They made the hypothesis that risk-perception, rather than willingness to take risks, could explain the decision to start a company, and they designed a laboratory experiment around a case study to validate this hypothesis and assess the role of several cognitive biases on risk perception. They found support for the hypothesis that lower risk perception is associated with the willingness to start a venture. They also identified illusion of control – the belief that one's skills can increase performance in a situation actually ruled by chance – and belief in the law of small numbers – drawing conclusion from a too small sample of inputs – as associated with lower risk-perception. The same two biases – although the law of small number was replaced by a more general “representativeness bias” but with a close definition – that were identified by Busenitz and Barney (1997).

In addition to their findings, this article discusses an interesting point of methodology, as they wished to study managerial decision-making in a laboratory experiment setting. On the relevance of laboratory experiments to study such strategic decisions as offshoring, they built upon Schwenk (1995), arguing that although the laboratory setting has flaws – artificial context, low stakes and pressure, college students subjects – it has value in allowing direct observation of decision-making, as opposed to retrospective accounts, often biased (Huber & Power, 1985; Schwenk, 1986) and artificially rationalized. A well-designed laboratory experiment has the potential for establishing causalities that would be impossible to determine via real-world observation.

Gray et al. (2017) followed the offshoring process of nine companies seeking lower costs. Initially, the companies’ decision process followed what the authors called a “Lowest per-unit landed cost” (p. 38) heuristic, meaning they focused only on the face value of unit costs, excluding all other factors that would make the decision too complicated. Six of the nine companies later reversed the process and reshored their activity, based on a more comprehensive analysis of supply-chain costs, which is a very costly way to acquire a broader understanding of offshoring costs.

Larsen et al. (2013) identified the complexity of offshoring as a driver of cost-estimation errors leading to a “wrong” offshoring, in the sense that is it later regretted and potentially reversed by the company. They found that 48% of the companies they analyzed made less costs savings than expected, despite the fact they studied services offshoring such as IT, call centers and administrative services, for which offshoring is arguably easier and more predictable than industrial offshoring. They also suggested that the driving force behind the decision, a strategic move rather than an opportunistic one based only on costs savings, has an impact on the success of the outcome, and its predictability.

Petit et al. (2010) drew a parallel between human behavior and animal behavior. They studied collective movements and the point when a group of animals decides to move from one spot to another. The authors argue that external conditions alone do not explain the trigger of such movements, and that besides leadership, a mimetic-based group process is at play. Each animal interacts with a limited number of peers through cues or signals, creating a distributed network of information. It is only when and if a certain threshold in the number of individuals in the group who want to move is reached that the group movement starts.

It is easy to see a parallel with the industry migration to China over the last 30 years. Each manager is influenced both by a few leader figures and by the peers he is in contact with, and when a certain threshold in the number of companies that offshore is reached, a tipping point occurs and the rest of the herd follows.

Moreover, several studies found that group decisions, as opposed to decisions taken individually, tend to foster more risk-taking (Blascovich & Ginsburg, 1974; Lamm, Trommsdorff, & Rost-Schaude, 1972), especially if the members of the group have an individual risk-taking tendency (Gardner & Steinberg, 2005).

Hahn et al. (2009) found that decision-makers in the information system industry, when faced with offshoring decisions, tend to imitate the leaders, learn by successive trials and errors and progressively go to riskier places as they gain experience. They also pointed out the role of environment trends, like an industry-wide movement that creates a pressure and fear of falling behind and triggers a “defensive” offshoring decision rationalized as an unavoidable necessity. As the peer effect seemed particularly relevant to offshoring decision, I decided to include it in my trial.

Musteen (2016) interviewed 22 top managers from small- and medium-size companies in various industries – information technology, life sciences, furniture, fashion and electronics – who faced an offshoring decision. Her intent was to assess how much of the decisions were based on a rational and comprehensive process – like computing costs, risks, market or talent access, Transaction Cost Economics approach – and how much relied on what could be considered behavioral factors in a broad sense of the term: influences of decision-makers' experiences, attitudes, emotions, cognitive limitations.

Seventeen of the 22 managers openly recognized and described using non-economic factors in making their decisions. The author classified these factors in three categories: previous personal experiences, personal attitudes and emotions and cognitive limitations. The personal attitudes and emotions categories contained a lot of reference to social responsibility and patriotic pride of the managers, which led me to include these aspects in my trial.

Das and Teng (1999) found that different modes of strategic decisions – rationality, avoidance, logical incrementation, political, randomness – lead to different biases in the process, but that no mode is immune. Not even one aspiring to rationality, as is it commonly subject to prior hypothesis and limited targets as well as creating an illusion of manageability.

Schoenherr, Rao Tummala and Harrison (2008) collaborated with a company in an action research project to develop a comprehensive and arguably rational framework for evaluating offshoring options. They used an algorithm for multi-criteria decision-making under uncertainty called Analytic Hierarchy Process to evaluate five alternatives for sourcing and assembly involving a combination of China, Mexico and the U.S.

The authors, using thorough interviews with the company and literature, listed 17 risk factors, with lead-time and mismatch costs being one of them, and weighted their importance. Ultimately, they benchmarked the relative performance of each alternative across the 17 factors and recommended the best options after consistency checks.

Their work is interesting not only for the risk-factors list they produced, but also because they showed what a comprehensive decision process would entail for a company: one year of committed work in collaboration with researchers and the use of complex algorithms the company does not master on its own. And this applies in the optimal case of a company that has already defined a limited list of offshoring alternatives. As such, it exemplified why such a process goes beyond the capabilities or willingness of most companies.

Schweitzer and Cachon (2000) conducted a laboratory study on the Newsvendor problem, a classic Operations management optimization problem in which participants have to decide on an order quantity for a unique sales period based on a stochastic demand function and the price, cost and salvage value of a product. Participants were found to order too many low-profit products and too few high-profit ones, as compared to the expected profit-maximizing order quantity. The authors attributed these errors to a heuristic that would favor reducing ex-post inventory error – rather than maximizing profit – and the anchoring and insufficient adjustment heuristic – with the mean as an anchor and a tendency to repeat the same order or insufficiently adjust toward the optimal order quantity.

This study is particularly close to what I want to do with my trials in the sense that it compares participants' decisions to a benchmark model to analyze their deviations, and investigates the heuristics susceptible to cause these deviations. In my case, the decision can be summarized as "how much are participants willing to pay to avoid facing the Newsvendor problem?" and the benchmark is given by the Cost Differential Frontier model by de Treville, Schuerhoff et al. (2014).

1.4) Active Learning and Simulation-Games

1.4.1) Active Learning

An important part of my work has been the development of a simulation-game to help teach and communicate the results of research on the value of lead-time.

This simulation-game artifact – not to be confused with the simulation I use in my trials on offshoring decision-making – is part of a teaching approach called Active Learning. This chapter gives an overview of the literature about Active Learning and simulation-games that inspired its development, while my artifact is described in detail in Chapter 4.

Active Learning is not a precise learning method, but a broad approach that encompasses diverse practices where the learner is an active player in the learning process, as opposed to the classic ex-cathedra lecture.

Prince (2004) proposed a meta-analysis of different types of Active Learning in the context of engineering teaching, and identified four types of methods:

- Student engagement, by breaking lessons with participative activities.
- Collaborative learning, with students working in a group toward a goal.
- Cooperative learning, group work with individual assessment.
- Problem-based teaching, by introducing problems before theory to provide context and motivation.

The author found extensive empirical support for all forms of Active Learning, measured not only in terms of academic achievement – test results – but also in terms of students' attitude improvement, as well as better retention of material compared to traditional lectures.

To go further on problem-based learning, Kapur and Lee (2009) explored how productive failure in mathematical problem solving could help students better assimilate the material. The concept of productive failure is to reverse the conventional instruction process, by challenging students with complex, ill-structured problems before receiving the relevant instructions and lecture content, with the intent to create a situation in which students will fail to produce satisfactory solutions but will be familiarized with key concepts that will allow for a more effective subsequent learning. An ill-structured problem is one where the initial state, the goals and the possible steps toward these goals are uncertain, undefined or subject to the gathering of data that are not obvious to the person attempting to solve it.

The authors opened the question as to when it is optimal to start giving structure in the learning process. While the traditional teaching model starts with a lot of structure at the beginning of the learning then gradually reduces it, Kapur and Lee suggest that delaying structure gives space to "learner-generated processing, conceptions, representations, and understandings" (p. 2633). Making mistakes or being stuck prompts the learner to use prior knowledge to fill the gaps, try to build links, be active from a cognitive point of view. Material learned this way builds a stronger degree of confidence in the learner.

An experiment was conducted on Grade 7 – 12- to 13-year-old – students, where one group had traditional lectures guided by the course workbook, and the other group used the same amount of time on ill-structured problem-solving attempts – and in most cases failing – alternating with consolidation sessions with the teacher. At the end of the learning period, both groups were tested on the material through two types of problems: basic well-structured items, and complex items. "Productive failure" condition students scored higher on both types of problems, with a difference particularly important on complex items. The authors concluded, consistent with Prince, that productive failure leads to a deeper understanding and appropriation of the material, and therefore an ability to reuse the knowledge in complex situations.

Another way of making students active in the learning process is testing. Little and Bjork (2011) demonstrated how to take advantage of tests not only to assess learning, but also to enhance learning through pretesting, testing learners on a material before teaching it.

It has already been shown (Kornell, Hays, & Bjork, 2009; Richland, Kornell, & Kao, 2009; Rothkopf, 1966; Soderstrom et al., 2014) that taking a test before studying can improve learning of the pretested information, but Little and Bjork went further in showing that pretesting improves recall of both tested information and non-tested related information.

The authors found that pretesting facilitates subsequent learning of the material by fostering involvement and helping identify the most important pieces of information and their relevance. The attempt itself changes the way we think and store future information, as retrieving a fact from our memory is not like opening a computer file, instead it alters our brain organization. Therefore, pretesting primes the brain, predisposes it to absorb new information, and helps hierarchize the thinking.

Multiple-choice questions appear to be the best suited format of pretesting as it is important that the students are at least able to consider plausible alternatives – a total absence of grasp of the material would not trigger intellectual activity. Moreover, multiple-choice questions encourage a learner to recall not only why the right answer is correct but also why the other alternatives are incorrect. The format helps fight the illusion of fluency effect: thinking that an answer is obvious when learning the material, but being confused when other plausible answers are proposed.

A short test can be organized at the beginning of a class session. It is well documented (Hartley & Cameron 1967; MacManaway 1970) that the signal to noise ratio in a traditional lecture is far from ideal, with students' attention declining after ten minutes and only about 20% of the content presented being memorized. Lang (2016) suggested the first five minutes of a class determines, consciously or not, the degree of interest and focus students will invest in the session, and teachers often waste this critical moment on administrative or logistical tasks. Instead, the author suggested asking a question that will be answered by the lecture or asking about what was learned in a previous session to reactivate the content in mind.

All the methods mentioned above can be applied in the context of a flipped classroom approach (Gilboy et al., 2015). In a flipped classroom setting, a lot of the theoretical content learning takes places outside the classroom, typically through such online media as video lectures and notes prepared by the teacher, which allows for self-paced acquisition of the base knowledge. Class time is then dedicated to activities and discussions among students – who already possess some knowledge on the topic – and the teacher. This interaction aims at building on the theoretical content and deepening the understanding and ability to use it in real-life settings, a task for which Active Learning methods are well suited.

The success of an Active Learning approach depends on the ability of the teacher to create content, foster interactivity and adapt the session to audience reactions while maintaining clarity on the purpose of each lecture and activity. These are challenging requirements that draw on skills different from the ones needed in traditional teaching methods (Yordanova et al., 2015). Creating quality interactive content requires a lot of effort, but is powerful in the sense that it is easily scalable, reusable and adaptable to online teaching.

1.4.2) Simulation-Games

Another tool that holds an important place in the Active Learning portfolio is a simulation-game. Computer-based serious games and simulations have seen a booming development over the past 30 years, as the democratization of information technologies simplified their diffusion and usage, while an easier access for practitioners and subject-matter experts to programming fostered the development of tools adapted to teaching, formation and communication.

Serious games on managerial topics are numerous and cover the full spectrum of disciplines and industries (e.g.: Commercial strategy (Ncube, 2010), Marketing (Bascoul et al., 2013), Project Management (Vanhoucke, Vereecke & Gemmel, 2005), Business Models (Tantan, Lang & Boughzala, 2015), Aeronautics (Proctor, Bauer & Lucario, 2007), Healthcare (Ribeiro et al., 2012), Crisis-management (Meesters & Van de Walle, 2013), Military (Zyda et al., 2005)). In the supply-chain field, the Beer Distribution Game (Sterman, 1989) developed by Jay W. Forrester at MIT in the 1960s to illustrate the Bullwhip effect is an early, and still influential, example.

Simulation-games require active participation from the learner. They are a type of problem-based learning that embeds the theoretical content in a more or less – at the teacher's discretion – structured scenario. Just like pretesting, simulation-games can be used as a priming tool, before theoretical learning, and generate productive failure and discussion. There is no consensus in literature over the terminology to designate these artifacts: "game," "simulation," "simulation-game," "serious game," among other options, are often used interchangeably. However, some authors have attempted to set definitions and the debate is instructive in the way it identifies fundamental attributes in a booming field that still lacks standards.

The dictionary definition (Flexner, 1970) of a game is "a competitive activity involving skill, chance, or endurance, played by two or more persons according to a set of rules, usually for their own amusement or for that of spectators." In that way, it is a close activity to problem solving in the sense of Simon (1996), summarized by Hevner et al. (2004, p. 88) as follows: "utilizing available means to reach desired ends while satisfying laws existing in the environment." Playing is a fundamental human activity, it is, after all, one way babies discover their environment and acquire skills.

Sauvé et al. (2007) built on several definitions found in the literature to identify attributes of games: player(s), a conflict or cooperation dynamic, rules, a goal and an artificial nature. If the game is to be educational, it includes an extra pedagogy attribute, a purpose beyond winning (Mitgutsch & Alvarado, 2012).

On the other side of the spectrum, simulations are models of reality defined as systems. These models must be dynamic, simplified as compared to reality, but accurate and valid. If the simulation is to be educational, it includes learning objectives.

Games imply active participation of the player, including decision-making, while it is not necessarily the case with simulations. In general, the learning aspect in a simulation tends to be explicit, while it tends to be more implicit in a game.

The literature is not unanimous on the importance of artificiality in games. Some authors like Ncube (2010) argue that an artifact, like the Lemonade game in her study, is a simulation because rules of reality apply, and it refers to reality. Other authors like Zyda (2005) ignore this attribute and would rather qualify it as a game.

Ellington (1981) suggested many of the artifacts we are talking about belong to a category where the definitions overlap – a winning aspect and a representation of real life – and that an appropriate name is simulation-games. I adopted this fitting terminology for my own artifact, but the debate and confusion live on in the literature, not to mention in practice.

The fact that reality is simplified and stripped of some aspects is a common pushback from practitioners when trying a simulation-game, and their focus goes right to the missing aspects that constitute the complexity of their jobs. However, abstraction and simplification of the real-life problem are necessary to focus on one aspect of reality, especially for teaching purposes. This simplification of some aspects and magnification of others is a purposeful feature of serious games and simulations, not a bug. Van der Zee and Slomp (2009) explained that simulation-games can be complementary and sometimes even preferred to on-the-job training in some companies because they allow isolation of a particular aspect – communication, cooperation or negotiation – that would otherwise be implicit and hidden, as well as replay and what-if scenarios.

When teaching more abstract notions like statistical reasoning, counterintuitive and non-linear effects, simulation-games have several strengths that make them useful tools. Through experience and trial and error, simulation-games de-ice the misconceptions of the player and help “shift learner’s personal paradigms” (Ncube, 2010, p. 568). They make it possible for the teacher to present situations that are rare in a natural setting but have the potential, when presented at the right time in the teaching process, to let the learner gain experience and, more importantly, expertise in the sense of Klein (2001). Thanks to immediate feedback, they allow for a clear understanding of cause and effect (Van der Zee & Slomp, 2009) and build confidence as the learner’s skills develop. Their dynamic aspect – the model behind the game responds to players actions – makes them an effective way to acquire a global or systemic perspective of phenomena (Pasin & Giroux, 2011; Machuca, 2000). Their exploratory nature – playing and understanding occurs at the same time – fosters intrinsic motivation (Saethang & Kee, 1998; Sauvé et al., 2007).

Many studies showed positive results in the use of simulation-games in teaching contexts. Blunt (2009) found positive results in teaching Business and Economics; Wong et al.

(2007) showed effectiveness when teaching Physiology to non-science major students; Gosen and Washbush (2004) found improvement in exam scores for undergraduate business students after use of a simulation-game; Dunbar et al. (2014) successfully applied serious games for mitigating the cognitive biases of individuals making decisions under uncertainty; Coller and Scott (2009) and Coller and Shernoff (2009) found more engagement when using serious games.

1.4.3) Limits in Artifact Evaluation

The main issue in the modern profusion of simulation-games is that many studies miss the target of showing their artifact is the appropriate teaching tool. The problem often lies in the evaluation of these tools, on two different levels.

First, the theoretical evaluation of the quality of the conceptual design is too often confused with the evaluation of the quality of the game (Mitgutsch & Alvarado, 2012). The question "Is it efficient at making the intended teaching point?" is often replaced by the simpler but less accurate question: "Is it a good game?" According to Mitgutsch and Alvarado, a key design element is the fit between the gameplay and the learning point. Conceptual design of a serious game should be made so that the style serves the content and both merge in a way that makes sense for the player. Putting an entertainment part and a learning part side by side does not make an effective serious game. Several frameworks exist to assess simulation-games – ARCS (Keller, 1987), DGBL (Prensky, 2001), SGDA (Mitgutsch & Alvarado, 2012) – but none emerges as a standard.

Secondly, experimental evaluation of the impact of serious games is often overlooked or incorrectly targeted. Conducting proper A/B testing on a randomly divided class through a semester, as did Kapur and Lee (2009), is organizationally complex and often against university rules, inciting simulation-game developers and practitioners to use less comprehensive approaches. A common evaluation method is distributing a questionnaire to participants (e.g.: Tantan, Lang & Boughzala, 2015; Arisha & Tobail, 2013), but this method limits the feedback to the feeling of participants toward the game, their degree of satisfaction with it as an activity or with the quality of its interface, or their self-assessment of the improvement of their understanding. It is poised to mix appreciation of the experience and learning effects.

Another common evaluation process is to compare the results of the participants on the first rounds of a game versus the last rounds (Pasin & Giroux, 2011). The bias here is that getting better at the game does not necessarily correlate with an improved understanding of the underlying teaching point. It is normal to become better at a game – be it serious or not – by getting a better grasp at the gameplay aspects, or in the worst cases, by memorizing the right answers. Therefore, it is “inappropriate to assess simulations using performance as a measure of learning” (Gosen & Washbush, 2004, p. 273).

Developing evaluation methods, as well as frameworks that would accurately assess conceptual design quality while being general enough to become a recognized standard in the field would be a major step forward, but is complicated by the immense variety of artifacts and the discrepancy in their definitions (Sauvé et al., 2007).

1.4.4) Lead-Time Manager

The second part of my work in this thesis, presented in chapter 4, is the development of a simulation-game called Lead-Time Manager, that aims at facilitating teaching and communication of the research insights about the value of shortening lead-time and increasing supply-chain responsiveness to reduce mismatch costs.

The challenges in transmitting this content are multiple. First, learners need to acquire a statistical and theoretical toolbox, including the Newsvendor model, volatility and fill rate calculations, and expected profit calculation. But beyond these skills, a full mastery of the content requires a deep shift in the learner's thinking process toward the offshoring problem, an upgrade to the learner's heuristic toolbox. It requires to deal with uncertainty that is not always reducible to risks, to acknowledge the existence of rare events, to overcome the intuitive attraction to lower unit costs to get a broader view of hidden costs, to see through blurred cause/consequences chains and to make sense of non-linear effects.

My goal is to leverage Active Learning methods to facilitate this knowledge transmission and prepare students and practitioners to apply the content to real life situations. But in order to build an effective teaching tool, I need to better understand the pitfalls, the naturalistic way this offshoring decision is treated by people. To build a tool that takes learners from where they are and brings them to a state where they are better-equipped and able to make an informed-choice, I need to identify where they are to begin with, what kind of tools they pick in their heuristic toolbox when faced with an offshoring decision. To that end, the first part of my work is an exploratory diagnosis of the decision processes at play, through two laboratory trials that are presented in chapters 2 and 3.

2) Biases in Assessing Uncertainty: Exploration of Operations Management Decision-Making

2.1) Introduction

Economists used to consider decision-making a pure, cognitive application of mathematics. Decision-makers were assumed to be completely rational, able and willing to gain a comprehensive understanding of their environment and all its relevant variables before computing an optimal choice.

Luckily, such concepts have evolved, starting in the 1950s with the introduction of the Bounded Rationality concept by Herbert Simon (1955, 1979), and enriched by the work of Kahneman and Tversky (1974) on heuristics in the 1970s.

The research community switched from a normative and unrealistic model of the human brain as a rational computer to the acceptance of Behavioral Economics as a theory that is more accurate in describing how we really make decisions (Kahneman & Tversky, 1984), without pretending to predict or even fully understand human choices.

Heuristics are a central element of modern research on decision-making. Heuristics can be defined as "rules of thumb," a set of thinking-methods that rely on systematic procedures to categorize, judge and simplify decisions. Heuristics are multiple, and although we can sort them in a handful of large categories (Kahneman & Tversky, 1974; Kahneman & Frederick, 2002), each instance is specific to a narrow range of situations. Indeed, heuristics are efficient to the extent that they take advantage of the structure of information in the environment at hand (Gigerenzer et al., 1999).

This powerful and generally efficient tool, however, comes with a downside: bias. As the same main heuristics are widespread, they lead to recurrent mistakes, systematic deviations from optimality. The mechanisms behind biases are not unanimously agreed upon. Proposed reasons include failure of conscious cognition to spot and correct errors of intuitive thinking (Kahneman & Tversky, 1974), oversimplification due to the substitution process in heuristics (Kahneman & Frederick, 2002) and the noisy information processing of human memory (Hilbert, 2012). Not only do biases lead to suboptimal decisions, but their systematic nature puts the decision-maker at risk of being predictable, or even manipulated.

Despite the richness of this research field, students in business and economics still learn, and managers still use, models that assume actors' rationality in a classical sense, accepting this hypothesis while knowing from experience how wrong it is.

I decided to focus on the case of heuristics and biases in a specific managerial decision: offshoring. Economic offshoring can be summarized as the choice between continuing to produce locally, where the company sells its products, or move to a country with cheaper labor. This decision presents a difficult tradeoff between low unit costs and the increase in lead-time with uncertainty about demand as the orders must be made earlier.

Other hidden costs exist beyond supply and demand mismatch, including intellectual property risks, transportation risks and costs, communication issues, loss of innovation, and quality issues. The literature (Musteen, 2016) also suggests social factors, like social externalities and reputation considerations, can complicate offshoring decisions.

I argue that because it involves a rich and complex environment, many variables and high stakes, offshoring is a good example of the need for a comprehensive and structured decision process as exemplified in Schoenherr, Rao Tummala and Harrison (2008).

Recent studies (de Treville, Schuerhoff et al., 2014; de Treville, Bicer et al., 2014) have shown the value of local production and risks of offshoring from the point of view of lead-time and volatility of demand.

A tool – Cost Differential Frontier (http://cdf-oplab.unil.ch) – was developed by de Treville et al. to help decision-makers deal with a counterintuitive choice that must balance two competing factors: unit costs and volatility of demand. Taking simple information on price, cost, residual value and volatility of demand as inputs, it gives an estimation of the supply and demand mismatch cost when increasing lead-time.

My goal is to study offshoring through the lens of heuristics and biases, and probe for deviations from rationality in offshoring decision-making processes. To that end, I designed and coded a computer-based simulation that puts the participant in the role of a manager facing an offshoring decision. I manipulate costs and demand volatility to create scenarios that could be optimally solved with the Cost Differential Frontier tool – not provided to participants – and compare the optimal strategy with participants' choices.

The task proposes an offshoring decision that is heavily simplified, stripped of many aspects to focus on mismatch costs. Unlike in real world, financial parameters are precisely defined and demand is modeled by a specific function, which effectively simplifies what would normally be a situation of high uncertainty to a situation of risk, and allows for the computation of an optimal solution, at least from the experimenter point of view. However, for the participant who is assumed to be unaware of the Cost Differential Frontier solution, the possible outcomes - understock, overstock - might be more or less grasped, but their probability and financial consequences are unclear, which puts them in a situation of uncertainty rather than risk, and opens the way to the use of heuristics.

My work lies within the tradition of Kahneman and Tversky in the sense that I intend to use a mathematically optimal solution as the rational benchmark and observe heuristics as deviations. This optimal solution will be computed based on a simplification of the problem, and using the assumptions and model from Treville, Cattani and Saarinen (2017), as will be explained in the next chapter. However, my method should not be interpreted as presenting heuristics as inferior decision strategies, but rather as a detection protocol, a way to cast a light of the heuristics used in this offshoring decision context. A decision strategies ranking would require to precisely understand the knowledge, motivation and resources of participants to determine their ecological rationality in this situation.

If participants can solve the offshoring problem, or use intuition and reach a result that satisfies them, this would suggest that a heuristic exists that is performant for this task. If not, it would highlight the need for teaching and decision-helping tools.

My research is guided by several questions:

- Are participants able to formulate a rational solution for a complex offshoring problem?
- Are participants able to evaluate the cost of uncertainty and volatility?
- Are participants aiming at mathematically optimal choices?
- Can we identify heuristics in participants' decision processes?
- Can we link the deviations from rationality to known biases?
- Can we influence participants' decisions?

These questions shape a very ambitious program, of which this paper is an exploratory early stage that aims at gaining a better understanding of the problem, but does not provide generalizable results. I consider this topic important because of the combination of three factors. Firstly, offshoring decisions are strategic and carry very high stakes for a company. Secondly, the use of heuristics is widespread. We use heuristics intuitively in daily routines, but we also use them in strategic decisions to help us cope with uncertainty, time pressure, overflow of information and lack of structure (Simon, 1979; Schwenk, 1984; Busenitz & Barney, 1997), regardless of our personality traits (Baron, 1998; Forbes 2005; Simon, Houghton & Aquino, 2000). Finally, current results of offshoring are subpar. Larsen, Manning and Pedersen (2012) found that 48% of companies did not achieve the expected savings when offshoring.

I argue that this combination of factors creates a large and valuable potential for improvement if managers become more aware of their decision processes, limits, shortcuts, potential traps and inherently bounded rationality. Given the ubiquitous nature of biases, tools such as simulations games and new teaching methods could be useful for a large array of people.

I envision this research project as a back and forth between laboratory trials and theory building, in which initial trials will inform theory and the improvement in theoretical models will allow for better targeted and better controlled experiments. This trial represents the first step in exploring the presence of biases in this offshoring decision, and I focus the investigation around three hypotheses:

- Hypothesis 1: Under conditions that are objectively favorable to local production, some offshoring will still occur, indicating existence of offshoring bias, consistent with Grey et al. (2017).
- Hypothesis 2: When contextual conditions change such that offshoring goes from economically unfavored to less unfavored, participants' degree of offshoring will vary uncorrelated with the new economically rational option.
- Hypothesis 3: Participants intend to adopt the economically rational option.

2.2) Trial Description and Methodology

2.2.1) Trial Design

I developed a simulation in the form of a web application, giving participants the role of the top manager of an electronic components company. In the initial situation, the company produces components in-house in the region where they are sold. The simulation lasts for 12 simulated "months" representing periods of production and sales. At each of these 12 periods, participants have the choice to maintain local production, or to offshore it, the latter being irreversible.

The offshore supplier offers a cheaper cost per unit ratio, if the participant successfully computes and compares the cost of production per unit and the cost per worker.

However, following the Cost Differential Frontier framework, ordering offshore instead of producing locally increases lead-time and therefore introduces uncertainty in the demand for each period, unlike local production that is considered to be made on-demand.

The balance between the costs and the volatility of demand – which evolves during the simulation – defines the optimal solution according to the Cost Differential Frontier model.

The simulation includes three parts:

- Briefing screen and demographic information form (age, occupation, country).
- The task itself with 12 periods.
- A feedback form with 5 questions:
    - Were your decisions based on analysis and calculations? (Yes / Somewhat / No).
    - Are you convinced you made the right decisions? (Yes / No).
    - What were the factors guiding your decisions? (Economic / Social / Both).
    - Which production option do you think was the most profitable? (Always Local / Always Offshore / Offshore after month 7 / Balanced).
    - How would you describe your general risk profile in life? (Risk Seeker / Risk Neutral / Risk Averse).
    - And an Open-comment field.

The following figures show the simulation interface at each of these three parts.

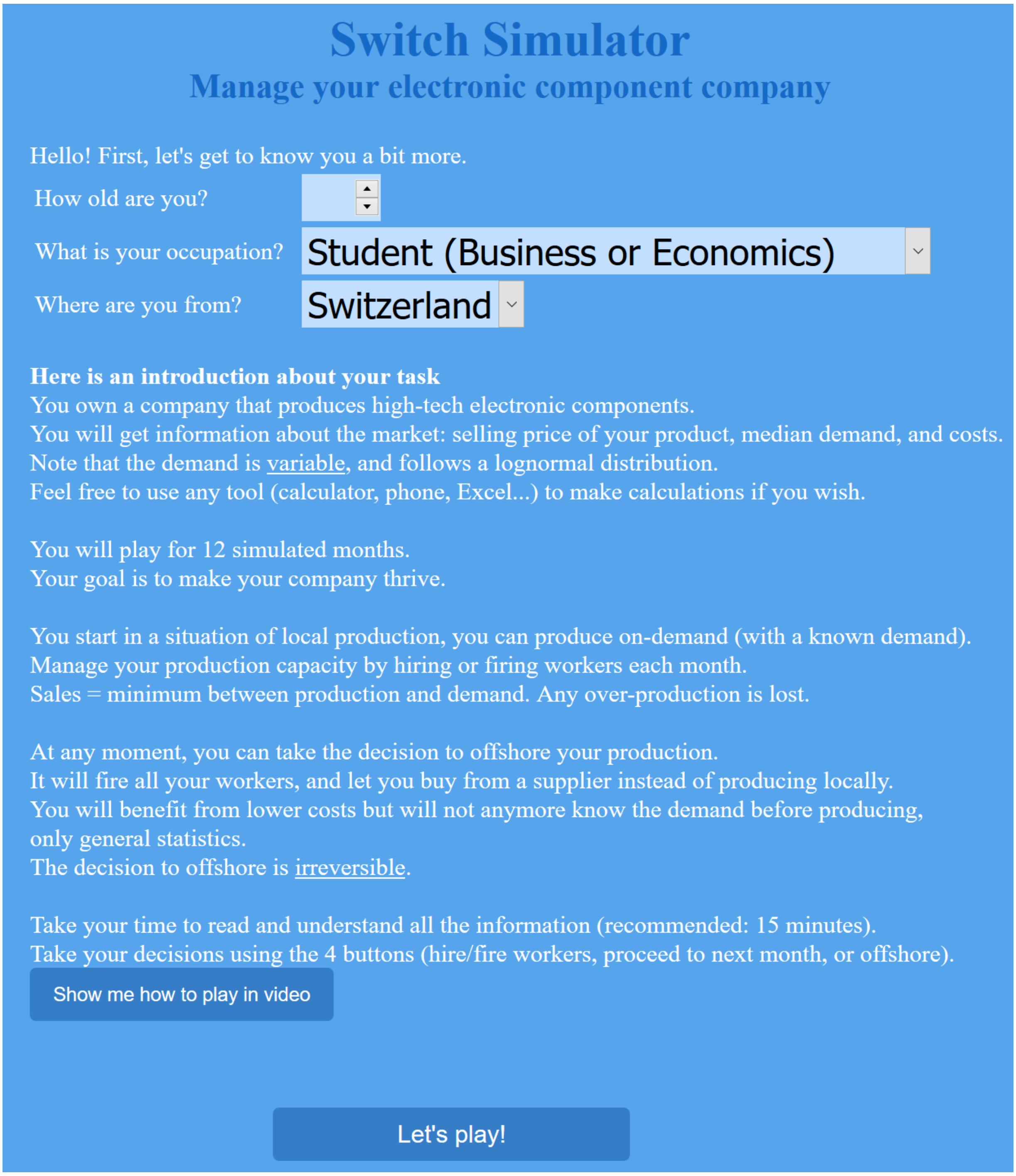

Figure 2.1: The simulation interface on the initial briefing screen.

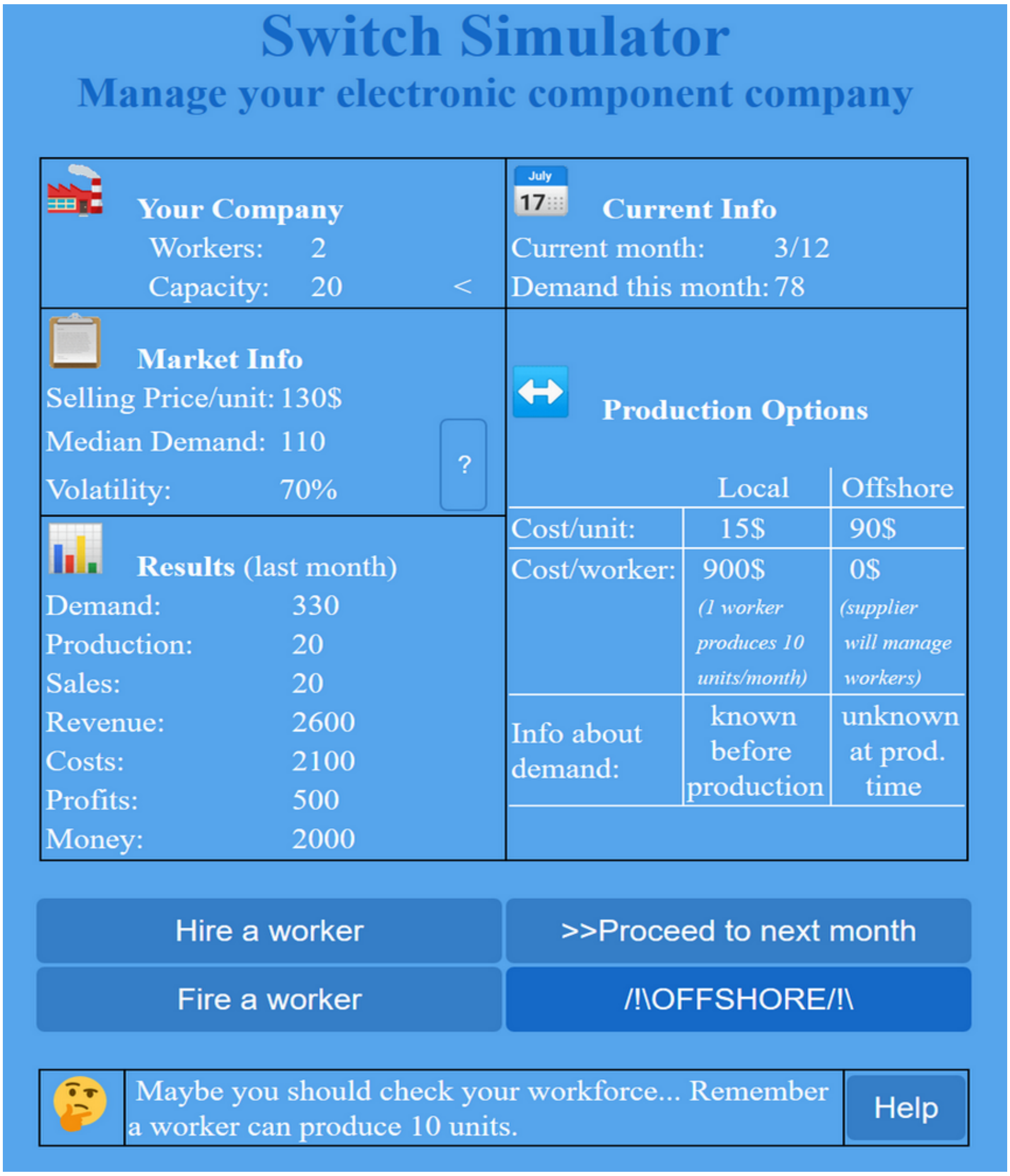

Figure 2.2: The simulation interface during the task.

During the task, as shown in figure 2.2 the screen has three elements:

- A board displaying economic information, demand data, and past month results.
- The decisions buttons the participant uses to enter choices, with four possible actions: hire a worker, fire a worker, proceed to next period, offshore production.
- A textbox displaying basic advice, occasional prompting from virtual shareholders seeking more profit after a bad month and a help button showing briefing info again.

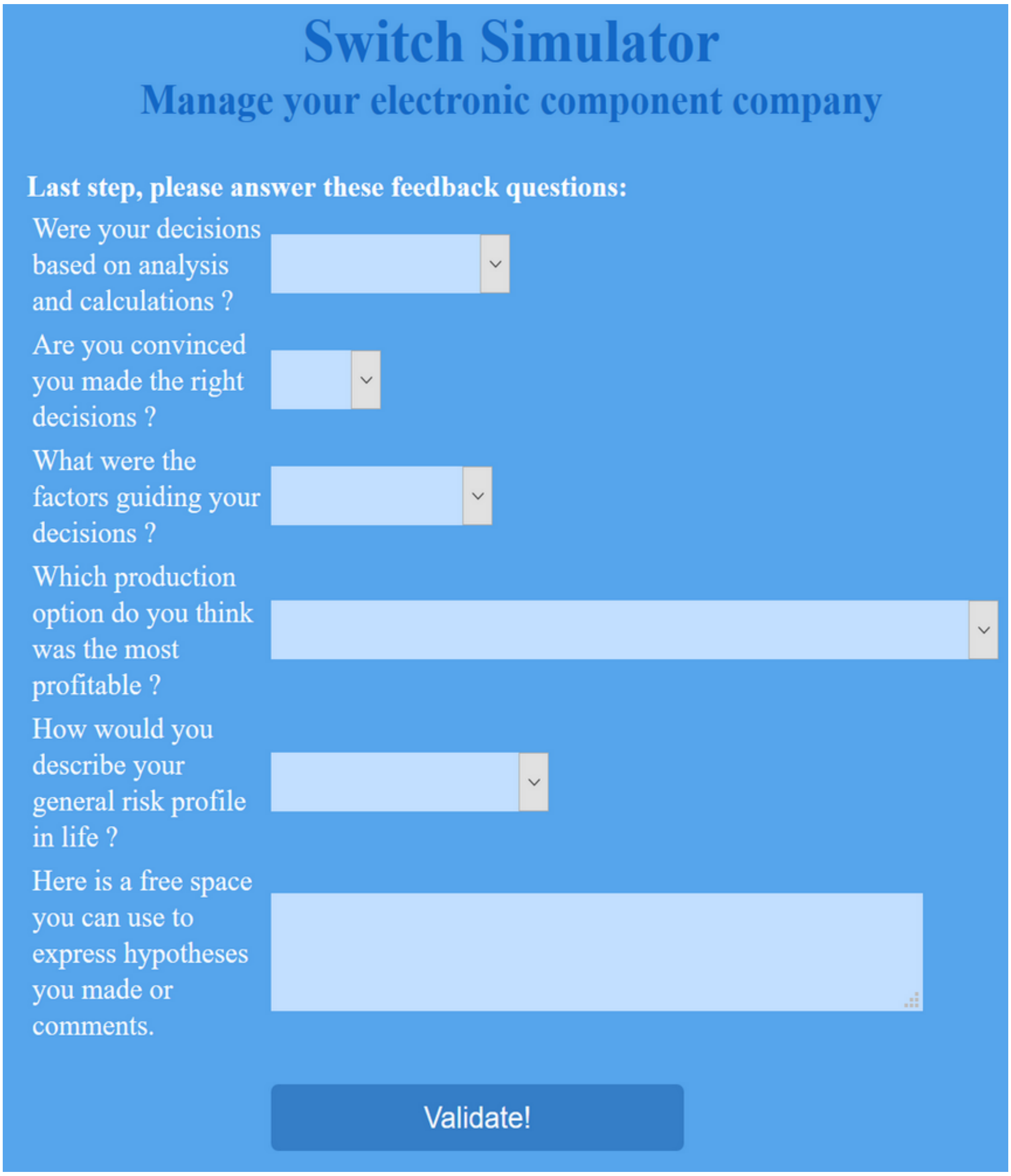

Figure 2.3: The simulation interface on the final feedback questionnaire screen.

To simplify the task so the participants focus on the decisions I study, no hiring or firing cost is incurred. Managing local production is therefore as easy as adapting workforce to current demand, whereas offshoring requires placing orders before knowing demand which places the participant in front of a Newsvendor problem.

Using the Cost Differential Frontier tool, the volatility of demand and the costs of production can be set to a point of financial equilibrium, where a rational decision-maker would be indifferent between producing locally, at a slightly higher cost, and offshoring, incurring demand uncertainty.

Here is how it can be done following the model from de Treville, Cattani and Saarinen (2017):
We model the demand as following a lognormal distribution.
We set a selling price of 130$ and a median demand of 110 units.
With a volatility of 0.7 (fast-moving product), average demand is 141 units/period.
If we set the offshore production cost at 90$/unit, following the Newsvendor model:
- The cost of underage (being one unit short in inventory and therefore missing one sale) is 40$.
- The cost of overage (having one unsold unit left in inventory at the end of the period) is 90$.
- The Service Level is $\frac{\text{Cost of Underage}}{(\text{Cost of Underage + Cost of Overage})} = \frac{40}{(40+90)} = 0.308$.
The optimal order quantity under uncertainty (offshore) in standard deviations is -0.502.
In terms of units, the optimal order quantity is 110 * EXP(-0.502 * 0.7) = 77.4 units.
The fill rate is estimated at 0.5.
Expected sales are 69.7 units, which gives an expected revenue of 69.7 * 130 = 9061$.
Expected leftovers are 7.7 units.
Expected offshore costs are 77.4 * 90 = 6966$.
We do not value nor penalize the remaining stock, considering that a fast-moving electronic product will not be sellable on the next period, but will be easily disposable.
Expected profit is therefore 9061 - 6966 = 2095$.
Locally, with same price and expected demand, expected profit = 141 * (130 - local cost).
To balance expected local and offshore profits, the local cost should therefore be set to 115$.
Selling price (130$) and median demand (110) will stay fixed in the simulation.
The local cost will also be fixed, at 105$, which creates:

- Condition A: very favorable to local (expected profit = 3513$ vs 2095$ offshore).

By adjusting the volatility and the offshore cost, conditions can be changed to:

- Condition B: volatility lowered to 0.6 which gives a mean demand of 132, and offshore cost lowered to 85$; still favorable to local (expected profit = 3300$ vs 2734$ offshore).
- Condition C: volatility lowered to 0.5 which gives a mean demand of 125, and offshore cost lowered to 80$; favorable to offshore (expected profit = 3464$ vs 3125$ local).

Participants are randomly assigned one of two scenarios. Both scenarios start in condition A, where producing locally is significantly better than offshoring. Then a change occurs at period 7. The idea is to manipulate decision environment variables and observe results in terms of variation in the decisions and outcomes. In scenario 1, simulation switches to condition B. In scenario 2, simulation switches to condition C. Participants are warned about the change by an attention-catching message and updated data twinkles.

To summarize:

- Scenario 1: very favorable to local at first, then less but still favorable to local.
- Scenario 2: very favorable to local at first, then favorable to offshore.

2.2.2) Procedure

Kahneman (2003) argues that in the context of heuristics and biases studies, within-participant designs attract participants' attention to the variables that are manipulated in different conditions and encourage them to adopt artificially consistent strategies. I opted for a between-participants methodology, with each participant being randomly assigned one of the two scenarios, and participating only once. Participants were not limited in their decision time. Average duration of the simulation was 22 minutes. As pointed out by Karahanna et al. (2018), online experiment without supervision risks losing internal validity. I limited this mode of administration to participants I really could not meet physically, representing only 8 out of 100, and therefore I had the opportunity to talk informally with some participants after their sessions.

Lonati et al. (2018) provide a useful set of good practices regarding experimental design in behavioral operations management research. Demand effects are one of the main pitfalls, with subjects reacting to cues about what constitutes the expected or desirable behavior instead of acting as they would in a natural setting.

Regarding experimenter and context influence, the random assignment of scenario to each participant is built in the software and as the experimenter, I was not aware of which scenario was being played. Participants were not aware of other treatments and my interactions with them were limited to making sure the instructions were clear.

I did not choose to create a fully "abstract frame" (Donohue, Katok & Leider, 2018, p. 15) for the task, and instead provided a clear context around the offshoring decision. Given the essence of such a decision, social desirability definitely plays a role in the decision process, but it is also a core element of a real-life offshoring, and is therefore suitable to reproduce the relevant mindset and activate in participants the same thought process they would use in practice. However, I made the instructions formulation (figure 2.1) as neutral as possible regarding the criteria of what a good decision would be. I voluntarily stated the goal for participants as "make your company thrive," with the intention to give them free interpretation of what "thrive" meant – profit, employment, demand satisfaction, sustainability...

All participants – across scenarios – had the same level of potential awareness of what the trial was about. I therefore argue that any possible demand effect was held constant.

Another risk pointed out by Lonati et al. (2018, p. 21) is “incorrectly specified comparisons between two levels of the same independent variable,” in the context of this trial, that would be comparing a group that experiences a sudden change in parameters with a group that keeps the same parameters all along, or two changes in parameters in opposite direction.

In order to avoid that issue, the trial is designed such as both groups experience a change in parameters in the same direction – both make offshoring more favorable than in the initial condition – scenario 1 being the “baseline treatment” and scenario 2 the “comparison treatment” (Donohue, Katok & Leider, 2018, p. 13).

The authors also warn against the lack of consequential decisions and outcomes and suggest that a compensation based on performance is a good practice. However, I opted against this option – and provided a fixed compensation for participation – in order to avoid having to disclose a clear performance indicator to participants, which would have led to strong demand effects. For example, linking participants’ compensation to in-game final profit would have made it the de-facto goal of the game, eliminating potential alternative goals such as local employment, goods transportation minimization, mismatch minimization. As previously discussed, the purpose of my design was to leave this aspect to each participant's appreciation.

2.2.3) Participants

The random assignment process – built-in the software using the Math.random() JavaScript function – led to a total of 48 participants in scenario 1 and 52 participants in scenario 2, which is in line with the unformal standard or 50 participants per treatment (Lonati et al., 2018).

I tried to avoid the usual “western sophomore science” bias by varying participants’ profiles, which are as described in figure 2.4.

Description	Number
Students at the University of Lausanne (mainly Swiss and French)	**58**
Studying Business or Economics	*46*
Studying Other Fields	*12*
Swiss professionals in the field of Supply-Chain or Operations	**3**
Academics (international)	**2**
Professionals in the field of Supply-Chain or Operations via Amazon MTurk (mainly U.S)	**8**
Philippines workers in various fields	**17**
Philippines students	**12**
Studying Business or Economics	*11*
Studying Other Fields	*1*
Total	**100**

Figure 2.4: Participants description. I started my study at the University of Lausanne, where the main demographics are Swiss and French students. Out of my 100 participants, 58 are European resident students, with 46 of them studying Business or Economics, and 12 studying other fields. Through word of mouth, I met 3 professionals in the field of management in Switzerland and 2 international academics. I used the Amazon Mechanical Turk platform to reach 8 more professionals, 7 of them from the U.S., in the field of supply-chain or operations at large. Finally, I administered the simulation in the Philippines with 17 workers in various fields and 12 students, 11 of them studying Business or Economics.

2.2.4) Data Analysis

I performed three checks to make sure participants understood the task, so their choices reflect decisions and not misunderstandings:

1) I ran pretests of the trial to improve clarity of interface and wording. These pretests were conducted as three sessions of the simulation with one or two volunteer students – for a total of five pretesters – unaware of the research topic, who agreed to give feedback on any misunderstanding about the task, as well as their step by step thinking process. A representative example of the improvements made through pretesting was changing the labels of what I initially called “demand periods” without any more specification, which consistently confused testers, who inquired if it referred to days, months or years. This detail does not make a difference in the model but as testers seemed put off by this designation, I settled label them months, and none of the subsequent participants in the trial raised any question about time frames.

2) During the simulation, after reading the briefing but before starting to make decisions, each participant had to take a short quiz, have it validated and, if necessary, corrected before they could start. The questions checked that participants understood the offshoring decision was

irreversible, demand was not correlated between months, and local production was more expensive than offshore when adding fixed and variable costs. The quiz is shown in figure 2.5.

Switch Simulator - Quiz

This quiz is to make sure you understood the instructions.
Please check the correct answer for each question.

If I decide to offshore on month 6, can I decide to go back to local on month 8?
[_] Yes, it's possible
[_] No, it's impossible

If the demand is 150 on month 2, what will be the demand on month 3?
[_] Also 150
[_] Between the median and 150
[_] It's impossible to say in advance

What is the total cost of producing 1 unit locally?
[_] 15$, it's cheaper than offshore
[_] 90$, it's the same as offshore
[_] 105$, it's a bit more expensive than offshore

Figure 2.5: The quiz used after reading the briefing screen but before starting the task, to make sure participants have understood the instructions.

3) During data treatment, I created a binary variable called “Understood” that was meant to determine if each participant had correctly understood the task of if the decisions suggested unusually misguided – or random – decisions. When local, producing more than 20% over or less than 20% under the displayed demand was considered a mistake. When offshore, ordering more than 400% of the median or less than 25% of the median was considered a mistake. More than three mistakes gave a 0 score. 93% of participants had a positive understanding score. I decided not to include this variable in the analysis after reading comments and discussing with participants who deliberately placed orders that would be flagged as misunderstandings. For example, a participant in the Philippines whose family runs a village convenience store, explained that she preferred selling a very small amount of goods every period with the certainty of a small profit, over having to manage more goods or risk any overstock. I did not remove these participants from the data for the same reason, and because it is probable some real-life offshoring decisions are taken without perfect understanding of the operations at work.

Each time a participant completed the simulation, raw data – that was already anonymized and only identified by a numerical code that the participant noted and presented to receive payment – was automatically sent via email to my server in the format showed in figure 2.6.

ID code: 893245
Condition: 2
Age: 23
Country: Switzerland
Occupation: Student (Business or Economics)
Total Time: 838

Month	1	2	3	4	5	6	7	8	9	10	11	12
Time	367	47	43	29	28	86	42	25	3	1	15	16
Offshore	0	0	0	0	0	0	0	1	1	1	1	1
Nb Worker	13	8	33	15	44	16	9	0	0	0	0	0
Capacity	130	80	330	150	440	160	90	0	0	0	0	0
Demand	210	63	327	154	437	156	93	195	114	46	113	111
Production	130	80	330	150	440	160	90	110	110	110	130	130
Sales	130	63	327	150	437	156	90	110	110	46	113	111
Cost Workers	11700	7200	29700	13500	39600	14400	8100	0	0	0	0	0
Cost Prod	1950	1200	4950	2250	6600	2400	1350	8800	8800	8800	10400	10400
Revenue	16900	8190	42510	19500	56810	20280	11700	14300	14300	5980	14690	14430
Profit	3250	-210	7860	3750	10610	3480	2250	5500	5500	-2820	4290	4030
Money	4250	4040	11900	15650	26260	29740	31990	37490	42990	40170	44460	48490

Calculations: Somewhat
Conviction: Yes
Decision factors: Economic
Rational guess: Local at first, Offshore after month 7
Risk profile: Risk averse
Comments: At first, even though the local option afforded a lesser unit profit margin, the certainty of demand was preferable due to market volatility. This advantage erroded at month 7, as offshore margin of profit became even greater and volatility decreased, making risk-averse me more enthusiastic about taking the off-shoring option

Figure 2.6: Raw data from a participant. Raw data include the initial demographic questions, the scenario experienced, the details of the parameters and decisions for each month of the simulation - including the demand, production decisions, sales, financial results and whether the participant has offshored or not - and the answers to the feedback questions.

The idea was to present raw data in a format that was readable for the experimenter so it would be immediately usable, for example to be discussed in an unformal way with the participant when time permitted. After all the laboratory sessions were completed, the data was then converted to CSV format, and analyzed using Microsoft Excel.

2.3) Results

2.3.1) Decision Profiles

In scenario 1, the economically optimal strategy to never offshore was adopted by 14 participants out of 48 (29%). In scenario 2, where the economically optimal strategy was to offshore after the switch of conditions at month 7, I considered any offshoring happening between month 7 and 12 as an adoption of the optimal strategy, and observe it for 22 participants out of 52 (42%). The rationale for this wider definition of optimal strategy is that being able to consider the feedback from degraded conditions – after having missed the earliest opportunity to offshore – to change course of actions is a well guided behavior. A stricter definition – only month 7 for example – does not change the sense of subsequent results. Across both scenarios, only 36% of participants adopted the economically optimal strategy.

Based on the scenario experienced and the month at which each participant decided to offshore, I defined four decision profiles:

1. The “Offshore anyway” profile applies to participants in any scenario who offshored sometime during the first six months of the simulation. The name refers to the idea that they offshored despite the economic conditions being very favorable to local production.
2. The “Easily triggered” profile applies to participants of scenario 1 who offshored sometime after the change of economic conditions on month 7. The name refers to the idea that their offshoring follows a switch in economic conditions that is not sufficient to make offshoring economically optimal.
3. The “Optimal strategy” profile applies to participants in scenario 1 who never offshored or to participants in scenario 2 who offshored sometime after the change of economic conditions on month 7. The name refers to the idea that their strategy matches the economically optimal choice.
4. The “Never offshore” profile applies to participants in scenario 2 who never offshored. The name refers to the idea that they do not offshore even when economic conditions become favorable to offshoring.

A classification algorithm, applied to each participant, would be:

```
IF(Offshoring_time < Month07)                                                                   {Profile=1;}
ELSE IF(Scenario==1 AND Offshoring_time <= Month12)                                             {Profile=2;}
ELSE IF((Scenario==1 AND Offshoring_time == NEVER) OR (Scenario==2 AND Offshoring_time <= Month12))  {Profile=3;}
ELSE IF(Scenario==2 AND Offshoring_time == Never)                                               {Profile=4;}
```

Note that I detailed the conditions for profile 4 but I could have used a simple ELSE condition as the four profiles cover all possible strategies adopted in the simulation. They are also mutually exclusive.

Figure 2.7 shows, for each scenario, the number of participants who offshored at each given month. It indicates the number of new offshorings each month, and not the cumulative number of participants having offshored at each point. As offshoring is irreversible in the simulation, each participant is counted once in the figure and belongs to only one decision profile. The decision profiles are represented by colors: red for profile 1, yellow for profile 2, green for profile 3, blue for profile 4.

For example, in scenario 1, nine participants offshored on month 7, and they belong to profile 2 "Easily triggered". Another example, in scenario 2, three participants offshored on month 3, and they belong to profile 1 "Offshore anyway". The sum of the table is 100 as there are 100 participants in the experiment.

	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Month 9	Month 10	Month 11	Month 12	Never
Scenario 1	2	1	4	1	3	0	9	2	2	4	3	3	14
Scenario 2	2	4	3	1	0	4	5	4	5	2	3	3	16

Figure 2.7: Number of participants who offshored each month in each scenario. In red, offshoring decisions taken despite conditions very unfavorable to offshoring. In yellow, offshoring decisions taken despite conditions slightly unfavorable to offshoring. In green, offshoring decisions taken when conditions were favorable to offshoring. In blue, no offshoring decision despite conditions favorable to offshoring. Offshoring is irreversible, each participant can only offshore once, or never.

Figure 2.8 shows the number of participants belonging to each decision profile.

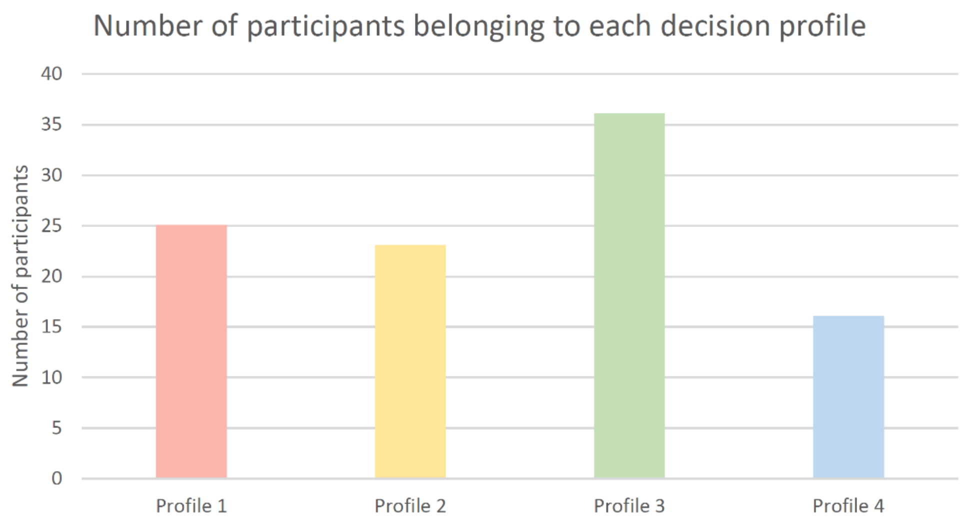

Figure 2.8: Number of participants belonging to each profile.

For each profile, I propose an interpretation and suggest heuristics that could potentially explain the strategy adopted by the participants. This associative interpretation of data should be taken as a motivation for follow-up experimental tests, based on formal model of the heuristics and the behavior we could expect if they are indeed at play.

1. The "Offshore anyway" profile. In both scenarios, around 25% of participants (23% in S1; 27% in S2) offshored in the first six months, despite conditions being very favorable to local production. As calculated in chapter 2.2.1, the initial economic conditions (Condition A) offer an expected profit of 3513$ locally, versus an expected profit of only 2095$ offshore. From an economic point of view – assuming that participants wish to maximize their profit – this strategy would be a mistake, provoking a 40% cut in expected profit, and would signal a bias toward offshoring in the decision process. Gray et al. (2017) suggest the initial impulse of a decision-maker facing a complex and uncertain offshoring decision is to rely on an oversimplistic heuristic focused on finding the lowest cost per unit. The authors argue that this decision strategy can be seen as an instance of the Take-the-best heuristic (Gigerenzer et al., 1999), in which the alternatives are staying local or offshoring, and the cue considered as having the top validity is the landed cost per unit. Therefore, if the two alternatives differ in terms of unit costs, the search stops without going beyond this criterion and offshoring is selected without hidden costs being considered. If this is the case, the issue would be the use of this heuristic in a context in which it is not ecologically rational. Experience can help overcome this bias by increasing the ability to consider harder-to-quantify factors: the hidden costs (Moser, 2011), of which the supply/demand mismatch cost of my trial is a prominent example.
2. The "Easily triggered" profile. Unsurprisingly, since that is when conditions change, month 7 counts the highest number of offshoring decisions. This profile applies to scenario 1 participants who offshored after a change in conditions that was not important enough to make offshoring optimal. Long and Nasiry (2015) highlight the importance of reference points in prospect theory. In the present case, we have provided a clear reference point to participants with the initial conditions, and suddenly expose them to a condition where offshoring becomes more favorable than this reference. Overreaction is a well-known mistake in finance (De Bondt & Thaler, 1985), rooted in Kahneman and Tversky's representativeness heuristic. People tend to overweight new information, violating Bayes' rule prescription, and falling into insensitivity to predictability and

insensitivity to base rate biases. Profile 2 participants self-identified as more risk-neutral than other profiles, had the longest average time spent on the simulation, and declared using slightly more calculations than others. They were looking for a clue, and when it came, they went for it even though it was delusive.

3. The "Optimal strategy" profile, as previously defined for each scenario, was adopted by 36% of participants, as they do not report using calculations more than other participants, subsequent investigations should be done to determine if these participants rely on specific cues, or on past experiences, or on a general intuition in their decisions.
4. The "Never offshore" profile, applies to scenario 2 participants who never offshored even after it became optimal. Underreaction relies on a symmetrical mechanism to profile 2, a status-quo bias potentially fueled by risk-aversion.

In this study, I do not make any assumption about the relative frequency of the four profiles. Instead, my claim is limited to the fact we see them all emerge, which suggests that the three types of deviations from the economically optimal strategy – as described for profiles 1, 2, and 4 – exist across participants.

Assuming that participants did not make decisions randomly, the existence of profile 1 concurs with hypothesis 1 as it appears that some participants (25% of them) decided to offshore under economic conditions that are objectively favorable to local production.

The existence of profiles 2 and 4 indicates that when contextual conditions change, participants' strategy do not always match the economically optimal option. Decisions in scenarios 1 and 2 need to be compared to investigate a possible support to hypothesis 2.

2.3.2) Reaction to Economic Conditions Change

A key result is the absence of significant correlation between the scenario experienced and the number of months spent offshore, as shown in figure 2.9. It appears that participants' offshoring decisions are not significantly different when offshoring becomes economically optimal in scenario 2 or when offshoring stays economically unfavorable in scenario 1, which gives support to hypothesis 2: participant's degree of offshoring vary uncorrelated with the new economically rational option when contextual conditions change. Participants do not appear to correctly value the price of demand uncertainty.

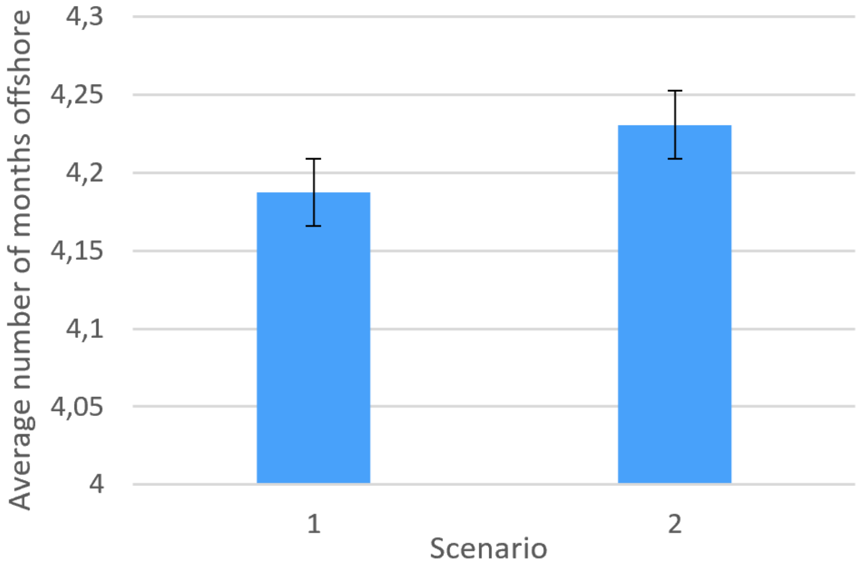

Figure 2.9: Impact of the scenario on the average number of months spent offshore. The degree of offshoring is not correlated with the scenario experienced. Even though conditions in scenario 1 would call for no offshoring at all, while conditions in scenario 2 would call for six months of offshoring, participants in both conditions spend in average around 4.2 months offshore. Error bars show standard error.

A feedback question at the end of the task asked participants about the strategy they thought to be the most profitable. Comparing the answer with the scenario assigned, I define the FigureItOut binary variable: 1 for a correct match, 0 for a mistake. Only 44% of participants figured out the optimal strategy post-hoc, a weak improvement over the 36% who applied it during the simulation (DidItRight variable). A Chi-square test on the frequency of the right answer in each scenario does not reject the null hypothesis ($\chi 2(1)=0.24$, $p=0.62$ in scenario 1; $\chi 2(1)=1.30$, $p=0.22$ in scenario 2), confirming an absence of correlation between answers and the scenario experienced.

2.3.3) Willingness to Pursue an Economically Optimal Strategy

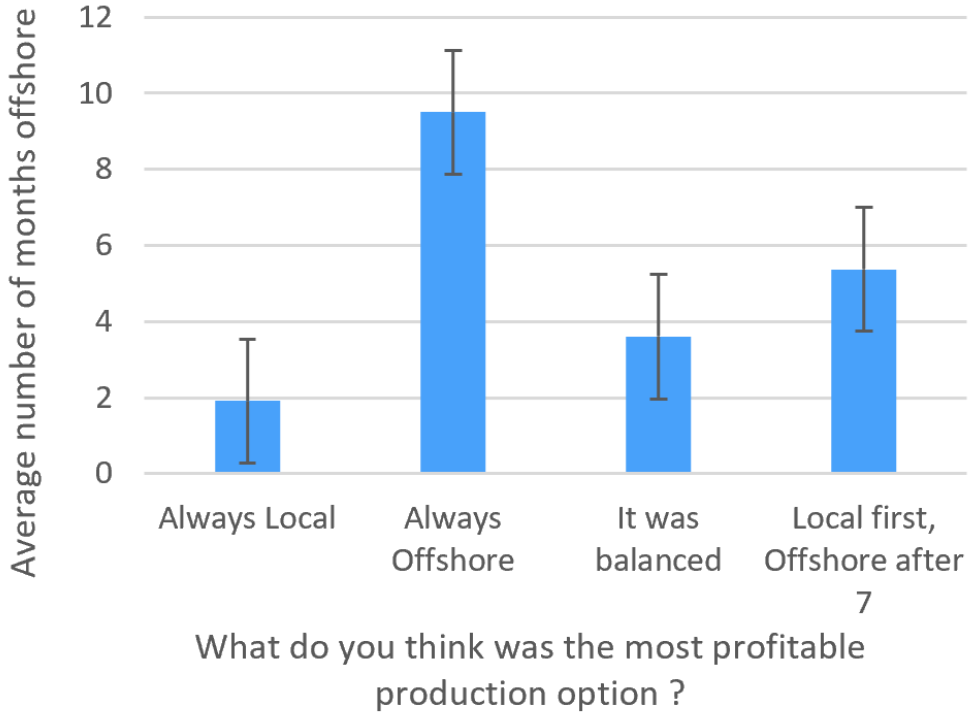

Figure 2.10: Impact of the strategy thought to be optimal on the average of months spent offshore. The offshoring decision that participants adopt appear to be correlated with the strategy that they identify as the most economically profitable. Error bars show standard error.

It appears that participants did seek to pursue the economically optimal strategy. An analysis of variance shows that the number of months spent offshore significantly differs depending on which strategy the participant identifies as optimal, as shown in figure 2.10, and is strongly and significantly ($p<0.01$) correlated with each of the answers, except, “It was balanced.”

Also, correlation between FigureItOut and the number of months offshored is negative in scenario 1 ($r(46) = -0.28$, $p = 0.06$), positive in scenario 2 ($r(50) = 0.28$, $p = 0.04$).

FigureItOut and DidItRight are positively correlated ($r(98) = 0.47$, $p<0.01$), suggesting that participants’ choices are consistent with what they think is economically optimal. They wish to adopt the profit maximizing strategy when they can identify it, and divergent strategies appear to result from of a failure to do so rather than a wish to pursue another goal. These results give support to hypothesis 3: participants intend to adopt the economically rational option.

When asked about the factors guiding their decisions, 53% of participants answered that it was based only on economic factors, 3% answered social factors only, and 44% both types of factors. This self-declaration does not correlate with the number of months offshored.

2.3.4) Feedback Questions, Demographics and Performance

Feedback questions show no difference in the use of calculations across profiles. Only one feedback question is moderately correlated with a profile: the self-assessed risk propensity, with risk seekers being more associated with "Always offshoring" profile 1 ($p<0.05$). The confidence in decisions is not significantly correlated with any profile but shows a remarkable trend as participants belonging to the "Optimal strategy" profile 3 express more confidence than profiles 1 and 2, but ironically not as much as participants belonging to "Never offshoring" profile 4, who display a higher but misguided confidence.

	Risk	*Calculations*	*Confidence*	*Profile 1*	*Profile 2*	*Profile 3*	*Profile 4*
Risk	1						
Calculations	-0,082	1					
Confidence	-0,156	0,377	1				
Profile 1	0,219*	0,010	-0,128	1			
Profile 2	0,049	0,048	-0,127	-0,316	1		
Profile 3	-0,151	-0,018	0,092	-0,433	-0,410	1	
Profile 4	-0,117	-0,043	0,175	-0,252	-0,239	-0,327	1

	alpha	r critical
* p < 0.05	0,05	0,197
** p < 0.01	0,01	0,256
n=100		

Figure 2.11: Correlation table of decisions profiles and answers to feedback questions about participants' risk profile, use of calculations and confidence in their strategy.

As a measure of performance on the task, I computed a %MaxProfit variable, which captures the ratio of final realized profit compared to maximum potential profit, given each participant's demand data. As it is calculated for a local-only production, it can be slightly over 1 with a successful offshoring. As expected, %MaxProfit is very significantly positively correlated with the Optimal strategy decision profile ($r(98) = 0.35$, $p<0.01$).

The impact of demographics on performance is limited. Age does not have any significant impact. Academics performed better, but with a sample size too small (2 participants) to draw conclusions, although it would be unsurprising that this group makes better educated guesses or calculations as they can recognize a familiar problem. Performance is lower in the South-East Asia group, but the decrease is only significant ($p<0.01$) for %MaxProfit. Possible explanations include a tendency for this group to include more social aspects in decisions ($r(98) = 0.20$, $p=0.05$), a greater reported risk seeking profile ($r(98) = 0.26$, $p<0.01$), and some cases of voluntary low production to assure a minimal profit. These factors lead to more extreme production decisions (Standard Deviation=108 vs 95).

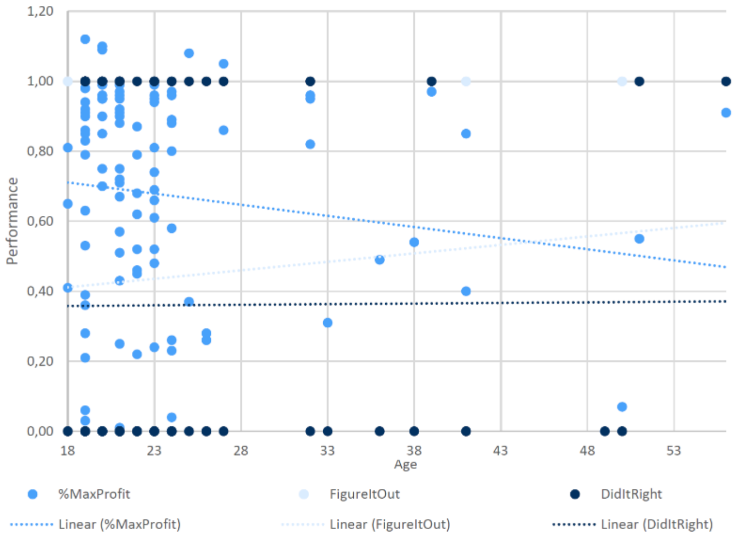

Figure 2.12: Impact of age on %MaxProfit, FigureItOut and DidItRight.

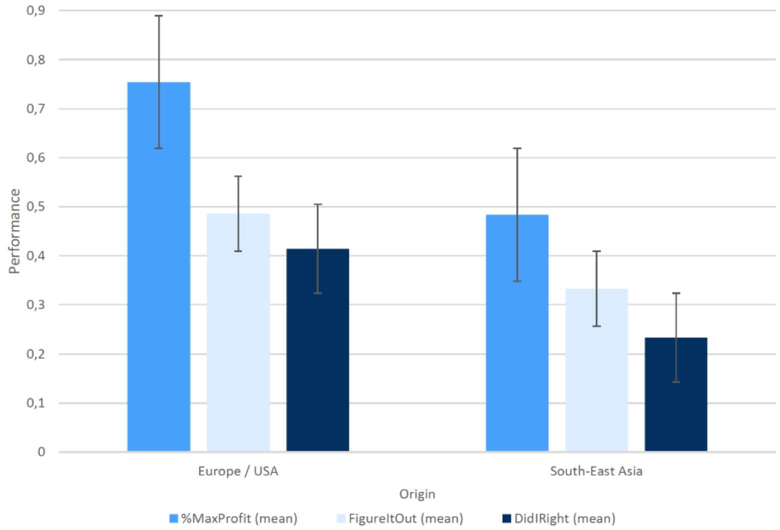

Figure 2.13: Impact of origin on %MaxProfit, FigureItOut and DidItRight. With standard error bars.

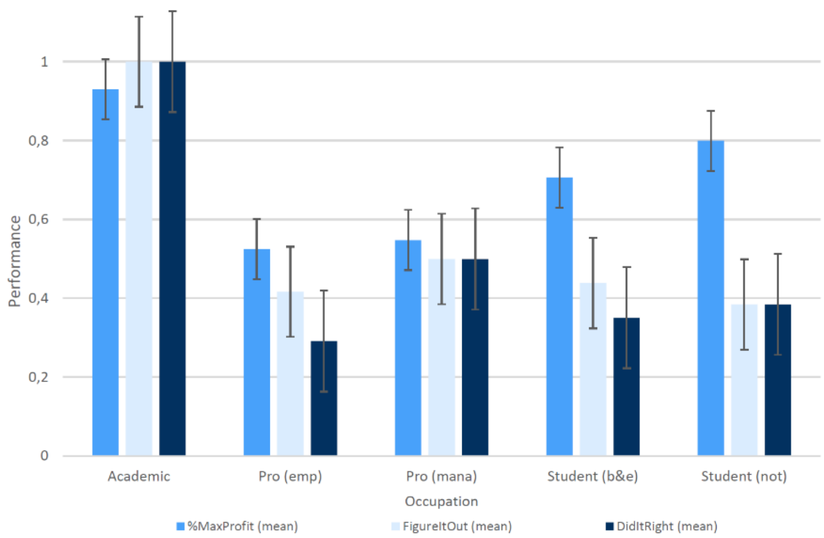

Figure 2.14: Impact of occupation on %MaxProfit, FigureItOut, DidItRight. With standard error bars.

2.3.5) Post-Offshoring Decisions

Focusing only on offshore orders decisions – made under demand uncertainty after participants decided to offshore – participants facing the Newsvendor problem seem to exhibit an anchoring bias toward the median demand given as 110. Only 2% of the orders were optimal, while 71% of orders were wrong in the direction of the given median. Figure 2.15 shows the mean order in each condition. But the factor that influences order decisions the most seem to be the demand experienced in the previous month.

	#	Average Order	Newsvendor Optimum	Given median
Condition A (both scenarios before month 7)	93	112	77	110
Condition B (scenario 1 from month 7 to 12)	159	122	87	110
Condition C (scenario 2 from month 7 to 12)	169	116	95	110

Figure 2.15: Summary of offshore orders, grouped by condition.

Using the data from the participants who offshored, I could replicate part of the experiment from Schweitzer and Cachon (2000). The authors found that, "Overall, most decisions (64.3% or 594 decisions) were characterized by repeat choice. When subjects did change their order quantity across rounds, they were more than twice as likely to adjust their order quantity in the direction of prior demand (24.7% or 228 decisions) than away from it (11.0% or 102 decisions)" (p. 412).

I analyzed the orders of participants who offshored for at least two months, excluding their first offshore order and their order on month 7 – since cost and volatility condition change. From my data, 56% of orders (184 decisions) were adjusted in the direction of prior demand, 13% (41 decisions) away from it, and 31% (101 decisions) were repeat orders across rounds. These results indicate a "chasing demand" heuristic in participants decisions as they were more than four times more likely to adjust their orders in the direction of prior demand than away from it.

2.4) Limitations and Follow-up

The scope of this exploratory trial is to introduce a new problem, that is more complex than the classic Newsvendor problem, as it adds an additional layer that requires the decision-maker to choose between two cost and demand volatility options. I observe the existence of decisions strategies that do not match the economically optimal options, and I suggest heuristics that could explain these strategies, but I do not claim to identify causality.

Regarding internal validity, the main limitation of my study is that I do not propose a causal model to explain treatment effects, or alternative models based on different potential utility functions (Schweitzer & Cachon, 2000). This lack of “theoretical guidance” (Donohue, Katok & Leider, 2018, p. 6) means that I cannot infer causality between the treatments and the decisions, and do not provide generalizable outcome at this stage of the research. I also do not provide control for external factors that may intervene in this offshoring decision. Going further, it will be necessary, for example, to assess the potential learning effects that may emerge. The task was purposefully designed around a repeated decision – an alternative design with only 2 game months instead of 12, one in initial conditions and one after the parameters switch, was ruled out – as the exposure to demand volatility and mismatch is an important part of the real-life offshoring decision, but the consequences of this design should be assessed.

I sought varied profiles for my participants in order to explore if age, origin or operations management skills – theoretical or practical – would yield differences in behavior, which indeed produced interestingly contrasted results between Western participants and South-East Asian participants that would deserve further investigation. However, this question was not my central in my research effort, and the sampling was not calibrated carefully enough. The resulting uneven sampling, and the fact that some subgroups are too small - especially Academics - might not have provided enough sensitivity to statistical tests.

Regarding external validity, generalizability to environments outside the laboratory is not possible and not the ambition at this stage. As with any laboratory task, it is challenging to replicate the real-life decision environment, even more so with a decision as strategic as offshoring, that supposes huge stakes and involvement. In addition to the incentive question discussed in chapter 2.2, the task is purposefully oversimplified and asks participants – some with no relevant qualification – an immediate answer to a question that is usually debated and studied for months.

In order to further develop research in this new problem space, the next step will be to structure it into an explicit theory so hypotheses can be tested more accurately.

2.5) Conclusion

I designed a software-based trial to explore decision-making processes in a complex supply-chain problem. One hundred participants from various backgrounds faced an offshoring simulation requiring them to balance costs and demand uncertainty. In this setting, participants appeared to rely on heuristics that make them “non-hyper-rational actors in operational contexts” (Croson et al., 2012, p. 1), and 64% of them failed to adopt a mathematically optimal strategy, despite a wish to do so. Their suboptimal strategies might be the result of a misuse of heuristics. Notably, participants seemed to chase past demand values, focus on lower unit costs rather than a holistic evaluation of costs and risks, and take initial conditions as a reference point that can alter their reaction to the subsequent evolution of economic conditions. The results do not seem to be attributable to individual characteristics, reinforcing the idea that biases are ubiquitous, and adding to arguments for the potential value of decision-support and teaching tools such as simulations to increase decision-makers’ expertise via trial, errors and exploration of interactions, and consequences of different options.

My contribution with this exploratory trial is the proposition of a new decision space for offshoring inspired by the Cost Differential Model (de Treville, Schuerhoff et al., 2014), in which the decision-maker has a choice between facing a Newsvendor problem to access lower unit costs, or pay a cost premium to eliminate demand uncertainty.

Unlike a behavioral economist, I do not approach the problem with the intent to quantify biases impact and debiase the decision process. Instead, my goal is to make a diagnosis of the heuristics at play and how they operate, in order to inform the design of decision-tools. These tools, aimed at decisions makers – practitioners and students – should be designed to help them improve their analysis of information, enrich and calibrate their mental models better so the outcomes of their heuristics become more accurate. As proposed by Klein (2001), a bad decision is when we regret not only the outcome, but the process.

This trial should be considered as a "pretheoretical work" in the sense of Hambrick (2007), that aims at reporting and documenting facts about an important phenomenon. It is even possible that unobserved covariates drive the relationship, but it does not invalidate the existence of the phenomenon, which at this point of the research, is enough to inform the design of targeted decision-helping tools.

3) Biases in Offshoring Decision-Making: Exploration of Non-Economic Factors Influences

3.1) Introduction

The study of decision-making, long considered a pure cognitive application of mathematics, has evolved over the second half of the 20th century toward a behavioral approach that better describes the way human beings make choices.

Herbert Simon introduced the concept of Bounded Rationality (1955, 1979), the idea that our mind does not possess the time and computational resources to solve problems to an optimum, contrary to what classic economy theories imply.

Kahneman and Tversky (1974) investigated how decision-makers really think with their experiences on heuristics – rules of thumb that simplify decision-making – and biases.

More recently, influential researchers like Gigerenzer (1999) and Klein (2001) demonstrated the power and general efficiency of heuristics, especially when they take advantage of the structure of information in the environment – what Gigerenzer calls ecological rationality – and when decision-makers develop expertise that allows them to match the right heuristic with the right problem. For Gigerenzer (1999) and Klein (2001), heuristics are efficient at satisficing, that is, reaching a good enough option, under time constraints and using a realistic amount of cognitive resources.

These modern views of human decision-making have an important common premise: the decision-maker is no longer considered an isolated rational computer humanoid, but as a part of an environment, and their interaction with this environment is key to understanding both the outcome and the process of a decision.

Despite their performance and usefulness, heuristics necessarily create biases – systematic deviations from rationality – even in the case of expert decision-makers and structured decision processes (Kahneman & Frederick, 2002).

As the bounded rationality of human decision-makers gains wider acceptance, biases are starting to be considered in the design of goods, services and infrastructures. Research (Thaler and Sunstein, 2008) and practitioners show great interest in nudges to trigger certain behaviors in certain contexts, such as using the stairs instead of the elevator, reusing the towels in hotel rooms or keeping the toilets cleaner. Unsurprisingly, the same methods have quickly been weaponized for less commendable purposes like dark patterns (Bösch et al., 2016) on websites and mobile applications to lure users away from information or into buying something.

The heuristics and biases perspective applies to all types of decisions and has been abundantly studied in the context of managerial decision-making.

The field of Operations Management offers a perfect example of a strategic decision in a complex environment: offshoring. I focus my research on the economic offshoring decision, which can be summarized as the choice between continuing to produce locally – where the company sells its products – or move to a country with cheaper labor. This decision presents a difficult tradeoff between low unit costs and the increase in lead-time, and, therefore, in uncertainty about the demand. Recent studies (de Treville, Schuerhoff et al., 2014; de Treville, Bicer et al., 2014) have led to the development of a model that quantifies the increase of the cost of mismatch between production and demand as lead-time gets longer due to offshoring. The Cost Differential Frontier tool (http://cdf-oplab.unil.ch) gives a simple output of this model as a quantifiable value of shortening lead-time.

Many other factors help shape an offshoring decision. Some are economic or at least can tentatively be attributed an economic value: transportation risks and costs, communication complication, quality issues, intellectual property risks, loss of innovation capability, reputation risk (Schoenherr, Rao Tummala & Harrison 2008).

Others can be classified as non-economic factors. Musteen (2016), through interviews with executives, identifies the influence of previous idiosyncratic experiences of the decision-maker such as personal affinity with a country or culture of the industry, personal attitudes and emotions, with patriotism being prevalent, and cognitive limitations. The social externalities, widely absent from managerial decision models, are remarkably present in decision-makers thinking processes.

I chose to focus my study on two non-economic factors that may influence offshoring decisions: peer influence, and the framing of the decision as a social choice.

The underlying idea of peer influence is that when in doubt, in an uncertain situation, people tend to trust the decision of peers. As described by Asch (1951, 1955) in the majority influence experiments, the phenomenon appears even when the peers do not possess more complete information or any better insight or skills about the decision at hand, and the subject has no rational reason to think that others know better. In a managerial context, decisions can heavily rely on an industry-wide culture (Hahn, Doh & Bunyaratavej, 2009) and "common wisdom." As noted by Musteen (2016), a manager confesses to not having conducted a cost comparison between U.S.A. and Mexico because of “certainty of cost savings there” (p. 3444). The study by Petit and Bon (2010) suggests animal collective movements are not only the results of external factors – in our case, costs – but that peer behavior is also an input in the decision. They describe a distributed decision process, in which some individuals with information want to initiate a movement and communicate it to a limited number of peers. The movement can fail, or if the number of movers exceeds a certain threshold, bring away the whole group. In a managerial context, I suggest the offshoring movement in the last 30 years has followed the same pattern, with a critical mass being reached and fueling a self-reinforcing loop.

The underlying idea of framing is that the same quantitative choice can lead to different preferences depending on what attributes are made cognitively available to the decision-maker. Kahneman and Tversky (1984) posit that, contrary to classic utilitarianism theories of rational choice, the invariance criterion can be violated depending on how a problem is described, or framed. The power of framing comes from the alteration of accessibility of information. By feeding the intuitive System 1 with oriented data, the structure of information can influence choices by playing on all three categories of heuristics identified by the authors: Representativeness, by answering a social question instead of an economic one; Availability, by filling the subconscious with ideas of ecology, social impact and patriotism; and Affect, by associating positive elements with local production.

My goal is to explore the impact of these non-economic factors in an offshoring decision. I chose to approach the problem with a laboratory trial. I designed and coded a computer-based simulation that puts the participant in the role of a manager facing an offshoring decision.

In a previous trial, I manipulated costs and demand volatility to create scenarios that could be optimally solved with the Cost Differential Frontier tool – not provided to participants – and compared the optimal strategy with participants’ choices. In this extension of the trial to non-economic factors, I will reuse these scenarios as a baseline, and add elements that simulate non-economic factors to assess their impact on the decisions. To simulate peer influence, I will let the participants think that most decision-makers in their situation decided to offshore. To frame the offshoring as a social one instead of a purely economic one, I will add elements evoking patriotism, such as the flag of a participant’s home country, on the interface and display messages emphasizing the positive employment and ecological impacts of the company in the initial local production setting.

I make three hypotheses:

- Hypothesis 1: Participants' decisions do not match mathematically rational options.
- Hypothesis 2: We can observe an effect on participants' decisions, when cueing them that most of their peers decided to offshore, that strengthens the offshoring tendency.
- Hypothesis 3: We can observe an effect on participants' decisions, when framing the decision as social instead of economical, that reduces the offshoring tendency.

This study is an exploratory trial that do not provide generalizable results, but aims at increasing the understanding of the role of non-economic factors in offshoring decision-making and paving the way to tailored experiments to characterize their influence.

My long-term goal in this research project is to identify the relevance of decision tools and design new tools to provide insights to practitioners, in line with the Hevner et al. (2004) concept of Information Systems as rooted in behavioral science and using design as a force to "extend the boundaries of human problem solving and organizational capabilities by providing intellectual as well as computational tools" (p. 76). On the model of what Osterwalder and Pigneur did for business modelling (Osterwalder & Pigneur, 2013) with the Business Model Canvas, it should be possible to create artifacts aimed at practitioners that act both as checklists and ways to organize and give sense to the available information when making an offshoring decision, beyond the over-simplification of purely computational models.

On the teaching and communication front too, tools and models that are informed by the true to life behavioral aspects of such decisions will bring much more added value to the knowledge transmission, and provide learners with insights that are applicable to work on the field.

Decision tools that do not account for non-economic aspects are bound to be as limited in their helpfulness as they are limited in their ability to comprehensively integrate all relevant aspects of the decision-maker's thinking. Moreover, tools that are based on heuristics are easier to adopt in practice because they fit in the decision process that people already employ, they "pick up people where they stand" (Hafenbrädl et al., 2016, p. 3), they propose an incremental improvement instead of requiring a complete overhaul.

The first step toward this goal is to identify the heuristics at play and the factors that influence these heuristics to inform the design of decision tools.

3.2) Trial Description and Methodology

3.2.1) Trial Design

I developed a simulation in the form of a web application, giving participants the role of the top manager of an electronic components company. In the initial situation, the company produces components in-house in the region where they are sold. The simulation lasts for 12 simulated "months" representing periods of production and sales. At each of these 12 periods, participants have the choice to maintain local production, or to offshore it, the latter being irreversible.

The offshore supplier offers a cheaper cost per unit ratio, if the participant successfully computes and compares the cost of production per unit and the cost per worker.

However, following the Cost Differential Frontier framework, ordering offshore instead of producing locally increases lead-time and therefore introduces uncertainty in the demand for each period, unlike local production that is considered to be made on-demand.

The balance between the costs and the volatility of demand – that evolves during the simulation – defines the optimal solution according to the Cost Differential Frontier model.

The simulation includes three parts:

- Briefing screen and demographic information form (age, occupation, country).
- The task itself with 12 periods.
- A feedback form with 5 questions:
    - Were your decisions based on analysis and calculations? (Yes / Somewhat / No).
    - Are you convinced you made the right decisions? (Yes / No).
    - What were the factors guiding your decisions? (Economic / Social / Both).
    - Which production option do you think was the most profitable? (Always Local / Always Offshore / Offshore after month 7 / Balanced).
    - How would you describe your general risk profile in life? (Risk Seeker / Risk Neutral / Risk Averse).
    - And an Open-comment field.

The following figures show the simulation interface at each of these three parts.

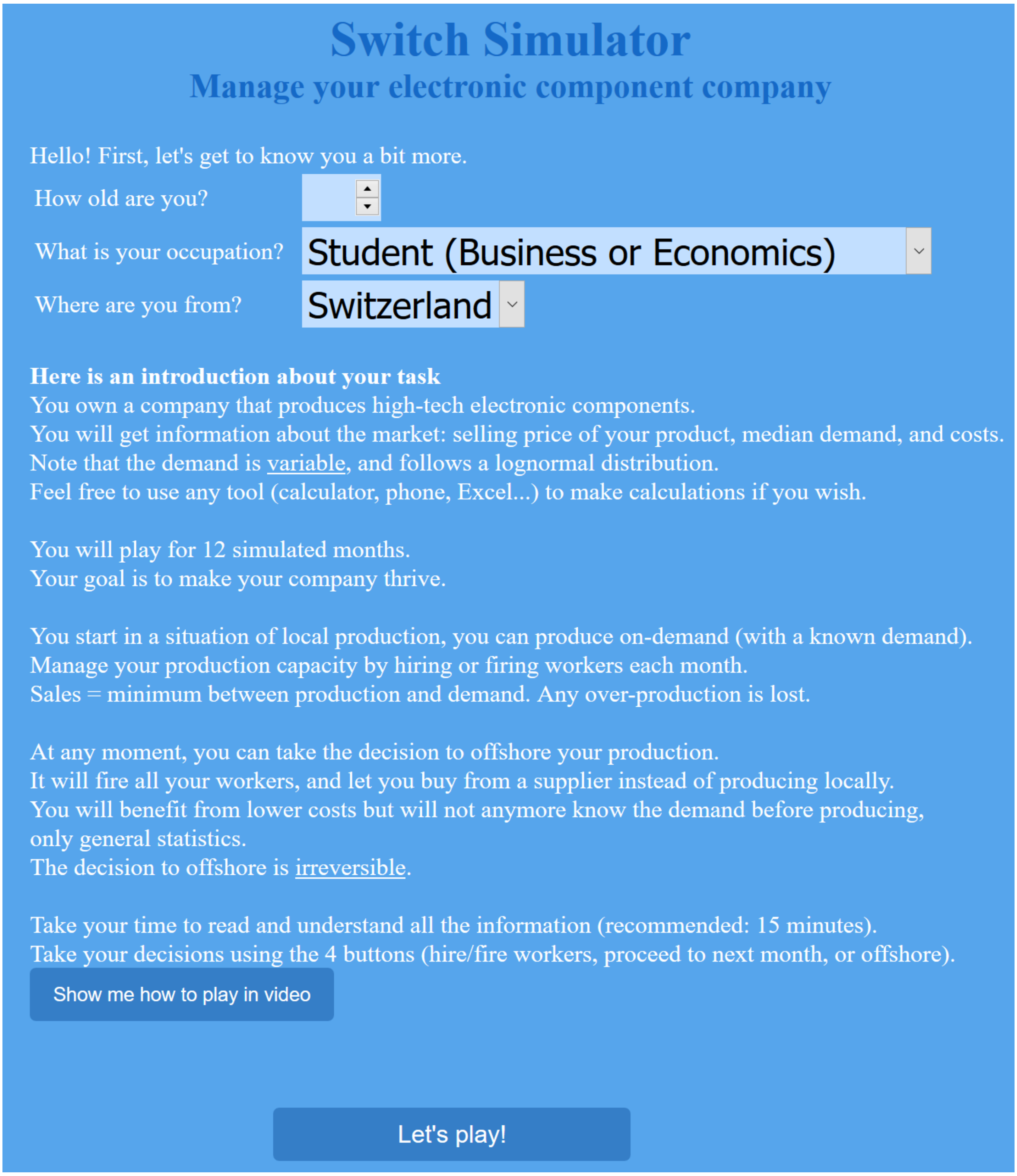

Figure 3.1: The simulation interface on the initial briefing screen.

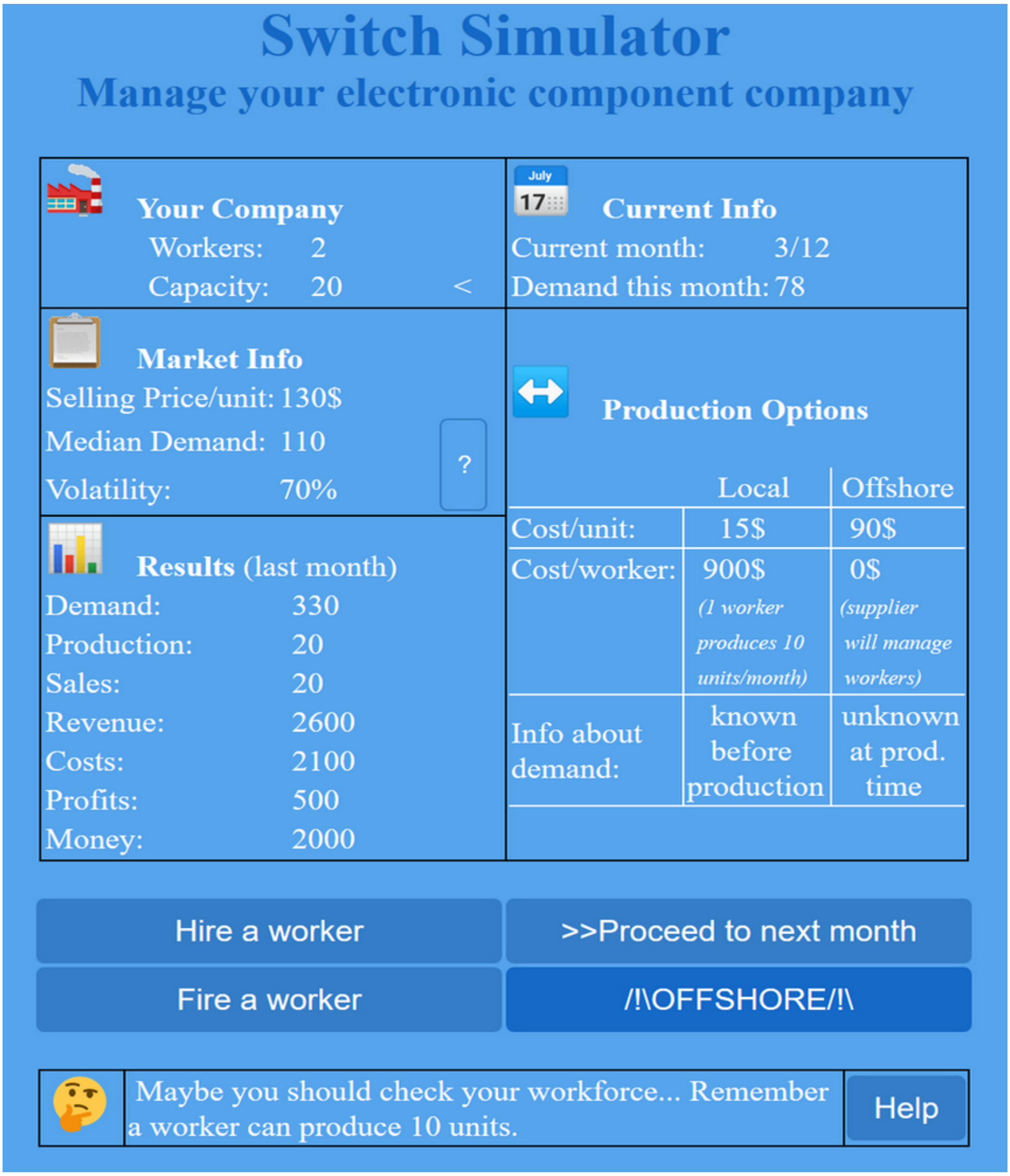

Figure 3.2: The simulation interface during the task.

During the task, as shown in figure 3.2 the screen has three elements:

- A board displaying economic information, demand data, and past month results.
- The decisions buttons the participant uses to enter choices, with four possible actions: hire a worker, fire a worker, proceed to next period, offshore production.
- A textbox displaying basic advice, occasional prompting from virtual shareholders seeking more profit after a bad month and a help button showing briefing info again.

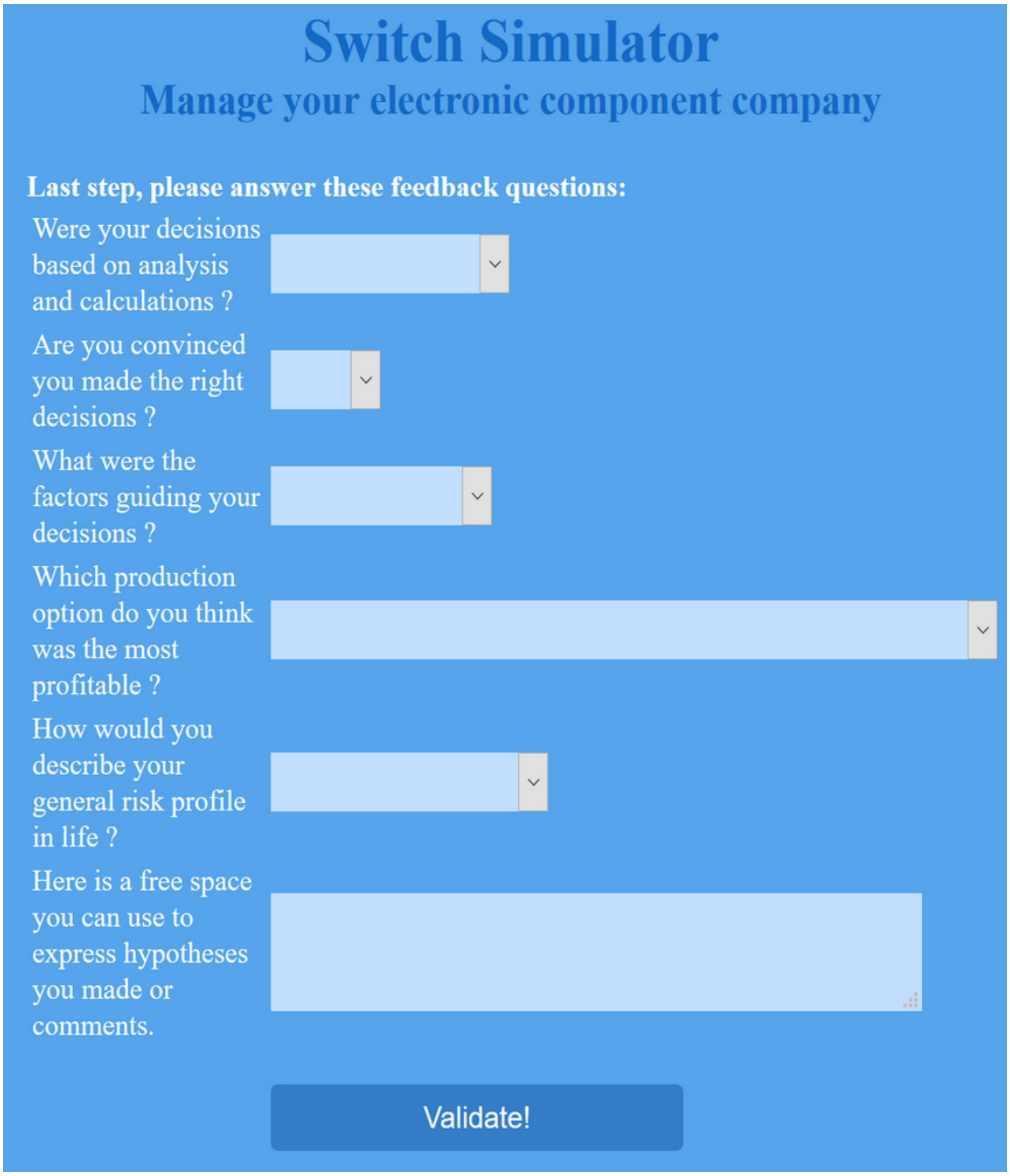

Figure 3.3: The simulation interface on the final feedback questionnaire screen.

To simplify the task so the participants focus on the decisions I study, no hiring or firing cost is incurred. Managing local production is therefore as easy as adapting workforce to current demand, whereas offshoring requires placing orders before knowing demand, which places the participant in front of a Newsvendor problem.

Using the Cost Differential Frontier tool, the volatility of demand and the costs of production can be set to a point of financial equilibrium, where a rational decision-maker would be indifferent between producing locally, at a slightly higher cost, and offshoring, incurring demand uncertainty.

Here is how it can be done following the model from de Treville, Cattani and Saarinen (2017):
We model the demand as following a lognormal distribution.
We set a selling price of 130$ and a median demand of 110 units.
With a volatility of 0.7 (fast-moving product), average demand is 141 units/period.
If we set the offshore production cost at 90$/unit, following the Newsvendor model:
- The cost of underage (being one unit short in inventory and therefore missing one sale) is 40$.
- The cost of overage (having one unsold unit left in inventory at the end of the period) is 90$.
- The Service Level is $\frac{\text{Cost of Underage}}{(\text{Cost of Underage + Cost of Overage})} = \frac{40}{(40+90)} = 0.308$.
The optimal order quantity under uncertainty (offshore) in standard deviations is -0.502.
In terms of units, the optimal order quantity is 110 * EXP(-0.502 * 0.7) = 77.4 units.
The fill rate is estimated at 0.5.
Expected sales are 69.7 units, which gives an expected revenue of 69.7 * 130 = 9061$.
Expected leftovers are 7.7 units.
Expected offshore costs are 77.4 * 90 = 6966$.
We do not value nor penalize the remaining stock, considering that a fast-moving electronic product will not be sellable on the next period, but will be easily disposable.
Expected profit is therefore 9061 - 6966 = 2095$.
Locally, with same price and expected demand, expected profit = 141 * (130 - local cost).
To balance expected local and offshore profits, the local cost should therefore be set to 115$.
Selling price (130$) and median demand (110) will stay fixed in the simulation.
The local cost will also be fixed, at 105$, which creates:

- Condition A: very favorable to local (expected profit = 3513$ vs 2095$ offshore).

By adjusting the volatility and the offshore cost, conditions can be changed to:

- Condition B: volatility lowered to 0.6 which gives a mean demand of 132, and offshore cost lowered to 85$; still favorable to local (expected profit = 3300$ vs 2734$ offshore).
- Condition C: volatility lowered to 0.5 which gives a mean demand of 125, and offshore cost lowered to 80$; favorable to offshore (expected profit = 3464$ vs 3125$ local).

Participants are randomly assigned to one of four scenarios. In all scenarios, participants start in condition A, where producing locally is significantly better than offshoring. Then a change in parameters occurs at period 7, leading to condition B or condition C depending on the scenario. Participants are warned about the change by an attention-catching message and updated data twinkles.

Two scenarios, serving as control, are limited to these variations of economic variables.

- In scenario 1, the simulation switches to condition B on month 7.
- In scenario 2 the simulation switches to condition C on month 7.

In two other scenarios, non-economic factors are added as treatments.

- In scenario 3, beside the same switch as scenario 1, participants receive the notice that "80% of players in this configuration chose to offshore production" through the textbox on months 4 and 9. The goal is to test whether peer influence can increase the tendency to offshore.
- In scenario 4, beside the same switch as scenario 2, the flag of the home country of the participant – asked at the briefing step – is displayed during the whole simulation, under the factory icon on the top left of the interface, right next to the number of workers. Additionally, messages about the positive social impact, "Your company just received an award for your positive impact on local social life and employment!" and ecological impact, "Your company is recognized as being eco-friendly! Your local production helps reduce CO_2 emissions" are displayed through the textbox respectively on months 4 then 9, and 2 then 8, assuming the participant did not offshore before any of these points, in which case only the flag remains. The goal is to test for an impact of framing of the decision, to play on information accessibility and affect. Note that the non-economic factors go against the economically rational decision of each scenario.

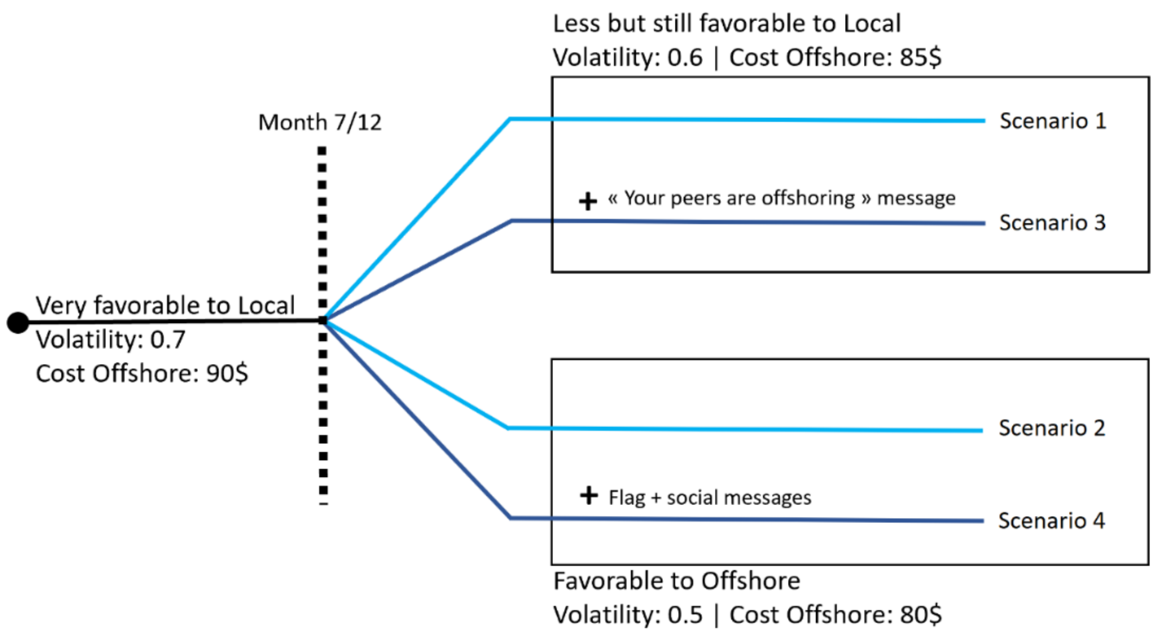

Figure 3.4: The four different scenarios.

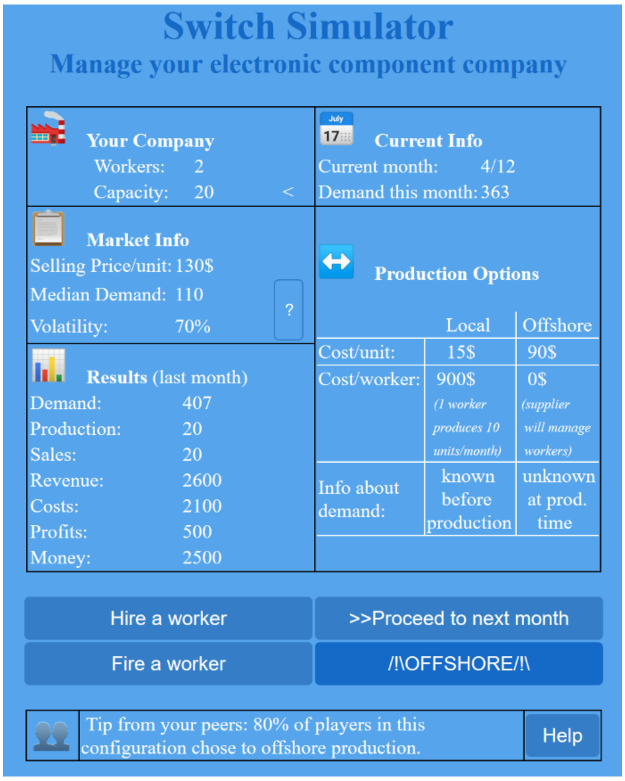

Figure 3.5: Peer-influence message at the bottom of the interface screenshot. In scenario 3, this message appears during months 4 and 9. The appearance of a new icon and text in the textbox situated just under the decisions button is designed to attract participant's attention.

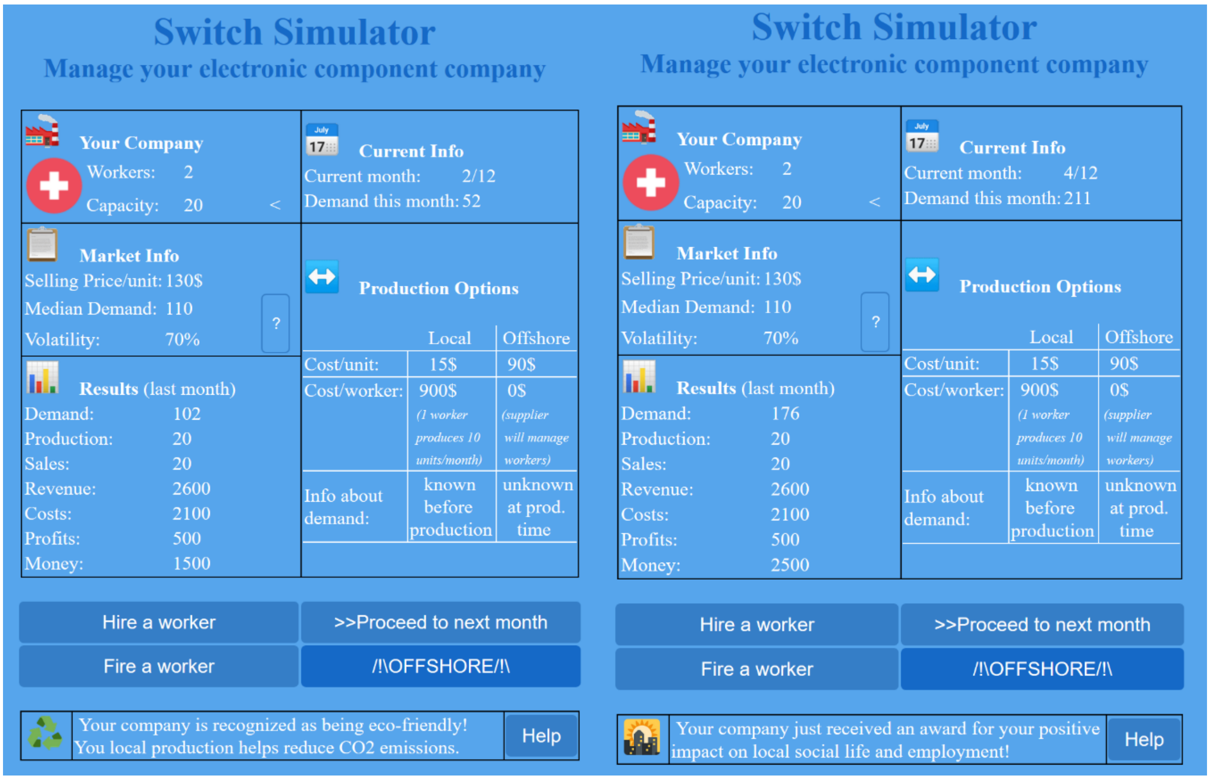

Figure 3.6: Ecological and social messages at the bottom of the interface screenshots, and the flag of the participant's country in "Your Company" at the top left of the interface. In scenario 4, these messages appear respectively during months 2 then 8, and 4 then 9. The appearance of a new icon and text in the textbox situated just under the decisions button is designed to attract participant's attention.

To summarize:

- Scenario 1: very favorable to local at first, then less but still favorable to local.
- Scenario 2: very favorable to local at first, then turns around to be favorable to offshore.
- Scenario 3: like scenario 1, but participants receive the message about their peers deciding to offshore, on months 4 and 9.
- Scenario 4: like scenario 2, but participants' home country flag is displayed, and they receive messages about their positive social and ecological impact on months 2, 4 8 and 9, unless they already offshored.

3.2.2) Procedure

Kahneman (2003) argues that in the context of heuristics and biases studies, within-participant designs attract participants' attention to the variables that are manipulated in different conditions, and encourage them to adopt artificially consistent strategies. I opted for a between-participants methodology, with each participant being randomly assigned one of the two scenarios, and participating only once. Participants were not limited in their decision time. Average duration of the simulation was 21 minutes. As pointed out by Karahanna et al. (2018), online experiment without supervision is a risk of loss of internal validity. I limited this mode of administration to participants I really could not meet physically, representing only 16 out of 200. Therefore, in addition to the open-comment field, I had the opportunity to discuss informally with some participants after sessions.

Lonati et al. (2018) provide a useful set of good practices regarding experimental design in behavioral operations management research. Demand effects are one of the main pitfalls, with subjects reacting to cues about what constitutes the expected or desirable behavior instead of acting as they would in a natural setting.

Regarding experimenter and context influence, the random assignment of scenario to each participant is built in the software and as the experimenter, I was not aware of which scenario was being played. Participants were not aware of other treatments and my interactions with them were limited to making sure the instructions were clear.

I did not choose to create a fully "abstract frame" (Donohue, Katok & Leider, 2018, p. 15) for the task, and instead provided a clear context around the offshoring decision. Given the essence of such a decision, social desirability definitely plays a role in the decision process, but it is also a core element of a real-life offshoring, and is therefore suitable to reproduce the relevant mindset and activate in participants the same thought process they would use in practice. However, I made the instructions formulation (figure 3.1) as neutral as possible regarding the criteria of what a good decision would be. I voluntarily stated the goal for participants as “make your company thrive,” with the intention to give them free interpretation of what “thrive” meant – profit, employment, demand satisfaction, sustainability...

All the participants – across scenarios – had the same level of potential awareness of what the trial was about. I therefore argue that any possible demand effect was held constant.

Another risk pointed out by Lonati et al. (2018, p. 21) is “incorrectly specified comparisons between two levels of the same independent variable,” in the context of this trial, that would be comparing a group that experiences a sudden change in parameters with a group that keeps the same parameters all along, or two changes in parameters in opposite direction.

In order to avoid that issue, the trial is designed such as all groups experience a change in parameters in the same direction – all make offshoring more favorable than in the initial condition. Moreover, scenarios are designed as two pairs of identical economical parameters – scenario 1 and scenario 3, scenario 2 and scenario 4 – so that in each pair, the first scenario is the “baseline treatment” and the second scenario is the “comparison treatment” (Donohue, Katok & Leider, 2018, p. 13).

The authors also warn against the lack of consequential decisions and outcomes and suggest that a compensation based on performance is a good practice. However, I opted against this option – and provided a fixed compensation for participation – in order to avoid having to disclose a clear performance indicator to participants, which would have led to strong demand effects. For example, linking participants’ compensation to in-game final profit would have made it the de-facto goal of the game, eliminating potential alternative goals such as local employment, goods transportation minimization, mismatch minimization. As previously discussed, the purpose of my design was to leave this aspect to each participant's appreciation.

3.2.3) Participants

The random assignment process – built-in the software using the Math.random() JavaScript function – led to a total of 48 participants in scenario 1, 52 participants in scenario 2, 52 participants in scenario 3 and 48 participants in scenario 4, which is in line with the unformal standard or 50 participants per treatment (Lonati et al., 2018). I tried to avoid the usual “western sophomore science” bias by varying participants’ profiles, which are described in figure 3.7.

Description	Number
Students at the University of Lausanne (mainly Swiss and French)	**122**
Studying Business or Economics	*95*
Studying Other Fields	*27*
Swiss professionals in the field of Supply-Chain or Operations	**7**
Academics (international)	**5**
Professionals in the field of Supply-Chain or Operations via Amazon MTurk (mainly U.S)	**16**
Philippines workers in various fields	**27**
Philippines students	**23**
Studying Business or Economics	*21*
Studying Other Fields	*2*
Total	**200**

Figure 3.7: Participants description. I started my study at the University of Lausanne, where the main demographics are Swiss and French students. Out of 200 participants, 122 are European resident students, 95 of them studying Business or Economics, and 27 studying other fields. Through word of mouth I got in contact with 7 professionals in the field of management in Switzerland and 5 international Academics. I used the Amazon Mechanical Turk platform to reach 16 more professionals in the field of Supply-Chain or Operations at large, 15 of them from the US. Finally, I administered the simulation in the Philippines, with 27 workers in various fields and 23 students, 21 of them studying Business or Economics.

This version of the trial is an extension of the one presented in chapter 2. Scenarios 1 and 2 serve here as baseline respectively for scenarios 3 and 4. Therefore, I reuse the data from the 100 participants of the study presented in chapter 2, and add 100 new participants experiencing scenarios 3 and 4. As the laboratory sessions for two parts of the trial took place at the same time, participants were effectively assigned randomly to each of the four scenarios.

3.2.4) Data Analysis

I performed three checks to make sure participants understood the task, so their choices reflect decisions and not misunderstandings:

1) I ran pretests of the trial to improve clarity of interface and wording. These pretests were conducted as three sessions of the simulation with one or two volunteer students – for a total of five pretesters – unaware of the research topic, who agreed to give feedback on any misunderstanding about the task, as well as their step by step thinking process. A representative example of the improvements made through pretesting was changing labels of what I initially called “demand periods”, which consistently confused testers, who inquired if it referred to days, months or years. This detail does not make a difference in the model but as testers seemed

put off by this designation, I settled label them months, and none of the subsequent participants in the trials raised any question about time frames.

2) During the simulation, after reading the briefing but before starting to make decisions, each participant had to take a short quiz, have it validated and, if necessary, corrected before they could start. The questions checked that participants understood the offshoring decision was irreversible, demand was not correlated between months, and local production was more expensive than offshore when adding fixed and variable costs. The quiz is shown in figure 3.8

Switch Simulator - Quiz

This quiz is to make sure you understood the instructions.
Please check the correct answer for each question.

If I decide to offshore on month 6, can I decide to go back to local on month 8?
[_] Yes, it's possible
[_] No, it's impossible

If the demand is 150 on month 2, what will be the demand on month 3?
[_] Also 150
[_] Between the median and 150
[_] It's impossible to say in advance

What is the total cost of producing 1 unit locally?
[_] 15$, it's cheaper than offshore
[_] 90$, it's the same as offshore
[_] 105$, it's a bit more expensive than offshore

Figure 3.8: The quiz used after reading the briefing screen but before starting the task, to make sure participants have understood the instructions.

3) During data treatment, I created a binary variable called “Understood” that was meant to determine if each participant had correctly understood the task of if the decisions suggested unusually misguided – or random – decisions. When local, producing more than 20% over or less than 20% under the displayed demand was considered a mistake. When offshore, ordering more than 400% of the median or less than 25% of the median was considered a mistake. More than three mistakes gave a 0 score. 93% of participants had a positive understanding score. I decided not to include this variable in the analysis after reading comments and discussing with participants who deliberately placed orders that would be flagged as misunderstandings. For example, a participant in the Philippines whose family runs a village convenience store, explained that she preferred selling a very small amount of goods every period with the certainty of a small profit, over having to manage more goods or risk any overstock. I did not remove these participants from the data for the same reason and because it is probable some real-life offshoring decisions are taken without perfect understanding of the operations at work.

Each time a participant completed the simulation, raw data – already anonymized and only identified by a numerical code that the participant noted and presented to receive payment – was automatically sent via email to my server in the format showed in figure 3.9.

ID code: 376562
Condition: 3
Age: 22
Country: Switzerland
Occupation: Student (Business or Economics)
Total Time: 1114

Month	1	2	3	4	5	6	7	8	9	10	11	12
Time	61	92	142	11	11	11	46	15	15	10	10	10
Offshore	0	0	1	1	1	1	1	1	1	1	1	1
Nb Worker	2	10	0	0	0	0	0	0	0	0	0	0
Capacity	20	100	0	0	0	0	0	0	0	0	0	0
Demand	172	104	113	217	114	77	68	100	227	93	123	367
Production	20	100	105	105	105	110	100	50	60	80	100	90
Sales	20	100	105	105	105	77	68	50	60	80	100	90
Cost Workers	1800	9000	0	0	0	0	0	0	0	0	0	0
Cost Prod	300	1500	9450	9450	9450	9900	8500	4250	5100	6800	8500	7650
Revenue	2600	13000	13650	13650	13650	10010	8840	6500	7800	10400	13000	11700
Profit	500	2500	4200	4200	4200	110	340	2250	2700	3600	4500	4050
Money	1500	4000	8200	12400	16600	16710	17050	19300	22000	25600	30100	34150

Calculations: Yes
Conviction: Yes
Decision factors: Economic
Rational guess: Local at first, Offshore after month 7
Risk profile: Neutral
Comments: du moment que les coût locaux étaient plus chers que les coûts étrangers, j'ai exporté ma production

Figure 3.9: Raw data from a participant. Raw data include the initial demographic questions, the scenario experienced, the details of the parameters and decisions for each month of the simulation - including the demand, production decisions, sales, financial results and whether the participant has offshored or not - and the answers to the feedback questions.

The idea was to present raw data in a format that was readable for the experimenter so it would be immediately usable, for example to be discussed in an unformal way with the participant when time permitted. After all the laboratory sessions were completed, the data was then converted to CSV format, and analyzed using Microsoft Excel.

3.3) Results

3.3.1) Overview of Offshoring Across Scenarios

Figure 3.10 shows the average number of months spent offshore in each scenario, while figure 3.11 shows the cumulative percentage of participants who offshored throughout the simulation.

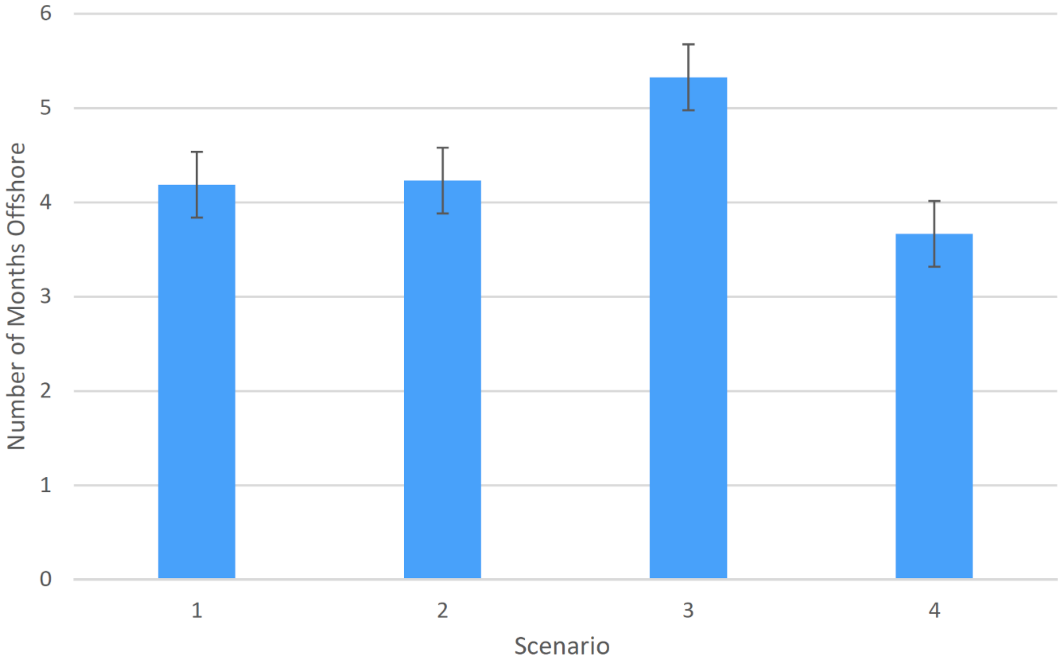

Figure 3.10: Impact of the scenario experienced on the number of months spent offshore. Error bars show standard error.

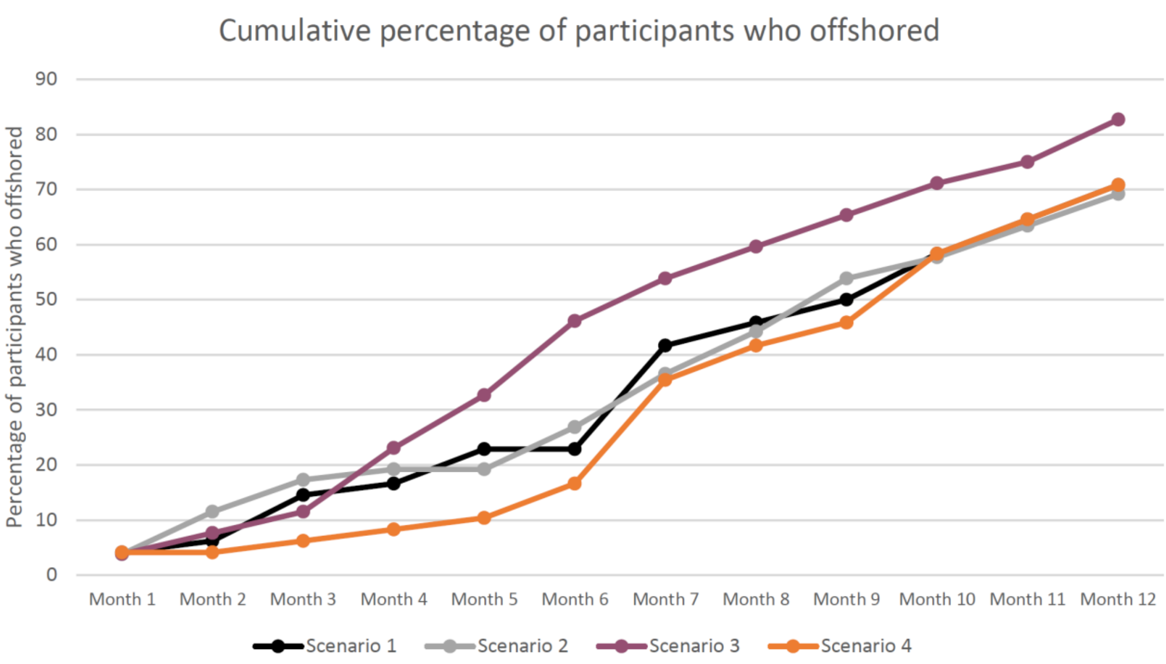

Figure 3.11: Cumulative percentage of participants who offshored throughout the simulation.

As a reminder, the switch in parameters – offshore cost and demand volatility – in scenario 2 and 4 is important enough to make offshore the optimal solution from month 7 onward, but scenario 4 frames the decision as a social choice in order to favor staying local while scenario 2 does not include any particular framing. In scenarios 1 and 3, the parameter switch is not important enough to make offshoring optimal, therefore participants should stay local, but scenario 3 hints that a large part of people in such situation did offshore while scenario 1 does not try to influence.

The number of participants – randomly – assigned to each scenario was balanced with 48 for scenario 1, 52 for scenario 2, 52 for scenario 3 and 48 for scenario 4. The overall average of months spent offshore across all four scenarios is 4.37. The number of months spent offshore by the participants in each scenario, as presented in figure 3.10, indicates a deviation from optimality, as scenarios 1 and 3 would, in theory, call for no offshoring, while in scenarios 2 and 4, optimal strategy would be 6 months of offshoring, giving initial support to hypothesis 1 that expects a mismatch between participants decisions and mathematically optimal options.

Instead, results show that participants in scenario 3 exhibit a higher number of months offshore (5.33), while participants in scenario 4 show a slightly lower number (3.67). In both scenario 3 and 4, the change in offshoring goes in the direction of the non-economic influence.

The difference is statistically significant in scenario 3 ($r(198) = 0.15$, $p<0.05$), which is in line with hypothesis 2 that expects an effect of peer influence toward an increase of offshoring. The difference is not significant in scenario 4, giving no support to hypothesis 3 that expects a decrease in offshoring as a result of the social framing of the decision.

3.3.2) Decision Profiles

Based on the scenario experienced and the month at which each participant decided to offshore, I defined four decision profiles:

1. The “Offshore anyway” profile applies to participants of any scenario who offshored sometime during the first six months of the simulation. The name refers to the idea that they offshored despite the economic conditions being very favorable to local production.
2. The “Easily triggered” profile applies to participants of scenario 1 or 3 who offshored sometime after the change of economic conditions on month 7. The name refers to the idea that their offshoring followed a switch in economic conditions that was not sufficient to make offshoring economically optimal.

3. The “Optimal strategy” profile applies to participants in scenario 1 or 3 who never offshored, or to participants in scenario 2 or 4 who offshored sometime after the change of economic conditions on month 7. The name refers to the idea that their strategy matches the economically optimal choice.
4. The “Never offshore” profile applies to participants in scenario 2 or 4 who never offshored. The name refers to the idea that they did not offshore even when economic conditions became favorable to offshoring.

A classification algorithm, applied to each participant, would be:

```
IF(Offshoring_time < Month07)                                          {Profile=1;}
ELSE IF((Scenario==1 OR Scenario==3) AND Offshoring_time <= Month12)   {Profile=2;}
ELSE IF(((Scenario==1 OR Scenario==3) AND Offshoring_time == NEVER)
     OR ((Scenario==2 OR Scneario==4) AND Offshoring_time <= Month12)) {Profile=3;}
ELSE IF((Scenario==2 OR Scneario==4) AND Offshoring_time == Never)     {Profile=4;}
```

Note that I detailed the conditions for profile 4 but I could have used a simple ELSE condition as the four profiles cover all possible strategies adopted in the simulation. They are also mutually exclusive.

Figure 3.12 shows, for each scenario, the number of participants who offshored at each given month. It indicates the number of new offshoring each month, and not the cumulative number of participants producing offshore at each point. As offshoring is irreversible in the simulation, each participant is counted once in the figure and belongs to only one decision profile. The decision profiles are represented by colors: red for profile 1, yellow for profile 2, green for profile 3, blue for profile 4. For example, in scenario 3, seven participants offshored on month 6, and they belong to profile 1 “Offshore anyway”. Another example, in scenario 4, three participants offshored on month 8, and they belong to profile 3 “Optimal strategy”. The sum of the table is 200 since there are 200 participants in the experiment.

	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Month 9	Month 10	Month 11	Month 12	Never
Scenario 1	2	1	4	1	3	0	9	2	2	4	3	3	14
Scenario 2	2	4	3	1	0	4	5	4	5	2	3	3	16
Scenario 3	2	2	2	6	5	7	4	3	3	3	2	4	9
Scenario 4	2	0	1	1	1	3	9	3	2	6	3	3	14

Figure 3.12: Number of offshoring decisions each month in each scenario. In red, offshoring decisions taken despite conditions very unfavorable to offshoring. In yellow, offshoring decisions taken despite conditions slightly unfavorable to offshoring. In green, offshoring decisions taken when conditions were favorable to offshoring. In blue, no offshoring decision despite conditions favorable to offshoring. Offshoring is irreversible, each participant can only offshore once, or never.

Figure 3.13 shows the number of participants belonging to each decision profile. We can observe that all four profiles emerge, but I do not make claims about their relative frequency.

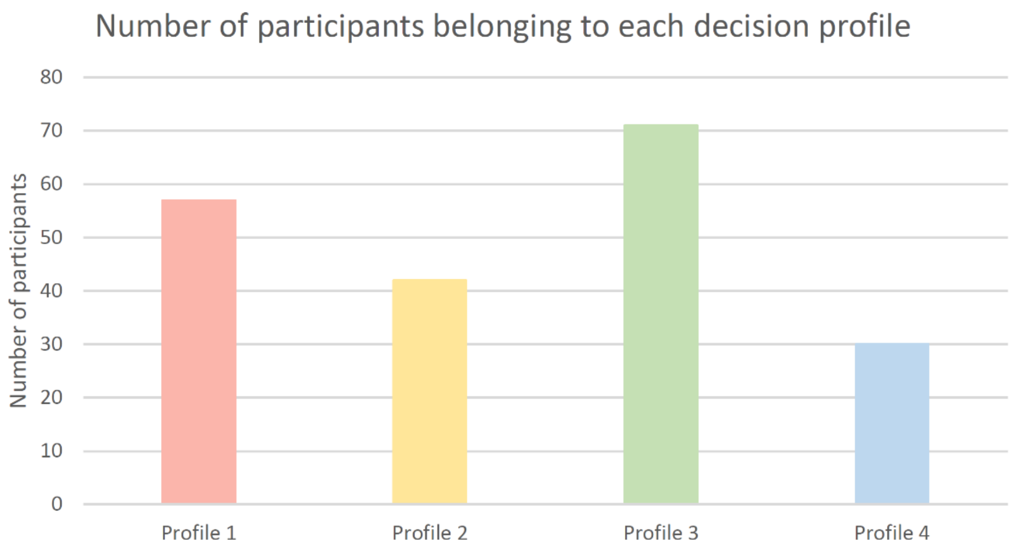

Figure 3.13: Number of participants belonging to each decision profile.

In scenario 1, the optimal strategy to never offshore was adopted by 14 participants out of 48 (29%). In scenario 3, with the optimal strategy being the same as in scenario 1 but with participants being told that their peers offshored, only 9 participants out of 52 (17%) adopted it. In scenario 2, where the optimal strategy was to offshore after the switch of conditions at month 7, I considered any offshoring happening between month 7 and 12 as an adoption of the optimal strategy, and observed it for 22 participants out of 52 (42%). In scenario 4, with the optimal strategy being the same as in scenario 2 but with participants being framed into considering the decision as social, 26 participants out of 48 (54%) adopted it. Across all scenarios, only 36% of participants adopted the optimal strategy, supporting hypothesis 1.

3.3.3) Peer Influence Effect

A Chi-square test ($\chi 2(1)=7.008$, $p=0.008$) shows that participants in scenario 3 were significantly more likely to offshore prematurely – during the first six months of the simulation when the conditions are very unfavorable to offshoring – than participants in scenarios 1 and 2. Note that taking both scenarios 1 and 2 as control here makes sense, as the first six months of the simulation are strictly identical for these three scenarios in terms of economic parameters, the only difference being the peer influence message. I excluded scenario 4 from this analysis as social framing messages appear during the first six months. Including scenario 4 would therefore artificially reinforce the correlation between scenario 3 and early offshoring.

Chi-Square Test: Scenario | Offshore Anyway

Actual	Scenario 3	Scenario 1 & 2	Total
Offshore Anyway	24	25	49
Other answer	28	75	103
Total	52	100	152

Expected	Scenario 3	Scenario 1 & 2	Total
Offshore Anyway	16,763	32,237	49
Other answer	35,237	67,763	103
Total	52	100	152

χ2	7,008
df	1,000
p-value	0,008

Figure 3.14: Chi-square test for "Offshore Anyway" behavior in scenario 3 vs scenarios 1 and 2.

Focusing the comparison on scenario 1 and scenario 3, that share the same economic conditions, it appears that the peer influence messages displayed on months 4 and 9 are accompanied by a shift in participants' behavior toward more offshoring.

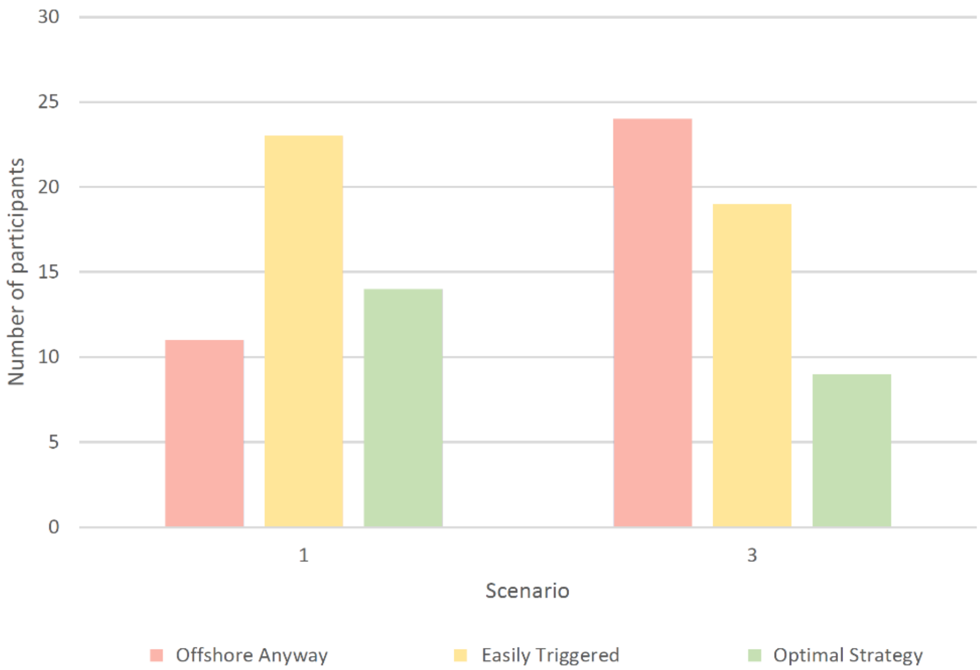

Figure 3.15: Repartition of participants among decision profiles in scenarios 1 and 3. Note that the optimal strategy in scenarios 1 and 3 is no offshoring at all.

A Chi-square test ($\chi2(1)=5.924$, $p=0.015$) restricted to scenario 1 and 3 shows that participants in scenario 3 are significantly more likely to offshore in the first six months. As shown in figure 3.11 and 3.12, the increase in offshoring decisions is important in scenario 3 on months 4, 5 and 6, right after the peer influence message is displayed. This observation gives support to hypothesis 2 regarding the existence of a peer influence associated with more offshoring. Differences in the later part of the simulation are not statistically significant.

Chi-Square Test: Scenario | Offshore Anyway

Actual	Scenario 1	Scenario 3	Total
Offshore Anyway	11	24	35
Other answer	37	28	65
Total	48	52	100
Expected	Scenario 1	Scenario 3	Total
Offshore Anyway	16,8	18,2	35
Other answer	31,2	33,8	65
Total	48	52	100
χ2	5,924		
df	1,000		
p-value	0,015		

Figure 3.16: Chi-square test for "Offshore Anyway" behavior in scenario 3 vs scenario 1.

3.3.4) Social Framing Effect

Comparing scenarios 2 and 4, it appears that the social framing of the offshoring decision did not produce measurable effects. A slight decrease in offshoring during the first six months of the simulation can be observed, but no result is statistically significant.

Moreover, on the feedback question about the main factor guiding their decision, participants who experienced scenario 4 did not select social factors any more than participants in other scenarios. Hypothesis 3 is not supported as we cannot observe a social framing effect.

It is disappointing not to be able to reproduce the prevalent impact of social considerations seen in real life offshoring studies. It may be that framing elements in the task design are too light to provoke a shift of perspective for participants, or that it is difficult to replicate affect and emotions in such a simulated setting.

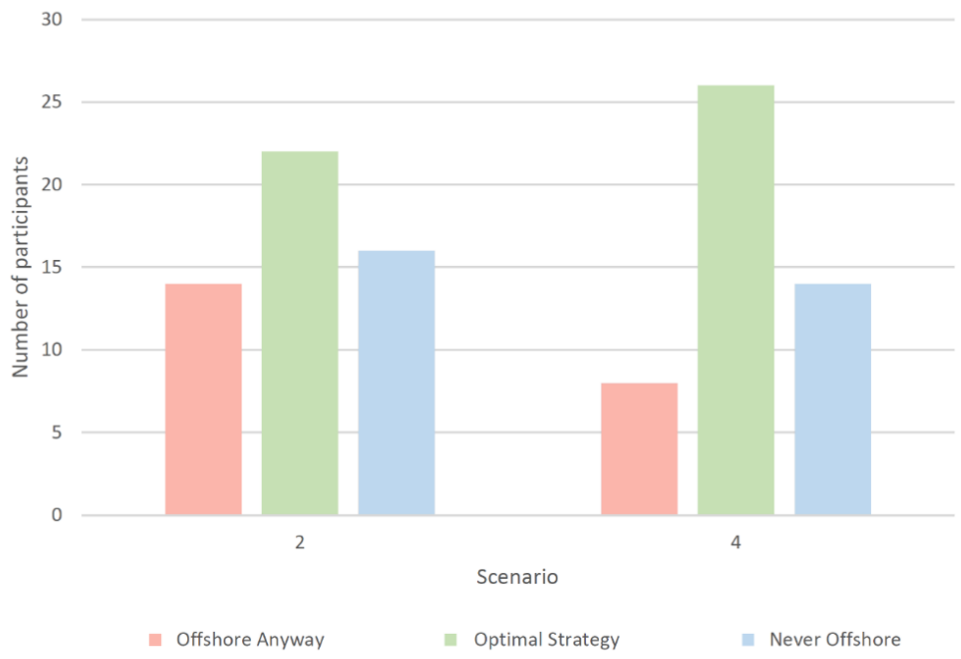

Figure 3.17: Repartition of participants among decision profiles in scenarios 2 and 4. Note that the optimal strategy in scenarios 2 and 4 is offshoring on or after month 7.

3.3.5) Open-Comments Analysis

As mentioned in the trial description, the last question of the feedback part is a facultative open-comment section. Out of 200 participants, 143 left a comment. I analyzed these comments with a methodology inspired by Musteen (2016) that consists in three steps:

1. Guided by the research question, I developed an initial list of themes – costs, demand volatility, social aspects – to facilitate the exploration of the raw data.
2. I conducted an in-depth within-participant analysis of each of the 143 comments, to tag them with one or several of the initial themes. The process was iterative, and the list of themes evolved as I noticed that some participants did not only comment about in-simulation aspects, but also at a more meta level about the task and their personal feelings about it. I also realized that the level of complexity of the comment itself – number of themes mentioned – may have an interest. At this step I voluntarily took comments out of their context by obfuscating the related data about the participant demographics, offshoring decisions and scenario experienced.
3. I switched to a cross-participants analysis to find patterns. At this step, I uncovered the context of each comment, including the scenario experienced by the participant who left each comment, and looked for potential in-group similarities and intergroup differences.

The comments I quote in this chapter are quoted in full and raw (uncorrected for typos).

Most comments focus on one aspect of the decision, notably costs: “As long as local costs were more expensive than foreign costs, I exported my production.” (Translated from French: “du moment que les coût locaux étaient plus chers que les coûts étrangers, j'ai exporté ma production”), demand uncertainty: “I think that the volatility was too high to take a risk of loosing money with offshoring”, or social responsibility: “I think a local production can help the economy of my country to increase. Whereas the off-shore will only help my own economy, but my reputation, my C02 print, will be bad”, and make no mention of the others.

This monothematic nature of comments echoes what Das and Teng (1999) identify as “Prior hypotheses and focusing on limited targets,” a common bias in decision-making characterized by tendency of people to focus “on those key objectives that appeal to their interest,” ignoring other equally important parts of the big picture. Participants are put in a legitimate situation of innumeracy (Gigerenzer, 2003) given the complexity of the calculation and abundance of information. They need to simplify the task by substituting the complex instruction given in the introduction to “make your company thrive” by one component of success – ethics toward workers, or fulfillment of demand, or cheaper cost – and apply a Take-the-best approach on this criterion of success.

Two recurring themes are the expression of personal feelings about the decision process with such terms as “nervous,” “hesitant,” “safe,” and expression of regret, with hindsight, about the decision taken.

In scenario 3 specifically, 38 participants out of 52 left a comment. Surprisingly, only one participant mentions the peer information message or peer influence in general: “I wanted to catch the market at the highs and make sure to not buy too many during the lows, but I couldn't seem to get that right, ever. I got the notice early in the game that most players offshore, but I wanted to keep using workers for the social aspect, but I succumbed to the temptation of more money.” Considering the importance of the effect and this apparent lack of identification, it would be interesting to conduct further tests on the level of awareness at which it operates.

In scenario 4, 33 participants out of 48 left a comment. Contrary to scenario 3, it seems that participants are aware and willing to write openly about the influence they received from the messages. 11 participants clearly mention social aspects as part of their decision process. 3 of them explicitly mention the simulated awards, for example: “I wanted to go offshore (because offshore productions became cheaper than they were before and volatility was reduced as well) towards the end but i kept getting rewards/achievements for employing people and being eco-friendly, so that made me stay with a local production.” Comments also tend to be more complex than in other scenarios, more frequently balancing the social and economic aspects, instead of focusing solely on one element: “My decisions were based on a desire to make a profit while keeping production local and avoiding the uncertainty of market volatility. Even if profit could have been maximized by going offshore, I felt more right by keeping it local.” Interestingly, 3 participants also mention social discomfort about staying local, specifically, having to hire and fire workers every month to adapt capacity to demand. They see offshoring as a way to free them from that unpleasant responsibility. One participant even mentions it as his main reason to offshore: “I was feeling uncomfortable to fire workers every months, that's why I decided to go offshore.. but was not the best decision ever, because then I had to satisfy stakeholders. I think stay in local production was the safe option.”

3.3.6) Demographics and Performance

In addition to the effect of non-economic factors, I used the extended set of data to redo calculations from my initial study on performance and demographics.
Performance of the participants can be measured with three distinct benchmarks:

- %MaxProfit: participant total profit compared to possible profit, given individual demand data, by staying local and always producing the right amount (successful offshoring can lead to values over 100%).
- FigureItOut: comparison between the actual optimal strategy in the condition played, and the answer to the debrief question about what strategy the participant thought was optimal (binary variable set to 1 for a right answer).
- DidItRight: consistency between the actual optimal strategy in the condition played, and the strategy adopted by the participant (binary variable set to 1 if participant offshored at the right time).

The impact of demographics on these performance benchmarks is limited.

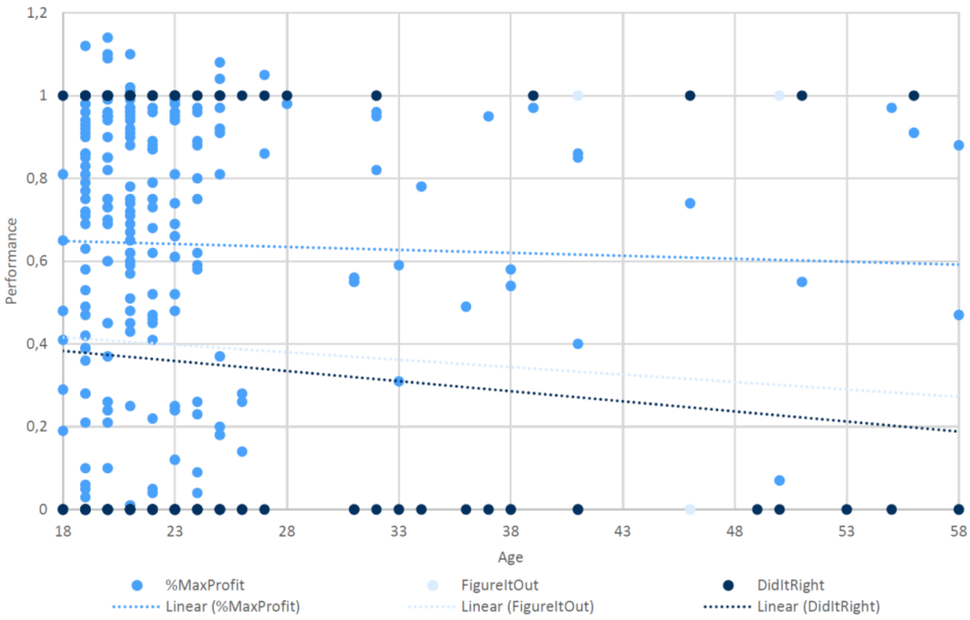

Figure 3.18: Impact of Age on %MaxProfit, FigureItOut and DidItRight.

Age, as presented in figure 3.18, has no statistically significant correlation with any of the performance indicators.

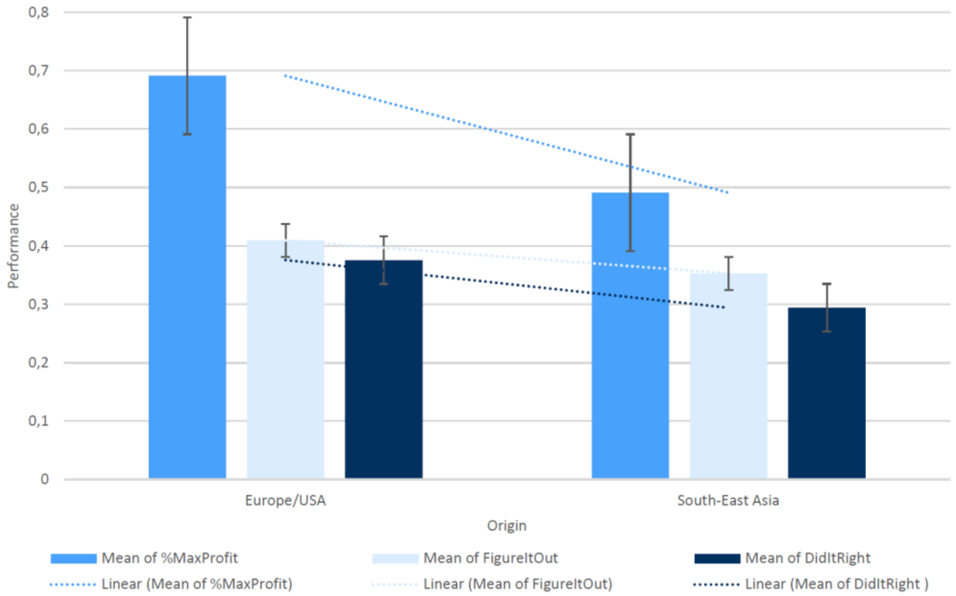

Figure 3.19: Impact of Origin on %MaxProfit, FigureItOut and DidItRight. Bars show standard error.

Participants from South-East Asia show lower overall performances than Western participants, as shown on figure 3.19, but only the %MaxProfit variable is significantly lower ($r(198) = -0.28$, $p<0.01$). As a possible explanation, feedback questions indicate that South-East Asian participants are less likely to take decisions on purely economic factors ($r(198) = -0.19$, $p<0.01$) and self-evaluate their profile as more risk-seeking ($r(198) = 0.21$, $p<0.01$).

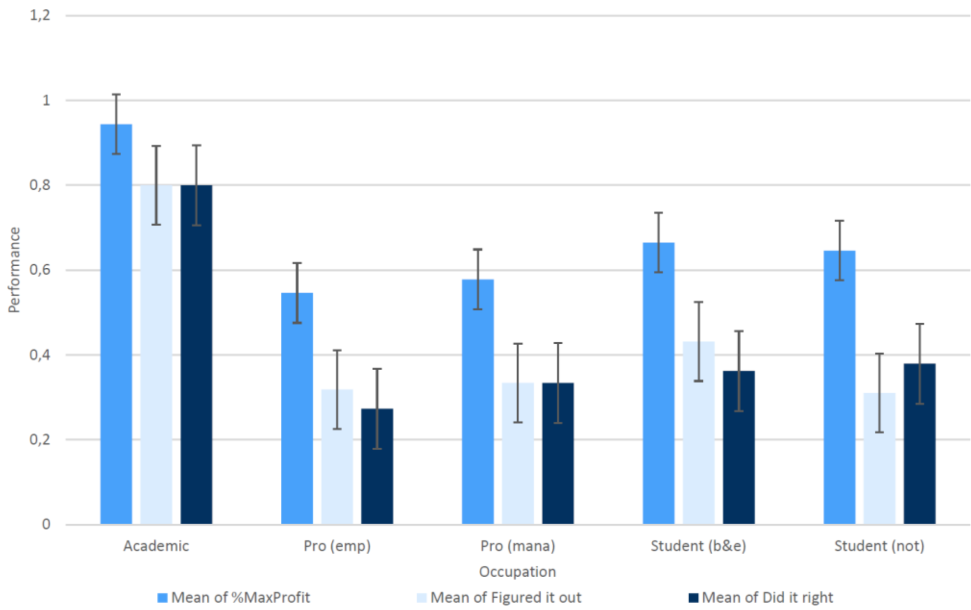

Figure 3.20: Impact of Occupation on %MaxProfit, FigureItOut and DidItRight. Error bars show standard error.

Regarding the Occupation variable, presented in figure 3.20, only the Academic profile is significantly associated with better performance ($p<0.05$ for %MaxProfit and DidItRight). The small number of Academic participants (5/200) precludes drawing conclusions, but it is not surprising that Academics in Operations are likely to make more accurate calculations or educated guesses in such a simulation presenting a familiar problem.

It is interesting to make a parallel between performance and the number of months spent offshore in the simulation. As a reference point, a participant offshoring at month 7, when changes in parameters occur, spends 6 months offshore: months 7 to 12.

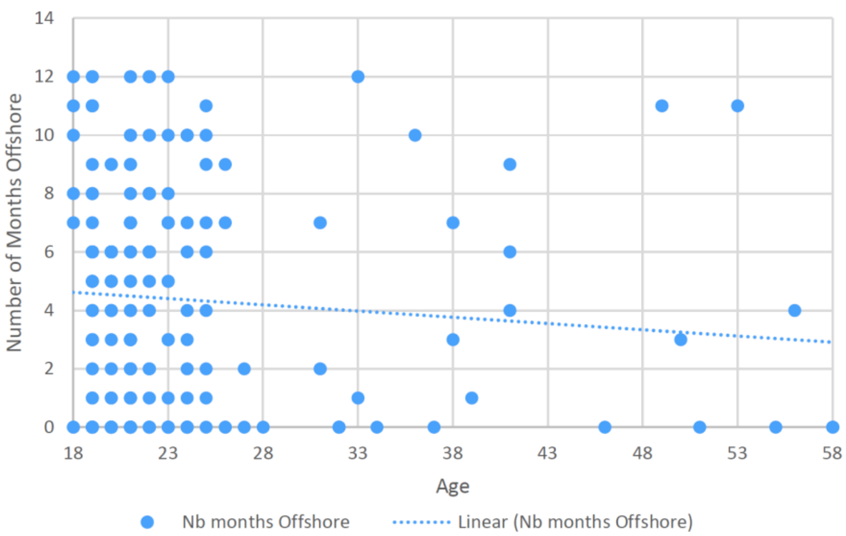

Figure 3.21: Impact of Age on the number of months spent offshore.

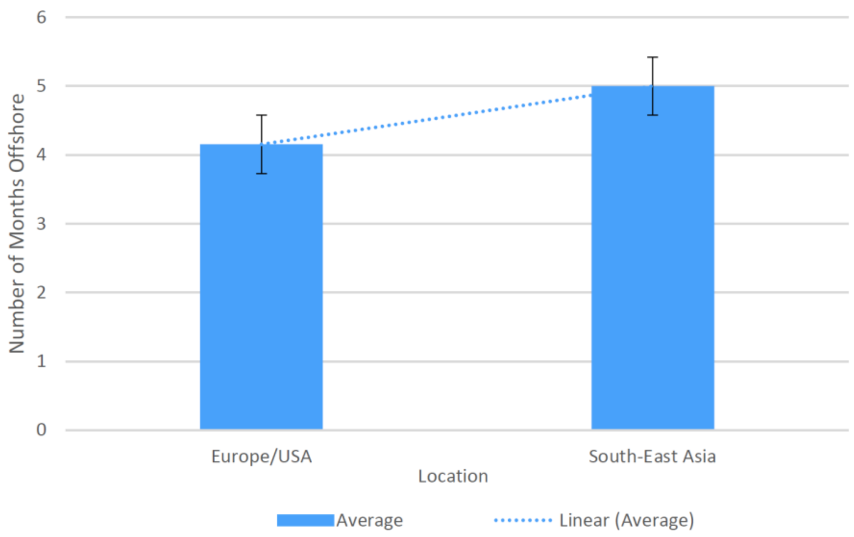

Figure 3.22: Impact of country of origin on the number of months spent offshore. Error bars show standard error.

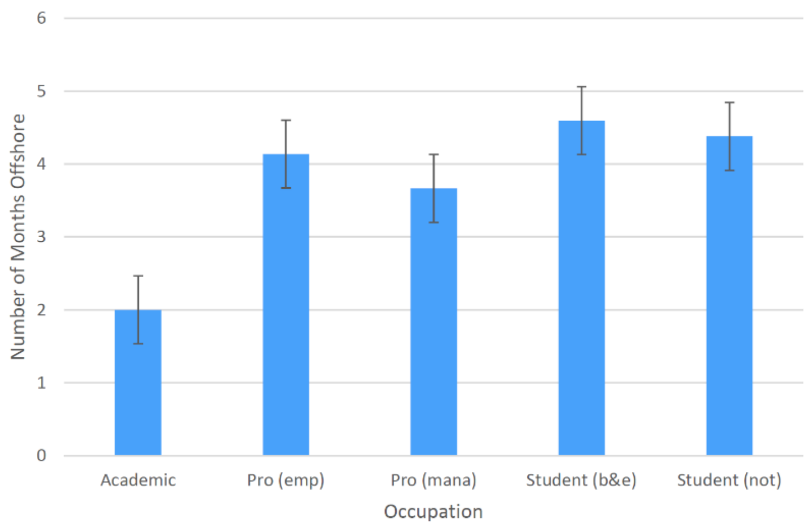

Figure 3.23: Impact of Occupation on the number of months spent offshore. Error bars show standard error.

Impact of age, origin, and occupation on the number of months spent offshore are presented respectively in figure 3.21, 3.22 and 3.23. Results appear to mirror performance benchmarks. As shown in figure 3.24, the number of months spent offshore across all scenarios is strongly negatively correlated ($r(198) = -0.40$, $p<0.01$) with the performance measured as %MaxProfit. The negative correlation between offshoring and performance suggests offshoring risk did not pay off on average, which can be explained by the greater difficulty of managing offshore production – having to bet on demand – and the fact that negative consequences from a wrong early offshoring can easily exceed the shortfall from missed offshoring opportunities.

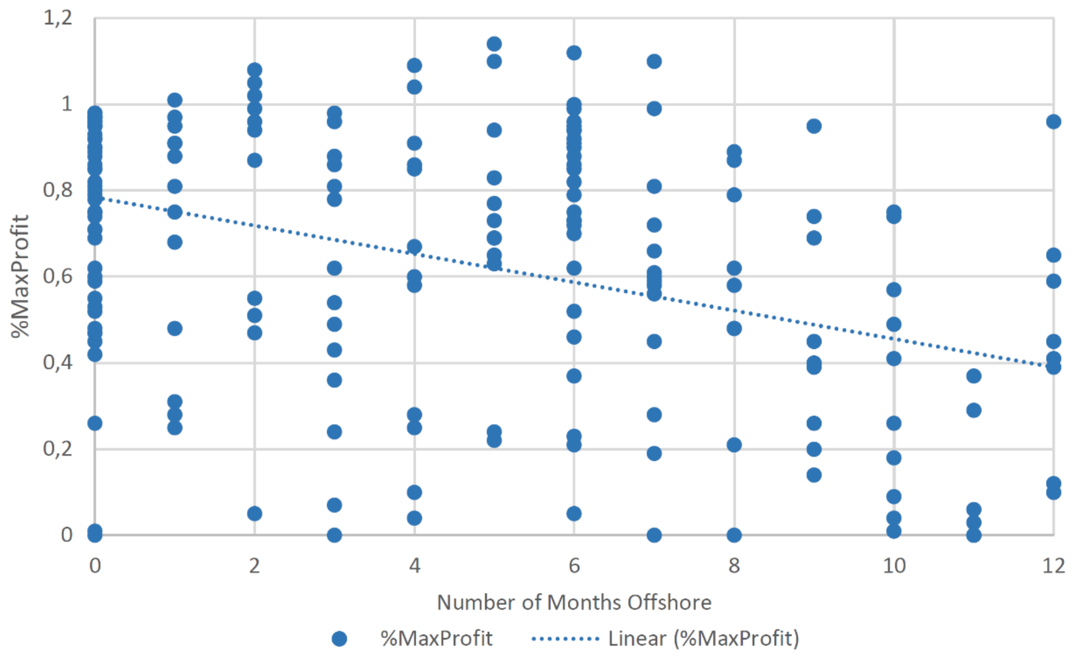

Figure 3.24: Impact of the number of months spent offshore on the profit performance.

As shown in figure 3.25, demographics – age, origin, occupation – are not correlated with the profiles, except for the aforementioned overperformance of the Academics, that translates into a moderate correlation between this occupation and profile 3 “Optimal strategy”.

	Age	*South East Asia*	*Student B&E*	*Student NOT*	*Pro (Mana)*	*Pro (Emp)*	*Academic*	*Profile 1*	*Profile 2*	*Profile 3*	*Profile 4*
Age	1										
South East Asia	-0,072	1									
Student B&E	-0,452**	-0,199**	1								
Student NOT	-0,177*	-0,176*	-0,484**	1							
Pro (Mana)	0,384**	0,032	-0,207**	-0,072	1						
Pro (Emp)	0,416**	0,409**	-0,624**	-0,219**	-0,093	1					
Academic	0,304**	-0,094	-0,188**	-0,066	-0,028	-0,085	1				
Profile 1	-0,011	0,113	-0,046	0,023	0,019	0,066	-0,101	1			
Profile 2	-0,014	0,036	0,091	-0,108	-0,019	0,023	-0,083	-0,326**	1		
Profile 3	-0,079	-0,074	0,017	0,021	-0,008	-0,091	0,149*	-0,468**	-0,382**	1	
Profile 4	0,136	-0,085	-0,068	0,066	0,008	0,014	0,022	-0,265**	-0,217**	-0,312**	1

	alpha	r critical
* p < 0.05		
** p < 0.01	0,05	0.139
n=200	0,01	0.182

Figure 3.25: Correlation matrix focused on profiles and demographics. Profiles are not correlated with demographics expect for Academic participants and profile 3 “Optimal strategy”.

3.3.7) Willingness to Pursue an Economically Optimal Strategy

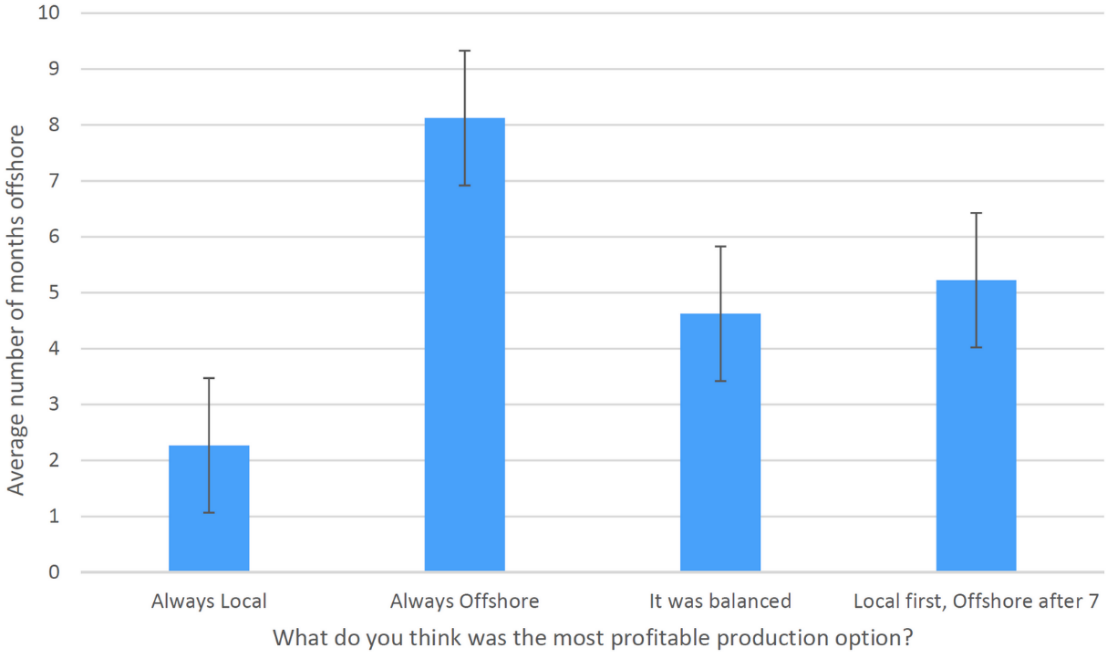

Figure 3.26: Impact of the option thought to be rational on the number of months spent offshore. Error bars show standard error.

Anova: Single Factor

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Always Local	67	152	2.269	10.836
Always Offshore	16	130	8.125	18.650
It was Balanced	32	148	4.625	18.177
Local First, Offshore after 7	85	444	5.224	8.128

ANOVA

Source of Variation	*Sum of Squares*	*df*	*Mean Square*	*F*	*p-value*	*F crit*
Between Groups	585.453	3	195.151	17.067	6.89083E-10	2.651
Within Groups	2241.167	196	11.435			
Total	2826.620	199				

Figure 3.27: An ANOVA shows that the number of months spent offshore is statistically different between groups formed based on the answer to the question about the option thought to be the most profitable.

Finally, there is a correlation between the decisions of participants and the strategy they identify as economically optimal. As shown in figure 3.26 and the accompanying ANOVA in figure 3.27, the degree of offshoring thought to be the most profitable is correlated with the number of months effectively offshored ($p<0.05$ for “Always Local” and “Always Offshore”, $p<0.1$ for “Local first, Offshore after 7”, not significant for “It was Balanced”). It must be noted that the question about the optimal strategy was asked after completion of the simulation, and could therefore be informed by the experience of the participant and does not permit to assume causality.

When asked, also at the end of the simulation, if they felt convinced that they took the right decision, 52% of participant answered yes, with little difference between scenarios (52% in scenario 1, 58% in scenario 2, 46% in scenario 3 and 50% in scenario 4). There is no correlation between this confidence indicator and and FigureItOut or DidItRight.

Also, there is no correlation between the scenario experienced and the strategy identified as economically optimal. However, there is a strong significant correlation ($r(198) = 0.35$, $p<0.01$) between FigureItOut and DidItRight, confirming the results of my previous study that participants adopt the strategy they identify as economically optimal, and suggesting that divergent choices come from a failure to identify it.

3.4) Limitations and Follow-up

The scope of this exploratory trial is to introduce a new and more complex problem than the classic Newsvendor, as it adds an additional layer that requires the decision-maker to choose between two cost and demand volatility options. I observe decisions patterns suggesting that participants use heuristics in ways that drive their choices away from the mathematically optimal option, but I do not claim to identify causality or assess magnitude of these effects.

In addition to the limitations mentioned in chapter 2.4 – lack of causal model and controls – I used no manipulation check to make sure the social framing produced the intended effect on participants. My confidence toward the efficiency of the cues was limited to self-report of a limited number of pretesters of the simulation. If we use the feedback question about decision factors – What were the factors guiding your decisions? Economic / Social / Both – as a manipulation check, we can suspect that social framing was not achieved, as participants in scenario 4 do not declare basing their decisions significantly more on social factors than participants in other scenarios. A different framing protocol, possibly using more immersive elements like images, videos or virtual reality settings could be considered.

Some participants even see offshoring as a way to avoid the social burden of firing people, a reversal of my intention which was to contrast the positive social impact of local jobs with getting rid of all internal workers to subcontract in a foreign country. This behavior might be an artifact of the simulation design, which – except for scenario 4 treatment – is voluntarily minimalistic in its definition of offshoring and its social consequences.

The briefing mentions “At any moment, you can take the decision to offshore your production. It will fire all your workers, and let you buy from a supplier instead of producing locally. You will benefit from lower costs but will not anymore know the demand before producing, only general statistics” but the emphasis in the task is on the latter part, the demand uncertainty increase and cost decrease. Consideration of social impact is left to the discretion of participants and their own opinions, and does not have consequences in the simulation.

An option would be to create a richer context around the task, a mini case that would present the pros and cons of the offshoring option in more details, including the firing of local workers. The use of virtual reality would make it even more powerful. However, enriching the context increases the risk of creating demand effects or involuntary framing of the decision. Another option would be to ensure the full understanding of the social stakes via pretesting several alternative briefing formulations.

A third option would be to control for it in the task, which could be achieved via a change in simulation design that would require participants to think aloud, verbalize all of their thinking process that would be recorded and analyzed in parallel with their decisions. This methodology is particularly interesting as it would not only inform about the social aspects understanding, but also give deeper insights into other elements of the decision-making process, showing how much attention participants give respectively to the costs differences, the demand volatility and the current financial results for example. An eye-tracking system could be informative to validate that treatment cues are noticed by all participants, and to determine which elements are considered before making a decision production, for how long, and in what order, which would also offer a more detailed outlook on the decision-making process. While the thinking aloud method could inform on the conscious thinking process, the eye-tracking might also reveal elements that are noticed but not consciously considered or at least not verbalized.

Another aspect, on the technical side of the simulation, is the irreversibility of offshoring. In case of regret about not offshoring, a participant can always correct the “mistake” on the next month, whereas a participant who regrets offshoring cannot go back and will have to stay offshore until the end of the simulation. For example, a participant in scenario 4 who would offshore straight from month 1 and regret on month 2 when he sees the social message, could not undo his decision. The decision to make offshoring irreversible came from a need to keep the simulation as simple as possible and reflects the fact that real-life reshoring is difficult and costly, but its impact on the results should be assessed.

I did not use a full factorial design, which would have meant dividing the participants into eight groups, four in each type of economic conditions with either peer influence, social framing, both treatments, or none of them. Instead, I designed the four scenarios so that three pairs of comparisons could be done:

- Scenario 1 with scenario 2 (to assess the impact of two different economic conditions)
- Scenario 1 with scenario 3 (peer influence in scenario 3 but same economic conditions)
- Scenario 2 with scenario 4 (social framing in scenario 4 but same economic conditions)

The first comparison is studied in chapter 2, the second and third are studied in this chapter. This design choice, in which non-economic factors go against the economically rational decision – peer influence happens in scenario 3 when offshoring is not actually the right strategy, social framing happens in scenario 4 when offshoring is made optimal by the economic factors – was made to put participants in front of conflicting decisions while simplifying the administration of the trial, keeping in mind that my ambition was to identify the existence of effects, but not to precisely measure their magnitude.

For the same reason, the cues used in the non-economic factors scenarios (3 and 4) are not fully symmetrical: social framing involves two messages appearing at four different periods in the simulation as well as the country flag, while peer influence only involves one message appearing at two different periods in the simulation.

The drawback is that effects of non-economic treatments cannot be disentangled from their respective economic context, and cannot be compared. The advantage is that groups are large enough – about 50 participants in each scenario, which was arguably a minimum as I also tried to explore the potential effects of some demographic factors – without having to recruit 400 participants, which I did not have the resources to do. For subsequent experiments aimed at rigorously testing targeted hypothesis, I would adopt a full factorial design.

3.5) Conclusion

My contribution with this exploratory trial is the proposition of a new decision space for offshoring inspired by the Cost Differential Model (de Treville, Schuerhoff et al., 2014), in which the decision-maker has a choice between facing a Newsvendor problem to access lower unit costs, or pay a cost premium to eliminate demand uncertainty. In this setting, participants appear to rely on heuristics that make them “non-hyper-rational actors in operational contexts” (Croson et al., 2012, p. 1).

Two hundred participants from various backgrounds faced a managerial decision-making task around an offshoring case, based on the mismatch cost due to demand volatility increase with lead-time, and including treatments to assess influence of non-economic factors.

Participants generally fail to identify the mathematically optimal strategy, despite an apparent wish to apply it, which suggests potential value for decision-tools allowing trial and error. The low impact of demographics shows ubiquity of similar biases and underlines the broad interest of such tools.

Peer influence can be simulated, and subsequent effects can be detected; in this simulation, a simple message indicating most peers in the same situation decided to offshore increases the likelihood that participants receiving it will themselves offshore.

However, the well documented effects of social factors and framing of the decision, which can reverse preferences by altering the accessibility of information, have failed to be reproduced well enough in my simulation to have an impact on the decisions, even if it seems to be noticeable in the thinking process of some participants.

Unlike a behavioral economist, I do not approach the problem with the intent to quantify biases impact and debiase the decision process. Instead, I wish to continue developing similar simulations to capture more insights about the offshoring decision process and ultimately provide decision-makers with tools and processes to increase the quality of their mental models, calibrate their heuristics better and make well-informed choices.

This trial should be considered as a “pretheoretical work” in the sense of Hambrick (2007), that aims at reporting and documenting facts about an important phenomenon. It lacks an explicit causal model at this stage, and it is even possible that unobserved covariates drive the relationship, but it does not invalidate the existence of the phenomenon, which at this point of the research, is enough to inform the design of targeted decision-helping tools.

4) Lead-Time Manager: Development of an Operations Management Simulation-Game

4.1) Games, Simulations, Serious games and Simulation-Games

The dictionary definition (Flexner, 1970) of a game is “a competitive activity involving skill, chance, or endurance, played by two or more persons according to a set of rules, usually for their own amusement or for that of spectators.” Playing games involves problem solving in the sense of Simon (1996) as summarized by Hevner et al. (2004, p. 88): “Utilizing available means to reach desired ends while satisfying laws existing in the environment.” Game-playing is a fundamental human activity in early stages of development that helps us acquire skills.

A lack of consensus exists in the literature – not to mention in practice – about the appropriate use of the terms “game,” “simulation,” and “serious games.” Sauvé et al. (2007) argue this blur is a source of discrepancy in the evaluation of artifacts and their efficiency. They formalize a definition of games by identifying their attributes: player(s), a conflict or cooperation dynamic, rules, a goal, an artificial nature, and, if the game is to be educational, a pedagogical aspect. On the other hand, simulations are models of reality defined as systems. They must be dynamic, simplified as compared to reality – although it frequently startles practitioners – but accurate and valid, and if the simulation is to be educational, include learning objectives. Games include a winning process and follow their own artificial rules. Simulations do not imply a competitive aim, not even necessarily user interaction – think of a solar system simulation – and their rules mimic those of a real, natural phenomenon.

Two visions exist regarding what qualifies a game as serious. Abt (1970, p. 9) argues that serious games “have an explicit and carefully thought-out educational purpose and are not intended to be played primarily for amusement.” Zyda (2005, p. 26) states that “pedagogy must, however, be subordinate to story – the entertainment component comes first.” Despite disagreement about the prevalence of amusement or pedagogy, the authors agree serious games have an educational purpose, which goes beyond winning the game and transforms it into a medium for learning. Possible purposes include, but are not limited to: persuading, raising awareness, communicating. The work of Zyda (2005) is focused on video games. He is the author of America’s Army, the first large-scale serious game used by the U.S. Army as a recruitment and training tool. This is reflected in his definition of serious games as “a mental contest, played with a computer in accordance with specific rules that uses entertainment to further government or corporate training, education, health, public policy, and strategic communication objectives" (p. 26), excluding offline forms like board games and role plays, which, ironically, were the first examples of military serious games. However, Zyda is correct that democratization of computers since the 1990s ignited an explosion in the development and use of serious games. Fueled by the availability of programming tools – and skills – for researchers and teachers, and a shift of mentality among digital natives about the meaning of playing, serious games and simulations developed in all fields, including supply-chain. An early and influential example is the Beer Distribution Game (Sterman, 1989) developed at MIT in the 1960s to illustrate the Bullwhip effect, which still inspires modern logistics collaborative games such as ColPMan (Mizuyama et al., 2016).

Ellington (1981, p. 15) proposes defining a simulation-games as "exercises which have the basic characteristics of both games (competitions and rules) and simulations (ongoing representation of real life)." In my opinion, this definition applies to many modern artifacts, including my Lead-Time Manager, a game based on a real-life model, grounded in research, but including an entertaining aspect and a goal, even though the conflict is internal, with no adversary other than the statistical model.

4.2) Our Operations Management Courses

At the University of Lausanne, we use the Lead-Time Manager simulation-game in two different courses: A Bachelor-level introductory course in Operations Management, and a Master-level course in Supply-Chain Analytics. The Bachelor-level course covers a wide array of Operations topics like process analysis, bottlenecks, lot sizes, optimal order quantities and queuing theory. However, the most important topic of the semester is matching supply with demand. We start with demand volatility, geometric Brownian motion and the idea that demand information gets noisier as decision lead-time – the length of time between the moment at which the production decision is made and when demand is observed – increases. We instruct the students in use of the Newsvendor model, the concepts of service level and fill rate. This allows us to cover the calculation of mismatch costs under uncertainty, taking into consideration the risks of overstock and understock. Although some of the material is technically challenging (e.g., the assumption arising from a forecast-evolution process that follows a geometric Brownian motion that demand follows a lognormal distribution), the course material brings students to a high level of expertise in balancing mismatch losses. Optimal strategies for balancing over and under stocks are often counterintuitive: a high-cost producer may well turn out to be competitive when we consider the real options that are created when we reduce the decision lead-time. We use the Lead-Time Manager to help students get familiar with demand volatility as they experience various demand values for the two different products, and to make them face the dilemma of choosing between lower cost offshore production with unknown demand, and higher cost, local on-demand production.

At the Master level, we build upon the technical knowledge and analyze case studies to challenge students to imagine supply-chain strategies that would give a competitive advantage to a company in a given industry. We analyze and classify the different types of products a company makes in terms of profitability and demand volatility. We encourage students to come up with "what-if" scenarios, reimagining the industrial organization. An example would be replacing a monolithic production line with versatile cells to allow more variety in production. The goal is to leverage a cut in lead-time, an increase in reactivity, to gain in competitiveness, create a servitizing or customizing activity around the product to add more value for customers, and make a local manufacturer, in a high-cost country, not only competitive but innovative and a leader in its industry. In recent years, there is increasing awareness of how manufacturing benefits local economy.

For these advanced users, the Lead-Time Manager can be understood in its full complexity and the challenge is to optimize the sourcing strategy by correctly balancing the portfolio of products that have different volatilities. Local capacity can be built to respond to the volatile demand of the high-margin product, which fully covers its costs. When demand for this product is low, the available capacity is not wasted thanks to a more standard product that can be made to stock if necessary, and that becomes profitable if you consider only its variable costs. Added bonuses are a maximal fill rate and a greener operation.

The challenges posed by the material we teach can be summarized in three points:

- Statistical reasoning: risk and rare events are difficult to grasp for the human brain.
- Counterintuitiveness: students must overcome gut feelings and preconceptions.
- Non-linearity: timing and interactions of decisions create divergent consequences.

Traditional teaching might be enough to convey knowledge, but it fails to prepare students to apply this knowledge to real-life situations. We need tools for that, and simulation-games fit the requirements to create a deeper meaning and make the link between theory and practice.

4.3) Why is a Simulation-Game Adapted to this Teaching Case?

The learning objective of the Lead-Time Manager is to switch players' thinking on the offshoring problem. Instead of using a default – and misguided – "Lowest per-unit landed cost" heuristic and realize buffer with inventory, we wish to provide learners the intuition and demonstration that they can approach the situation as a capacity allocation problem and realize buffer with local capacity, which is a much more tractable problem and induces less detrimental biases. As mentioned in chapter 4.2, the obstacles are the difficulty of reasoning with statistical demand risk, the non-linearity of the lead-time effects, and the counterintuitiveness of the local production solution.

Simulation-games can touch all three types of memories – visual, auditory, kinesthetic – and can be asynchronous and therefore self-paced for the learner. The games allow teachers to select events that can be rare in a natural setting, but give the learner the chance to gain experience and more importantly, expertise (Klein, 2001).

The learning process in simulation-games can be approached through the Experiential Learning framework described by Kolb (2014), and its four phases: Experience, Process, Generalize and Apply. Ncube (2010, p. 568) notes that "games are especially relevant in the generalization and application phases by helping shift learner's personal paradigms."

De-icing misconceptions is the first key to learning counterintuitive material. Van der Zee and Slomp (2009, p. 21) note that "[a long] time span is problematic for a clear understanding of cause and effect." Simulation-games can clearly match an error with its consequence or a good decision with its reward, thanks to immediate feedback, replay and what-if scenarios. It is key when teaching complex phenomena like statistical risks, and gives a sense of empowerment and competence to learners as they acquire skills.

Simulation-games foster intrinsic motivation of the player as their exploratory aspect is a strong source of engagement. According to Sauvé et al (2007, p. 250): "during the game, the learner plays first, understands after, and then generalizes." The authors find that assessment to be even more pertinent in electronic games, as players usually deduce the rules as they go.

Finally, simulation-games have been found to be effective tools for learning about complex concepts or dynamic situations (Pasin & Giroux, 2011), and acquiring a global perspective toward systemic effects and unintended consequences (Machuca, 2000). This deep learning can be attributed to the opportunities players have to "learn from model responses to their decision-making" (Van der Zee & Slomp, 2009, p. 17), which is what the gaming layer offers over a classic simulation where the model is hardcoded. Jones (1998, p. 326) argues that a simulation-game "is essentially a case study, but with participants on the inside", participants become part of the model themselves which puts them "in the hot seat for it is they job to take decisions."

For these positive outcomes to occur, I identified four required features of simulation-games:

1) Trial and error structure: making useful mistakes – that convey a lesson – should be part of the process and can be prompted by design. Progress in the game should come through a mistake elimination process, which is elegantly summarized by the expression from Annetta (2010, p. 108): "Pleasurable frustration."
2) Interaction and immediate feedback: the point of adding a game layer on a simulation model is to make it reactive and interactive. Causality between a player's actions and model's reactions should be made obvious through immediate feedback for the teaching point to be clear.
3) Challenging but safe environment to experiment: the player should be encouraged to try many strategies, free from any real-life consequences – including the risk of losing face – or self-censorship. A simulation cannot fully reproduce real life's stakes or stress, but should be challenging enough to be engaging.
4) Gameplay and learning point synergy: Conceptual design of the game should be made so that style serves content, gameplay serves teaching point, and both are designed to merge coherently. Mitgutsch and Alvarado (2012) explain how simply putting the entertainment part and the learning part side by side does not make an effective serious game. Arisha and Tobail (2013) offer a good example by choosing to make their simulation-game real-time to mimic the dynamism and time pressure of the environment they simulate.

In the next chapters, I detail the simulation-game that I developed: The Lead-Time Manager, which is freely accessible at https://forio.com/app/lausanne/ltmle/

4.4) Lead-Time Manager: Scenario

In the basic version, the player takes the role of the top operations manager of a skiwear shop in the mountains of Europe that sells two kinds of products. The Fashion ski jacket has a comfortable financial margin, but a volatile demand, and overstocked products cannot be stored. The Standard ski jacket has a considerably smaller financial margin, but also a more stable demand, and potential overstock can be stored, at a reasonable cost, to be sold the following year at full price: the residual value of the standard jacket is the acquisition cost less the holding cost. The rationale behind these storage rules is that Fashion jackets belong to a collection specific to the current sales period, will be out of fashion next season and will need to make room for the new collection, while Standard jackets are basic - plain black or white - items that do not follow fashion cycles.

The main goal is to maximize the company's profit. To reach this goal, the player controls sourcing and production decisions, for a predefined number of in-game years. The player can choose between ordering the jackets from a low-cost offshore supplier, or building local capacity to produce on-site and on-demand, at a cost premium.

Each year is divided in three periods. The first period takes place a few months before the selling season. At this point, the player does not know what the demand for the year will be, but has to place an order for both types of jackets to the offshore supplier – because of production and delivery delay – and to build local capacity for the year if desired – hire employees and buy machines for the upcoming season. All the player knows is the mean and median demand for each type of product.

The second period takes place during the selling season. The player discovers the demand for both products, receives the offshore order placed on the first period, and takes control of the amount of local capacity that was built. The goal is to use this local capacity to react to the discovered demand and try to match it with an appropriate supply. If local capacity is insufficient, potential sales are lost. If local capacity is too big, the player can produce Standard jackets to stock or let workers idle. If the offshore order is already greater than actual demand, there will be unsold jackets.

The third period takes place after the selling season and is simply a time for the player to analyze the results of the year. Each year goes through the same three-period cycle.

To spice up the experience, real-life inspired events can be set to happen during the game. They include quality issues, offshore delivery problems, accounting errors, as well as such opportunities as short notice orders for custom jackets with very high profitability margin.

These events truly capture the uncertainty of the supply-chain world, beyond demand risk modeling efforts. They will challenge the player's ability to react to unexpected hurdles, the robustness and resilience of the production structure that follows the player's sourcing strategy. Alternative goals, beyond profit, can be pursued as the interface displays sustainability indicators like the transportation carbon footprint and the number of scrapped jackets.

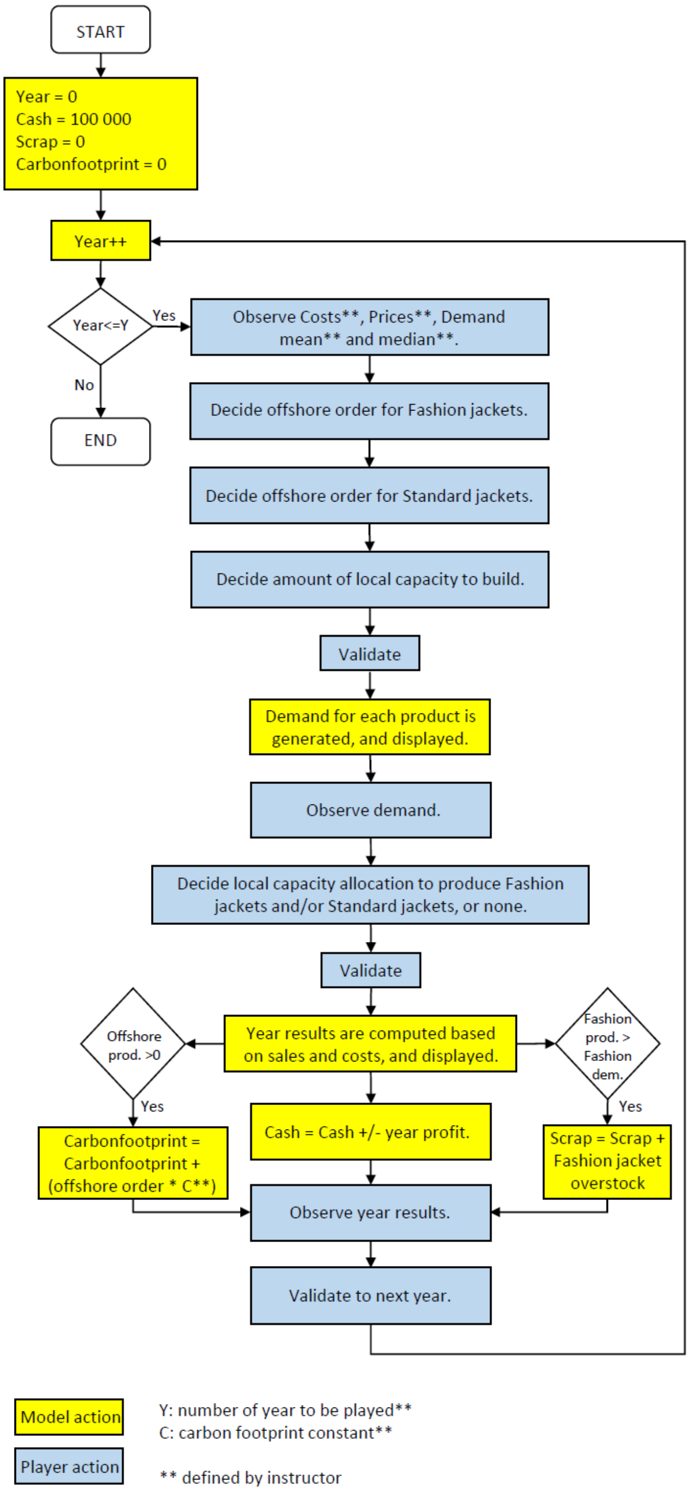

Figure 4.1: Lead-Time Manager game flow

4.5) Lead-Time Manager: Model

As shown in the game flow in figure 4.1, the simulation model intervenes at two different points in the game: generation of the demand, which is the key feature, and computation of the results.

The Lead-Time Manager follows the Quantitative-Finance-based model from de Treville et al. (2017). Demand for each product is assumed to follow a lognormal distribution, which captures the peaks inherent in volatile demand and avoids negative demand.

Players are given mean and median demand for each of the two products. Because of the assumption that demand follows a lognormal distribution, the mean is greater than the median. The player is expected to use the ratio of the mean to the median to estimate demand volatility for the two products.

For example, with a median of 100 and a mean of 120 for the Fashion jacket, we can estimate that $\frac{120}{100} = 1.2 = e^{volatility^2/2}$. Therefore volatility = $\sqrt{2\ln(1.2)}$ = 0.6.

With that information and the use of the Newsvendor model to estimate the optimal order quantity given the price, cost and residual value of each product, the player can compute the expected fill rate, sales, leftover inventory and profit for each product, and can thus make an informed decision about how to balance offshore and local production.

To comply with this mathematical structure of the problem, the role of the model at this point is to generate a demand value according to a lognormal distribution with the parameters set by the administrator. The scenario of the game asks for a rather important volatility for the Fashion jacket, and a more modest volatility for the Standard jacket. This core feature makes the repetition of play possible for the Lead-Time Manager. Even with the same parameters, every run of the simulation generates different values, testing the robustness of the player's strategy.

However, it also means that two runs are hardly comparable, as a player might be lucky over the 10 or 15 years of a run and have only high demand values that flatter even a wobbly strategy, while another player might get mostly low values that undermine a sound one. To keep it a fair competition, each run result is compared with its own possible optimal result given the demand values – which can be done using the data trace from the backend. Alternatively, it is possible to replace the stochastic demand generator with preset demand data for a special event or a class in which student will benchmark their strategies.

The second task of the model is to compute results at the end of each year, which is a set of basic calculations that can be summarized as follows for each product:

Available products	= offshore order + local production.	
Sales	= MIN(demand ; Available products).	
Leftovers	= MAX(0 ; Available products – demand).	
Offshore costs	= order cost * offshore order.	
Local costs	= fixed costs + (variable cost * local production).	
Storage costs	= storage cost * Leftovers.	[if storable]
Earnings	= Sales * price.	
Total cost	= Offshore costs + Local costs + Storage costs.	
Profit	= Earnings – Total cost.	
Money	= Money + Profit.	

4.6) Lead-Time Manager: Interface

Buchanan et al. (2011) note that different types of game interfaces fit different learning objectives, and that 3D worlds do not offer added value for knowledge acquisition. Instead, casual games' basic controls speed up the interface learning curve and focus on content.

The Lead-Time Manager interface does not represent any particular environment or display any skeuomorphic elements. Instead, it focuses on presenting only the figures necessary for player decision-making along the lines of a classic management game.

The interface is built around five main blocks, four of them display information while the central block is used to gather player's input for each period. Figure 4.2 shows the schematic representation and figure 4.3 shows the interface of the simulation-game.

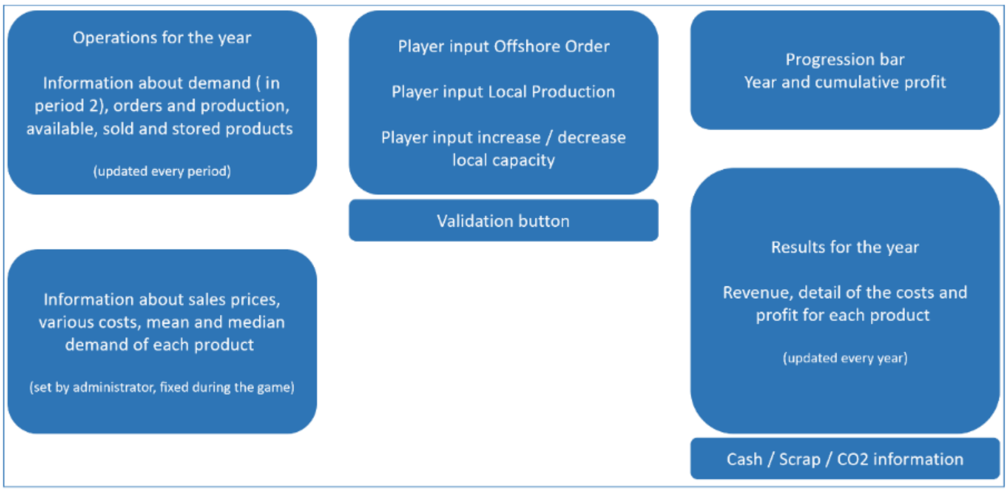

Figure 4.2: Schematic representation of the Lead-Time Manager interface.

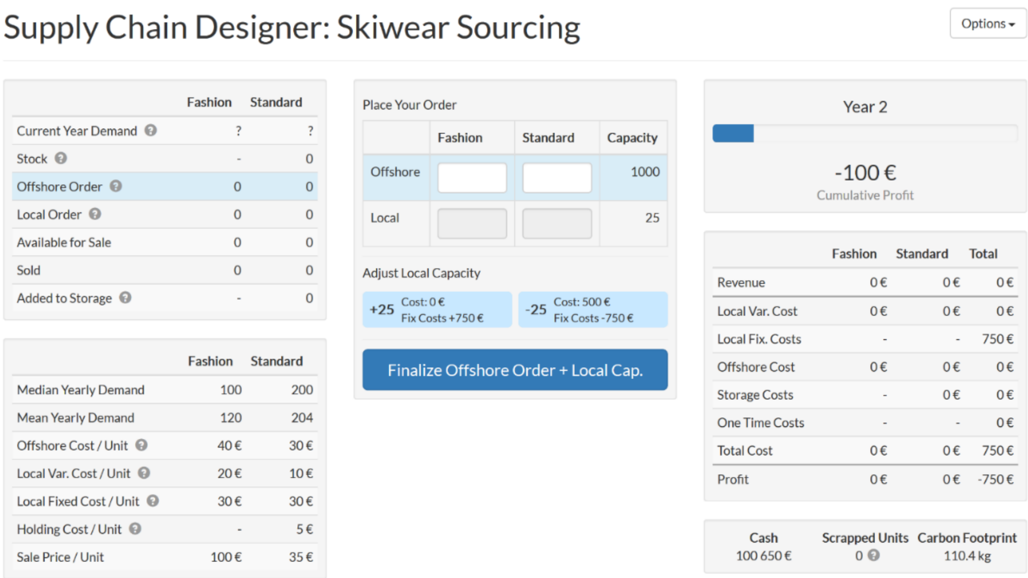

Figure 4.3: Lead-Time Manager interface.

Figure 4.4 shows the interface during the first period of each year.

Demand is not yet known. The player is prompted for the offshore order decision for each product and can increase or decrease the local capacity that will be available later in the year.

In the case shown here, the player decides to order 50 Fashion jacket and 100 Standard jackets offshore, and increases the local capacity to 75 units for a fixed cost of 2250€.

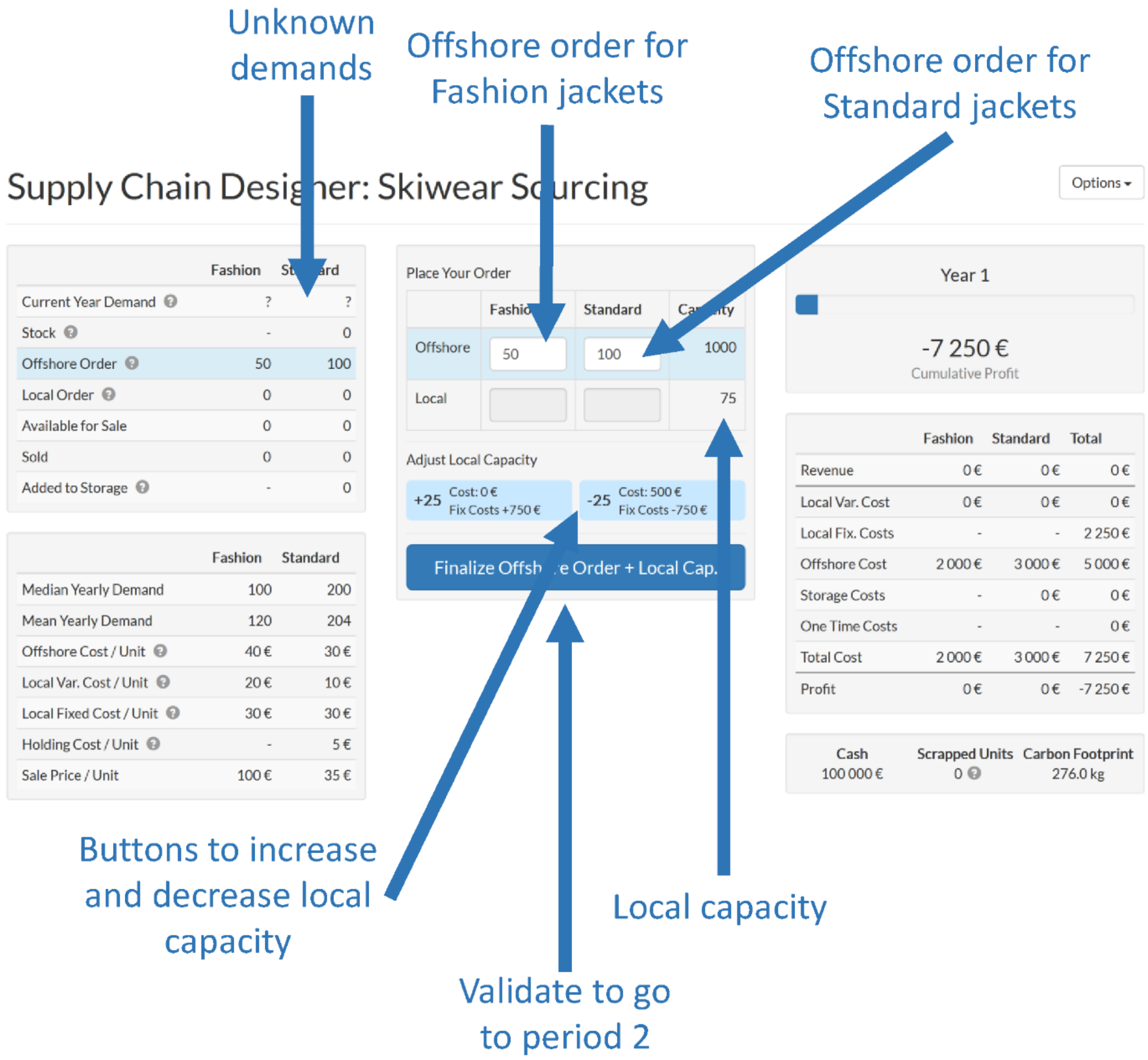

Figure 4.4: Annotated interface of the Lead-Time Manager during period 1.

Figure 4.5 shows the interface during the second period of each year.

Demand is now known. The player is prompted to allocate local capacity to the production of the different products.

In the case shown here, the player chose in period 1 to increase the local capacity to 75, and to make an offshore order for 50 Fashion jackets and 100 Standard jackets.

Discovering that the demand this year is respectively for 110 and 230 units, the player chooses to allocate 60 units of local capacity to the production of Fashion jackets – which added to the 50 from offshore is enough to cover the demand – and is left with only 15 units to allocate to Standard jackets production, and is therefore not able to satisfy all the demand.

Figure 4.5: Annotated interface of the Lead-Time Manager during period 2.

Figure 4.6 shows the interface during the third period of each year.

No input is required at this step. The goal is simply to give the player a chance to analyze the results of the year, including product sourcing, financial summary and environmental data, and to think twice about the adjustments to the strategy that can be made the next year. Clicking on the green button starts the period 1 of the next year.

In the case shown here, the player managed to make a profit of 6425€, mainly driven by the fulfillment of all the demand for Fashion jackets. No units have been scrapped because no Fashion jacket was produced in excess. The carbon footprint is not negligible due to 2/3 of the production having been made offshore.

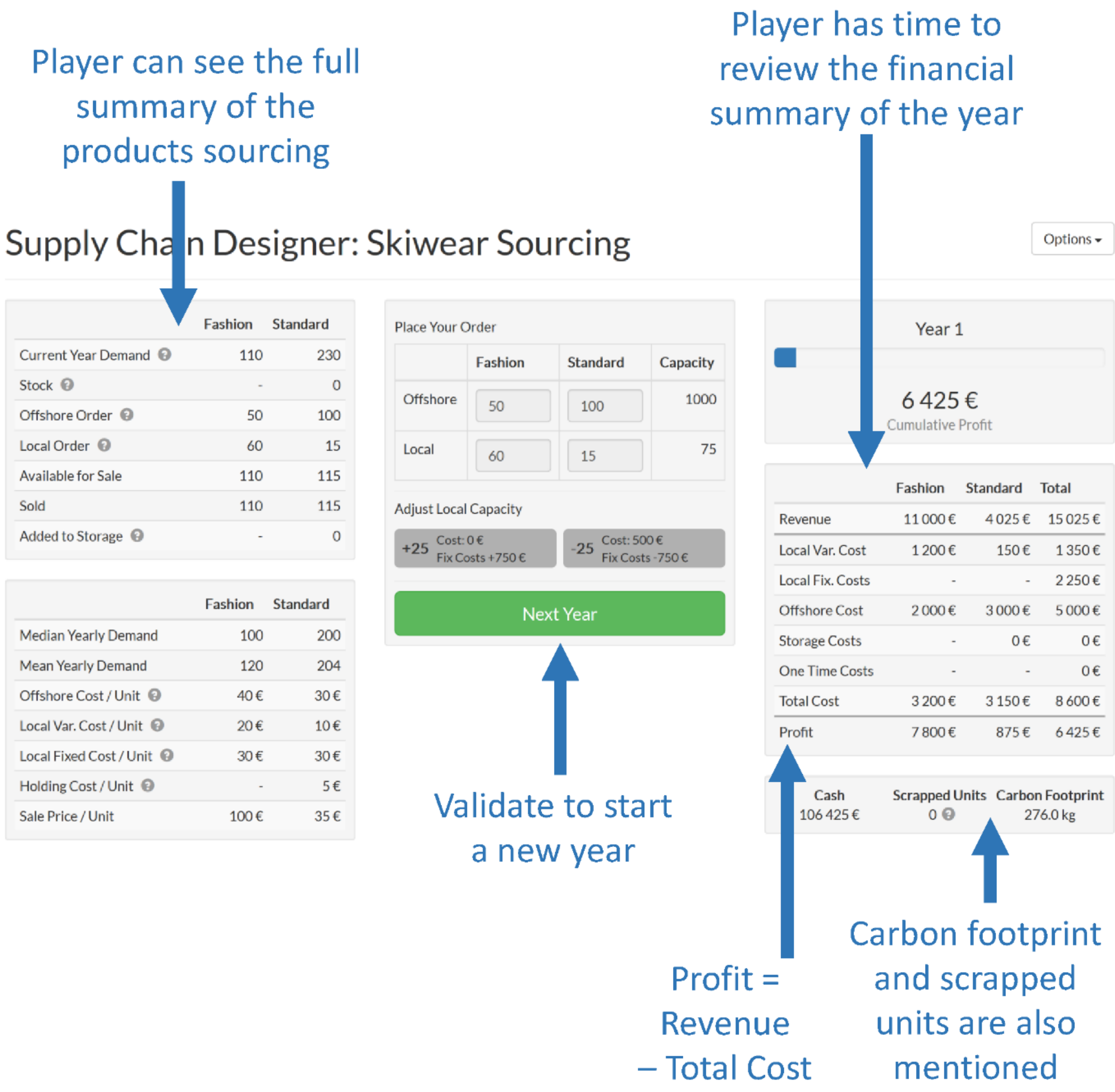

Figure 4.6: Annotated interface of the Lead-Time Manager during period 3.

4.7) Lead-Time Manager: Pedagogical Point and Course Integration

At the Bachelor level, we want to familiarize students with demand volatility and production optimization under uncertain demand by minimizing mismatch costs.

At the Master level, we want students to build a sustainable operations strategy by creating a portfolio of products with different volatility and leverage responsiveness.

At both levels, we start by making a basic version of the game available to students before teaching the material in class. In the spirit of the Experiential Learning theory (Kolb, 2014), we let students discover by themselves.

After a week, students learn the relevant theory, and are encouraged to play the simulation-game in teams to come up with more sophisticated solutions. Surprising events are added to the game, which, we agree with Wouters et al. (2013, p. 261), yields "a higher level of deep knowledge."

After another week, students are asked to play a run in-class, and to fill in a report explaining their strategy. By comparing recorded data of the player's run and the report, we evaluate consistency, strategy soundness and level of understanding of the material.

It is important to give students time to learn the ropes of the simulation-game; trial and error is, as mentioned, the heart of the learning experience with this kind of tool.

A usual gap – and common student concern – in the university learning process is the lack of application, hands-on experience, which in the sense of the Experiential Learning theory, makes it incomplete. University knowledge sometimes feels like lyophilized food, waiting for the water of professional experience. Simulation-games provide students with some experience, some edible food, instead of just loading them with powder.

The Lead-Time Manager has been positively reviewed by students, their feedback emphasizing an increase in meaning of course material after playing the game.

4.8) Lead-Time Manager: A Wide Spectrum of Applications

We started using the Lead-Time Manager as a teaching tool. First, it was an experimental accessory, and as it improved through the iterations, we developed accompanying content and activities, and made it more central to the teaching plan. As the work of Professor de Treville drew attention in discussions about developed countries competitiveness and reshoring, we were invited to address leaders in politics and industry.

The Lead-Time Manager proved its formidable efficiency as an intervention tool, making research outcomes understandable to non-academics and provoking debates on aspects that are crucial, but usually too technical for such gatherings. Our scenario in public settings is to briefly present the context and mechanics of the game, and ask participants to make decisions. Early decisions are usually wrong, but the ice is broken, the room starts engaging and participants understand not only the gameplay but the operation of the model, bypassing the wall of technicalities.

We also used the game at an event organized for senior citizens, and developed a spin-off simulation for a laboratory trial.

The design and code of the Lead-Time Manager make it easy to customize. It is straightforward to change products' profiles, price, costs and demand data, and to add events or alter their occurrence in the scenario. For example, in the spring of 2020, we added a custom event in which a pandemic blocked the cargo ships in the ports, resulting in the offshore order arriving too late to be sold during the season. The fit with current news helps players engage and see the relevance of the exercise.

It is also possible to customize the game to adapt it to a different industry or to a company that would share its data with us.

As a communication tool, it adds more impact if the simulation-game is adapted to the topic of the conference or gathering. As a teaching device, it demonstrates to students that the methods they learned can be applied to a wide range of industries and problems.

4.9) Good Practices From our Experience

Looking back on five years of development and use of the Lead-Time Manager, here are a few lessons learned and good-practice advice for such endeavors.

First, it is paramount to get the technical aspects right. Nothing ruins a class session like a bad bug or a piece of software that cannot run on some computers. Another tool that we use in the course, with a powerful teaching message, has stopped evolving and can only be run on old computers of the university lab. Although this software is powerful, the fact that it can no longer run on a student's devices dramatically reduces their engagement with it. Avoiding these pitfalls with our tool translated into two objectives: compatibility and robustness. HTML 5 web-apps have limits in terms of performance and features compared to native programs, but reliability, multi-platform compatibility and ease of use with any modern web browser have been such an asset in so many cases that it was the right option. The developer and the teaching team must have this discussion at an early stage of the project.

The second point, to paraphrase Osterwalder et al. (2014), is not to fall in love with your first idea. Opt for an iterative development and accept necessary changes even when they do not fit your original idea. I started developing the Lead-Time Manager in 2015 as a personal project, to help myself understand course theory. I then became a course assistant and showed the tool to Professor de Treville who had an enthusiastic vision for developing it further, but did not hesitate to change many aspects – interface, scenario, gameplay – through an iterative process fueled by students' feedback. In 2016, we obtained funding from University of Lausanne to hire a professional developer to improve the interface and create a backend allowing us to record participants runs, and we benefited from a partnership with Forio, a well-known and reliable platform, so anyone can access our simulation-game for free on any device with a modern web browser. Five years later, we still regularly tweak the program.

Third, in accordance with Van der Zee and Slomp (2009, p. 25), make sure to not only record the performances and results, but also a "decision trace" of the players choices, so that they can replay their run and identify turning points. Pasin and Giroux (2011) add that simulations must be transparent enough – as opposed to copyrighted black boxes – that students can understand the mechanics of the model step by step.

Finally, it is fundamental to integrate gracefully and meaningfully the "serious" and gamified parts. Planting a décor and unrelated gameplay around a teaching point does not make an efficient teaching tool. Asking a Biology question at the end of a Mario Kart race does not make a serious game, even if you get a bonus mushroom for a right answer.

4.10) Proposed Validation Protocol

The Lead-Time Manager has received praise from students in teaching evaluations, as well as enthusiastic feedback from practitioners in conferences, but at this point it lack a formal validation process. In this chapter, I propose a plan of what such a validation process could consist of. As explained in chapter 1.4.3, A/B testing on students is against university rules, while questionnaires can inform on some aspects of participants' attitude but do not accurately capture all the dimensions that we want to evaluate.

These dimensions are:

- Full acquisition of the skills necessary to analyze and make a reasoned decision about an offshoring problem involving mismatch costs.
- Attitude toward the acquired material: interest in the material, assessment of the level of importance of mismatch costs in an offshoring decision, confidence in the ability to apply the analysis in real-life conditions.
- Ability to apply the acquired skills to real, possible ill-structured, problems.

A proposed protocol would be to recruit workers on the Amazon Mechanical Turk platform, and divide them between into two groups, one undergoing a classical ex-cathedra training on the topic, the other undergoing a training based on Active Learning principles with the Lead-Time Manager playing a central role. Considering our target public with the Lead-Time Managers is wide but based on a interest in supply-chain management, I recommend not basing the recruitment on demographic criteria, but restricting it to people studying or working in the fields on business, management, supply-chain, procurement, operations. A total sample size of 120 participants randomly assigned to one of the two groups would permit to teach to a class size comparable to a university Master level course and would provide a 20% buffer to end with at least 50 participants in each condition in case of dropouts.

In order to follow the usual course integration described in chapter 4.7, the study would consist in 8 sessions of one hour each, that I propose to spread over four weeks to give time to participants to digest and think through the material. Sessions 1, 3, 5 and 8 are common to both groups and could be given simultaneously to eliminate the risk of involuntary difference in treatments. The sessions could be organized as presented in figure 4.7.

	Ex-cathedra group	Active Learning group
Week 1 | Session 1	Introduction about offshoring and mismatch cost.	
Week 1 | Session 2	Theory class about volatility of demand.	Free exploration of a basic version of the simulation-game.
Week 2 | Session 3	Theory class about Newsvendor, order quantities, fill-rate.	
Week 2 | Session 4	Theory class about expected sales, leftovers, profit.	Play the full version of the simulation-game in groups.
Week 3 | Session 5	Presentation and discussion of an offshoring case.	
Week 3 | Session 6	Exercise on the case involving calculation of mismatch cost and strategy recommendations.	Individual round of a version of the simulation-game base on the case, writing of a strategy report.
Week 4 | Session 7	Correction of the exercise.	Feedback on the strategy reports.
Week 4 | Session 8	Evaluation.	

Figure 4.7: Organization of the sessions for the Lead-Time Manager validation protocol.

The final evaluation would present data about a company facing an offshoring opportunity, as well as an interview from the manager explaining the cost savings expectations of the company. Part of the data would be ill-structured, and some figures would need to be estimated, but all the content necessary to a mismatch cost analysis would be retrievable.

The first part of the exercise would consist in filling an Excel template and computing basic outputs such as a volatility analysis, an optimal order quantity using the Newsvendor model, a fill rate estimate. The second part of the exercise, a less guided task, would ask participants to make a recommendation - offshore or stay local - and justify it with a short essay. A questionnaire would finally be distributed asking participants about the confidence they have in the answers they just submitted, their overall ability and willingness to apply the learned material outside of the experiment. The percentage of dropouts in each condition could also be an indicator of the interest in the material generated by each teaching method.

4.11) Conclusion

Serious games, or pedagogical simulation-games, mix a real-life-based model with the mechanics of games. The recipe for creating an effective simulation-game is not simple and cannot easily be standardized because it is essential that gameplay and educative aspects have an authentic synergy and coherence, and that the technical aspects be on point. When this sweet spot is found, a simulation-game can be a powerful teaching and communication tool.

The aim of the Lead-Time Manager simulation-game is to transmit research insights about the value of lead-time and the competitivity of local manufacturing.

Given the counterintuitive, non-linear and mathematically sophisticated nature of the content, we draw on pedagogical assets of simulation-games such as trial and errors process, immediate feedback and challenging gameplay to provoke a shift in players' heuristics and approach of the problem.

This simulation-game can be used in various settings, and the level of analysis around it can be adapted to these different settings. In conferences with practitioners and policymakers it can be used as medium to introduce in an intuitive way a complex problem and start a discussion at an unusual level of technicality. In a university Operations Management course, it can be integrated in a pedagogical active learning plan to increase students' appropriation of the course theoretical content, and their ability to understand the applications of this content to real-life problems.

Development and use of Lead-Time Manager over the past five years increased the impact of our Operations management courses and research insights. We are now developing formal methods to measure the effect of game playing on student self-efficacy beliefs and on their ability to make a counterintuitive but profitable decision.

5) Conclusion

Recent research has shown that local manufacturing in a high-cost environment can be viable and competitive. However, managers often fail to see it because such concepts as demand uncertainty, mismatch cost and volatility portfolio are counterintuitive and difficult to cognitively apprehend in a decision-making process. In this thesis, I studied offshoring decision-making through the lens of bounded rationality, and developed a simulation-game to help communicate research insights with an active learning approach.

My premise is absolutely not to discourage the use of heuristics in Operations decision-making. Rather, it is to push for more understanding of the role of heuristics in offshoring problems, and to propose tools for their improvement and calibration, which in turn allows for a switch in decision-makers' perspective, and for the development of responsive production strategies. The operations field, and supply-chain management in particular, happens in what is fundamentally an environment made of uncertainty. This makes heuristics the appropriate tools to find suitable solutions to intractable problems, using limited resources. Meanwhile, the historical focus in research and in practice has been on optimization, which requires an artificial reduction of uncertainty to manageable risks, and has led to an oversimplification of the models, that end up having limited relevance for real-life problems. In this context, managers are on their own in front of complex problems, such as offshoring decisions. They can end up relying on unsuitable heuristics – as a default solution for lack of a better fitting tool in their mental heuristic toolbox – or failing to calibrate properly these heuristics when they cannot access a relevant representation of information of the environment, that would allow for ecologically rational reasoning in the sense of Gigerenzer (2003). My idea of the path to an improvement in the field of offshoring decision-making relies on two pillars: the analysis of heuristics used in such tasks, and the development of tools to transmit applicable research insights. In this thesis, I proposed three papers that I hope can open a way to meaningful contributions.

In the first paper, I studied an offshoring decision in a laboratory experimental context. My results suggest that participants, even those studying business and management, failed to identify the optimal solution to a problem involving costs and demand volatility. Their decision-making seems to be prone to biases leading to either too much offshoring, or not enough. It is also notable that this deviation from the optimal decision was not the result of a wish to pursue other goals than profit maximization, such as social or ecological concerns, and that demographic factors do not have a significant impact, highlighting the ubiquity of biases.

In the second paper, I modified the trial to include non-economic factors. Peer influence was successfully used as a trigger for more offshoring, apparently unbeknownst to the participants. Social framing of the decision did not produce measurable effects, and I suggest this aspect is difficult to reproduce in a laboratory setting.

Both papers contribute to underlining the need for decision helping tools. I introduced this thesis by asking why decision-makers keep offshoring their production, the core of their industrial structure and know-how, despite the self-inflicted constraints it creates on their supply-chain and the noxious social and environmental externalities. My conviction is that in many cases, this decision is the result of a framing error of a complex offshoring problem. The oversimplified approach that reduces the scope of the problem to cost minimization has spread to the point of becoming the norm, but its myopic focus on unit costs does not serve well the higher-level objectives of companies, not even their profit in contexts where mismatch costs matter. In order to make better-informed choices, to make an efficient use of the right heuristics, to select more accurate decisions strategies, decision-makers should first be empowered to have a fuller grasp of the problem, its intertwined consequences, its context. An alternative approach of the offshoring problem exists, that offers a broader view of the stakes and consequences, and turns offshoring into a capacity allocation problem that reveals the value of responsiveness through the lead-time reduction allowed by a local production. The second part of my work is to convey these research insights.

In the third paper, I described the development, and use cases of, the Lead-Time Manager, a simulation-game that addresses the complex notions related to lead-time involved in an offshoring decision. This tool can be used both as a teaching tool in a university course within the framework of Active Learning, and as a communication tool in events involving practitioners and policymakers. In both contexts, the simulation-game generates discussions at a level of technicality and involvement higher than with traditional approaches.

I wish to pursue the development of tools that contribute to decisions improvement in situations where responsiveness and lead-time reduction matter. The next step is to conduct a formal evaluation of two aspects of the Lead-Time Manager: performance – becoming better at evaluating offshoring options, and attitude – gaining confidence to effectively apply knowledge in real-life situations. Defining a test protocol applicable to various simulation-games would be an important contribution to the field of Active Learning and serious games. In parallel, I wish to develop an online course around the Lead-Time Manager to reach a broader audience of students and practitioners and increase the impact of the tool.

6) Data

Raw data of the Switch trial (Chapters 2 & 3) are attached.
Below is a simplified presentation of the data, formatted as follows:

- **PID** (integer): unique identifier of each participation in the simulation.
- **Age** (integer): age of the participant, asked on the briefing screen.
- **Country** (string): country of origin of the participant, asked on the briefing screen.
- **Occupation** (string): category of occupation of the participant, asked on the briefing screen. Options: student (business or economics), student (not business or economics), professional (employee), professional (manager), academic, other.
- **Scenario** (integer): which of the four scenarios was experienced by the participant.
- **%MaxProfit** (integer): ratio of final profit to maximum profit possible given each participant data. As it is computed based on a local-only production, it is possible to go beyond 100% in case of a successful offshoring.
- **Time** (integer): time in seconds spent on the simulation by the participant.
- **Time Brief** (integer): time in seconds spent on the briefing screen by the participant.
- **When Offshore** (integer): month at which the participant decided to offshore. 13 means the participant never offshored as the task lasts for 12 simulated months.
- **Rational** (string): answer to the feedback question, “Which production option do you think was the most profitable?” Options: always offshore, always local, local at first then offshore after month 7, it was balanced.
- **Factors** (string): answer to the feedback question, “What were the factors guiding your decisions?” Options: economic, social, both.
- **Risk Profile** (string): answer to the feedback question, “How would you describe your general risk profile in life?” Options: risk seeker, neutral, risk averse, I don't know.
- **Calc** (string): answer to the feedback question, “Were your decisions based on analysis and calculations?” Options: yes, somewhat, no.
- **Conv** (string): answer to the feedback question, “Are you convinced you made the right decisions?” Options: yes, no.

PID	Age	Country	Occupation	Scenario	%MaxProfit	Time	Time Brief	When Offshore	Rational	Factors	Risk Profile	Calc	Conv
1	21	Switzerland	Stu (b&e)	1	67	1077	376	9	Local first, Offshore after 7	Economic	Averse	Some	Yes
2	23	Switzerland	Stu (b&e)	2	94	838	136	8	Local first, Offshore after 7	Economic	Averse	Some	Yes
3	19	Portugal	Stu (b&e)	1	79	1203	333	13	Always Local	Both	Averse	Yes	No
4	20	Switzerland	Stu (b&e)	2	110	985	148	8	Local first, Offshore after 7	Economic	Averse	Yes	Yes
5	21	Other	Stu (b&e)	3	69	550	209	8	Local first, Offshore after 7	Economic	Averse	Some	No
6	21	Switzerland	Stu (b&e)	2	95	776	462	4	Local first, Offshore after 7	Economic	Seeker	Some	No
7	23	Switzerland	Stu (b&e)	2	69	849	287	13	Local first, Offshore after 7	Economic	Averse	No	No
8	23	Switzerland	Stu (b&e)	2	74	898	112	3	Always Offshore	Economic	Averse	Some	No
9	21	Switzerland	Stu (b&e)	3	101	1064	228	12	Always Local	Both	Averse	Yes	Yes
10	22	Switzerland	Stu (b&e)	1	52	1435	478	7	Always Local	Economic	Seeker	Some	No
11	24	Switzerland	Stu (b&e)	4	62	1181	669	13	Always Local	Both	Neutral	Some	Yes
12	21	France	Stu (b&e)	2	100	1873	347	7	Local first, Offshore after 7	Economic	Seeker	Yes	Yes
13	20	France	Stu (b&e)	2	109	1872	670	9	Local first, Offshore after 7	Economic	Averse	Yes	Yes
14	23	Switzerland	Stu (b&e)	1	48	861	11	5	Always Local	Both	Neutral	Some	No
15	22	Switzerland	Stu (b&e)	3	96	1446	117	13	Local first, Offshore after 7	Social	Averse	No	Yes
16	21	Switzerland	Stu (b&e)	2	96	2356	1088	1	It was balanced	Both	IDK	Some	No
17	20	Switzerland	Stu (b&e)	1	70	2088	592	7	Local first, Offshore after 7	Both	Seeker	Some	No
18	19	France	Stu (b&e)	3	77	1589	449	8	Local first, Offshore after 7	Economic	Seeker	Yes	Yes
19	21	Switzerland	Stu (b&e)	4	62	1460	535	10	Local first, Offshore after 7	Economic	Neutral	Some	Yes
20	21	Switzerland	Stu (b&e)	1	71	1380	643	13	Always Local	Economic	Averse	Yes	Yes
21	19	France	Stu (b&e)	2	86	1264	299	9	Local first, Offshore after 7	Economic	Averse	Yes	No
22	21	Switzerland	Stu (b&e)	4	62	666	139	5	Always Local	Economic	Neutral	Some	No
23	20	Switzerland	Stu (b&e)	3	21	164	6	7	Always Local	Social	Seeker	Some	No
24	19	Switzerland	Stu (b&e)	3	96	1441	802	10	Local first, Offshore after 7	Economic	Averse	Yes	Yes
25	21	Switzerland	Stu (b&e)	2	97	925	222	13	Always Local	Economic	Seeker	Some	Yes
26	20	Switzerland	Stu (b&e)	4	95	471	182	7	Local first, Offshore after 7	Economic	Neutral	Some	No

27	21	Switzerland	Stu (b&e)	2	75	1234	724	13	Always Local	Economic	Neutral	Yes	Yes
28	20	France	Stu (b&e)	3	60	1480	407	9	Always Local	Economic	Averse	Yes	Yes
29	20	France	Stu (b&e)	1	75	137	6	13	Always Local	Economic	Averse	Yes	No
30	22	Switzerland	Stu (b&e)	3	75	1114	680	3	Local first, Offshore after 7	Economic	Neutral	Yes	Yes
31	21	Switzerland	Stu (b&e)	3	65	1157	417	8	Always Local	Both	Neutral	Some	No
32	25	Switzerland	Stu (b&e)	2	37	1015	246	2	Always Offshore	Both	Neutral	Yes	Yes
33	20	France	Stu (b&e)	1	96	1278	344	7	Always Local	Economic	Seeker	Yes	No
34	20	France	Stu (b&e)	2	95	913	335	13	Always Local	Economic	Averse	Some	Yes
35	23	Switzerland	Stu (b&e)	1	95	557	183	13	It was balanced	Economic	Averse	No	Yes
36	21	France	Stu (b&e)	2	43	960	360	10	Local first, Offshore after 7	Both	Averse	Some	No
37	21	Switzerland	Stu (b&e)	3	97	844	122	13	Always Offshore	Both	Neutral	Some	Yes
38	20	Switzerland	Stu (b&e)	3	26	1121	385	4	It was balanced	Economic	Seeker	Some	Yes
39	24	Switzerland	Stu (b&e)	2	58	845	318	9	Local first, Offshore after 7	Both	Seeker	Some	No
40	19	Other	Stu (b&e)	4	71	1121	354	13	It was balanced	Both	Averse	Some	Yes
41	21	Other	Stu (b&e)	4	102	899	218	11	Always Local	Economic	Averse	Some	No
42	21	Switzerland	Stu (b&e)	3	1	980	287	13	Local first, Offshore after 7	Both	Averse	Yes	No
43	24	Switzerland	Stu (b&e)	1	96	2382	416	11	It was balanced	Both	Neutral	Yes	Yes
44	19	France	Stu (b&e)	1	98	1729	247	13	Always Local	Both	Neutral	Some	Yes
45	22	Switzerland	Stu (b&e)	1	45	600	135	1	Always Offshore	Economic	Seeker	Some	No
46	24	Switzerland	Stu (b&e)	4	75	726	225	13	Always Local	Both	Neutral	No	No
47	23	Switzerland	Stu (b&e)	1	24	2057	440	8	It was balanced	Economic	Averse	Some	No
48	34	Other	Stu (b&e)	4	78	3038	209	13	Always Local	Economic	Averse	Yes	Yes
49	20	Switzerland	Stu (b&e)	4	94	1032	213	11	Local first, Offshore after 7	Both	IDK	Some	No
50	19	France	Stu (b&e)	3	28	732	377	9	Always Local	Economic	Averse	Yes	No
51	19	France	Stu (b&e)	3	47	900	215	11	Local first, Offshore after 7	Economic	Averse	Some	Yes
52	22	Switzerland	Stu (b&e)	3	87	1561	584	5	Local first, Offshore after 7	Both	Averse	Some	No
53	20	Switzerland	Stu (b&e)	2	95	830	292	13	Always Local	Economic	Averse	Yes	Yes
54	21	Switzerland	Stu (b&e)	3	110	1319	253	6	Local first, Offshore after 7	Economic	Neutral	Yes	Yes
55	20	France	Stu (b&e)	4	45	1162	651	13	Always Local	Economic	Neutral	No	No
56	22	Other	Stu (b&e)	4	79	909	293	7	Local first, Offshore after 7	Both	Seeker	Yes	No
57	20	Switzerland	Stu (b&e)	4	85	380	146	13	It was balanced	Both	Seeker	Yes	Yes
58	19	France	Stu (b&e)	3	10	820	485	1	It was balanced	Both	Averse	No	No
59	20	Switzerland	Stu (b&e)	3	45	533	292	4	Always Local	Economic	Neutral	No	No
60	18	France	Stu (b&e)	3	29	772	234	2	Always Offshore	Economic	Seeker	Some	Yes
61	18	Switzerland	Stu (b&e)	4	19	535	66	6	Local first, Offshore after 7	Economic	Averse	Some	No
62	19	France	Stu (b&e)	2	91	1100	590	7	Local first, Offshore after 7	Both	Neutral	Some	No
63	19	Switzerland	Stu (b&e)	2	63	1168	555	8	Local first, Offshore after 7	Both	Neutral	Some	Yes
64	25	Russia	Stu (b&e)	3	20	660	422	4	It was balanced	Economic	Neutral	Some	No
65	21	Switzerland	Stu (b&e)	4	96	700	188	10	It was balanced	Both	Neutral	Yes	Yes
66	19	Switzerland	Stu (b&e)	2	83	1096	529	8	Local first, Offshore after 7	Economic	Neutral	Some	No
67	19	France	Stu (b&e)	1	85	1096	638	7	Local first, Offshore after 7	Economic	Neutral	Yes	Yes
68	22	Switzerland	Stu (b&e)	4	5	772	181	11	It was balanced	Both	Seeker	Yes	No
69	19	Switzerland	Stu (b&e)	4	81	266	7	12	Local first, Offshore after 7	Economic	Seeker	Some	No
70	22	Switzerland	Stu (b&e)	4	88	802	465	7	Local first, Offshore after 7	Economic	Averse	Some	Yes
71	20	Other	Stu (b&e)	4	114	889	260	8	Local first, Offshore after 7	Economic	Averse	Some	Yes
72	20	Switzerland	Stu (b&e)	1	99	653	177	7	Local first, Offshore after 7	Economic	Averse	Some	No
73	20	Switzerland	Stu (b&e)	4	75	744	200	12	Local first, Offshore after 7	Both	Seeker	Some	No
74	19	France	Stu (b&e)	3	5	954	474	7	Local first, Offshore after 7	Both	Seeker	Some	No
75	20	France	Stu (b&e)	2	85	750	149	13	Always Local	Both	Averse	Some	Yes
76	32	Switzerland	Pro (emp)	1	96	1342	370	13	It was balanced	Both	Averse	Yes	Yes
77	21	Switzerland	Stu (b&e)	4	59	1566	1081	13	Always Local	Social	Neutral	Some	Yes
78	21	Switzerland	Stu (b&e)	2	92	1764	455	13	It was balanced	Social	Seeker	Yes	Yes
79	21	Switzerland	Stu (b&e)	1	57	1169	581	3	Always Local	Economic	Seeker	Some	No
80	18	Switzerland	Stu (b&e)	2	65	84	7	1	Local first, Offshore after 7	Both	Neutral	Yes	Yes
81	21	Other	Stu (b&e)	3	45	1510	489	6	Local first, Offshore after 7	Economic	Averse	No	No
82	21	USA	Stu (b&e)	3	74	1787	386	4	Always Offshore	Economic	Neutral	Yes	Yes
83	19	France	Stu (b&e)	2	94	1091	516	7	It was balanced	Economic	Averse	Some	No
84	21	Switzerland	Stu (b&e)	2	25	1517	421	9	It was balanced	Economic	Seeker	Some	No
85	19	Switzerland	Stu (b&e)	1	90	1253	280	13	Always Local	Both	Neutral	Some	Yes
86	20	Switzerland	Stu (b&e)	4	69	1128	237	4	It was balanced	Economic	Neutral	Some	No
87	20	Other	Stu (b&e)	4	24	1166	238	10	It was balanced	Both	Seeker	Some	No
88	19	Switzerland	Stu (b&e)	1	98	1079	349	13	Always Local	Economic	Averse	Yes	Yes
89	21	Other	Stu (b&e)	4	0	909	206	6	Always Local	Economic	Seeker	Yes	No
90	22	France	Stu (b&e)	1	62	749	252	7	Local first, Offshore after 7	Both	Averse	Some	Yes
91	31	USA	Pro (emp)	3	56	673	210	6	Always Offshore	Both	Averse	Yes	No
92	58	USA	Pro (mana)	4	47	1132	916	13	Always Offshore	Both	Averse	Some	Yes
93	41	USA	Pro (emp)	1	85	1086	399	9	Always Local	Both	Seeker	Yes	No
94	38	USA	Pro (emp)	1	54	578	379	10	It was balanced	Both	Averse	Yes	Yes
95	49	USA	Pro (emp)	2	0	612	428	2	Always Offshore	Economic	Averse	Yes	No
96	32	USA	Pro (emp)	2	82	772	421	13	Always Local	Both	Averse	Yes	Yes
97	41	USA	Pro (emp)	1	40	614	206	4	Local first, Offshore after 7	Economic	Averse	Yes	No
98	37	USA	Pro (emp)	4	95	844	207	13	It was balanced	Both	Averse	Some	Yes
99	50	USA	Pro (mana)	1	7	2202	176	10	Always Local	Both	Neutral	Some	No
100	33	USA	Pro (emp)	4	59	487	23	1	Always Offshore	Economic	Seeker	Yes	Yes
101	36	USA	Pro (mana)	1	49	397	229	3	Always Offshore	Both	Averse	Yes	No
102	41	USA	Pro (emp)	3	86	1471	192	7	Always Local	Economic	Seeker	Yes	No
103	38	USA	Pro (emp)	3	58	267	91	6	Always Offshore	Economic	Seeker	Some	No
104	31	USA	Pro (emp)	3	55	149	36	11	Local first, Offshore after 7	Both	Averse	Yes	Yes
105	46	USA	Pro (emp)	3	74	992	531	13	It was balanced	Both	Neutral	Yes	Yes
106	23	Philippines	Pro (emp)	2	61	1760	1114	6	It was balanced	Both	Seeker	Some	No
107	55	USA	Academic	4	97	1373	781	13	Always Local	Economic	Averse	Yes	Yes
108	25	Switzerland	Pro (emp)	3	91	2737	238	12	Always Local	Economic	Averse	Yes	Yes
109	18	Other	Stu (not)	3	48	433	195	13	Always Local	Economic	Seeker	Some	No
110	19	Other	Stu (not)	2	53	667	136	13	It was balanced	Both	Averse	Some	No
111	23	Other	Stu (not)	2	81	723	320	10	Local first, Offshore after 7	Both	Neutral	Some	No
112	18	Other	Stu (not)	2	41	584	213	3	Local first, Offshore after 7	Economic	Seeker	Yes	Yes
113	22	Switzerland	Stu (not)	3	89	827	476	5	It was balanced	Economic	Neutral	Some	No
114	22	Switzerland	Stu (not)	3	41	169	12	1	Always Offshore	Economic	Neutral	Some	No
115	19	Other	Stu (not)	4	75	200	9	7	Local first, Offshore after 7	Economic	Seeker	Yes	Yes
116	24	Switzerland	Stu (not)	2	97	944	462	13	Always Local	Both	Seeker	Yes	Yes
117	21	France	Stu (not)	4	78	981	277	10	Always Offshore	Economic	Seeker	Some	Yes
118	19	Switzerland	Stu (not)	1	92	891	223	13	It was balanced	Both	IDK	Some	Yes
119	21	Switzerland	Stu (not)	3	60	1122	647	6	Local first, Offshore after 7	Economic	Averse	Some	No

120	19	Other	Stu (not)	2	112	1361	669	7	Local first, Offshore after 7	Both	IDK	Some	Yes
121	19	France	Stu (not)	3	0	686	243	5	It was balanced	Economic	Seeker	Some	No
122	23	Switzerland	Stu (not)	2	96	954	512	13	Always Local	Both	Neutral	Some	Yes
123	27	Other	Stu (not)	2	105	915	569	11	Local first, Offshore after 7	Economic	Seeker	Some	Yes
124	19	France	Stu (not)	4	42	866	532	13	Always Local	Both	Seeker	Some	Yes
125	20	Other	Stu (not)	3	60	815	148	13	Always Local	Economic	Neutral	Yes	No
126	26	Switzerland	Stu (b&e)	3	14	1032	766	4	Always Local	Economic	Seeker	Some	No
127	20	Switzerland	Stu (not)	4	10	1027	240	9	Always Local	Economic	Neutral	Some	No
128	18	Switzerland	Stu (not)	3	48	1105	660	5	Local first, Offshore after 7	Economic	Averse	Some	No
129	22	Other	Stu (not)	1	68	999	570	12	Local first, Offshore after 7	Economic	Neutral	Some	No
130	20	Germany	Stu (not)	4	82	937	479	7	Local first, Offshore after 7	Economic	Averse	Some	No
131	19	Switzerland	Stu (not)	4	93	1102	438	13	Always Local	Social	Neutral	Some	No
132	20	Switzerland	Stu (b&e)	3	95	1235	590	12	Always Local	Economic	Neutral	Yes	Yes
133	19	France	Stu (not)	3	58	1286	275	5	Local first, Offshore after 7	Economic	Seeker	Some	No
134	24	Other	Stu (b&e)	1	88	1515	516	12	Local first, Offshore after 7	Economic	Neutral	Yes	Yes
135	51	Switzerland	Pro (mana)	1	55	2394	1001	13	Always Local	Economic	Averse	Yes	Yes
136	21	Other	Stu (not)	1	72	1793	814	7	Local first, Offshore after 7	Economic	Averse	Some	No
137	22	Other	Stu (b&e)	1	79	1118	354	5	Local first, Offshore after 7	Both	Neutral	Some	Yes
138	18	Switzerland	Stu (not)	2	81	1172	517	13	Always Local	Economic	Neutral	Some	No
139	23	Switzerland	Stu (not)	4	12	786	219	1	Always Offshore	Economic	Seeker	Some	No
140	20	Switzerland	Stu (not)	2	90	908	353	7	Local first, Offshore after 7	Economic	Neutral	Some	No
141	19	Switzerland	Stu (b&e)	1	36	716	351	10	Local first, Offshore after 7	Economic	Seeker	Some	No
142	25	Switzerland	Pro (emp)	4	104	2242	1079	9	Always Local	Both	Averse	Yes	No
143	32	Other	Academic	1	95	496	223	13	Always Local	Economic	Seeker	Yes	Yes
144	56	Other	Academic	2	91	1104	572	9	Local first, Offshore after 7	Economic	Averse	Some	No
145	25	Other	Academic	3	97	1870	299	13	Always Local	Economic	Averse	Yes	Yes
146	25	Switzerland	Academic	4	92	3489	527	7	Local first, Offshore after 7	Economic	Averse	Yes	No
147	22	Russia	Stu (b&e)	3	97	1628	366	13	Always Local	Economic	Neutral	Yes	Yes
148	39	Switzerland	Pro (emp)	2	97	1278	635	12	Local first, Offshore after 7	Economic	Seeker	Some	No
149	58	Switzerland	Pro (emp)	4	88	1446	452	13	Always Local	Both	Seeker	Some	Yes
150	28	Switzerland	Pro (emp)	3	98	1388	623	13	Always Local	Both	Averse	Some	Yes
151	24	Philippines	Pro (emp)	1	4	1431	709	3	Always Local	Both	Seeker	Some	No
152	25	Philippines	Pro (mana)	2	108	2055	860	11	Always Local	Economic	Averse	Some	Yes
153	24	Philippines	Pro (emp)	3	9	2054	827	3	It was balanced	Economic	Seeker	Yes	No
154	24	Philippines	Pro (emp)	1	23	2006	338	7	Local first, Offshore after 7	Social	Seeker	Yes	Yes
155	23	Philippines	Pro (emp)	2	99	2043	547	6	Local first, Offshore after 7	Economic	Neutral	Yes	Yes
156	19	Philippines	Stu (b&e)	1	39	1320	515	1	It was balanced	Economic	Neutral	Yes	Yes
157	53	Philippines	Pro (emp)	3	0	1753	438	2	It was balanced	Economic	Neutral	Yes	Yes
158	23	Philippines	Pro (emp)	1	52	957	669	13	Always Local	Both	Averse	Yes	Yes
159	22	Philippines	Pro (emp)	1	22	3040	973	8	Local first, Offshore after 7	Both	Neutral	Yes	Yes
160	25	Philippines	Pro (mana)	3	81	2450	1195	6	Local first, Offshore after 7	Economic	Seeker	Some	Yes
161	26	Philippines	Pro (emp)	2	28	2231	656	6	Local first, Offshore after 7	Both	Neutral	Some	Yes
162	25	Philippines	Pro (emp)	4	18	2655	675	3	Always Local	Both	Seeker	Yes	No
163	22	Philippines	Pro (emp)	4	47	1529	39	13	Always Local	Both	Neutral	Yes	Yes
164	22	Philippines	Pro (emp)	2	87	2207	489	11	Always Local	Both	Seeker	Yes	Yes
165	23	Philippines	Stu (b&e)	4	98	2349	629	10	Local first, Offshore after 7	Both	Neutral	Yes	Yes
166	26	Philippines	Pro (emp)	2	0	1175	375	13	Local first, Offshore after 7	Both	Seeker	No	No
167	24	Philippines	Pro (emp)	1	80	1331	16	13	Always Local	Both	Neutral	Yes	Yes
168	24	Philippines	Pro (emp)	2	89	339	19	13	Always Local	Economic	Averse	Yes	Yes
169	24	Philippines	Pro (emp)	2	26	1123	421	3	Local first, Offshore after 7	Economic	Seeker	Yes	Yes
170	26	Philippines	Pro (emp)	1	26	949	725	13	Local first, Offshore after 7	Both	Neutral	Some	Yes
171	21	Philippines	Pro (emp)	2	91	1340	832	12	Local first, Offshore after 7	Economic	Seeker	Yes	Yes
172	33	Philippines	Pro (emp)	1	31	1966	1059	12	It was balanced	Both	Seeker	Some	No
173	21	Philippines	Pro (emp)	3	48	959	193	12	Local first, Offshore after 7	Both	Neutral	Some	No
174	22	Philippines	Pro (emp)	4	73	2371	1101	7	Local first, Offshore after 7	Both	Averse	Yes	Yes
175	23	Philippines	Pro (emp)	4	25	2934	1448	12	Always Local	Economic	Neutral	Yes	No
176	27	Philippines	Pro (emp)	2	86	450	35	13	Always Local	Both	Neutral	Yes	Yes
177	19	Philippines	Stu (b&e)	1	3	1740	541	2	Local first, Offshore after 7	Economic	Seeker	Yes	No
178	19	Philippines	Stu (b&e)	2	6	1741	831	2	Local first, Offshore after 7	Social	Seeker	Some	Yes
179	24	Philippines	Pro (emp)	3	59	3472	698	6	It was balanced	Social	Seeker	Some	No
180	19	Philippines	Stu (b&e)	4	72	1112	1002	6	Local first, Offshore after 7	Both	Seeker	Yes	Yes
181	20	Philippines	Stu (b&e)	3	37	1920	1506	7	Local first, Offshore after 7	Both	Averse	Yes	Yes
182	20	Philippines	Stu (b&e)	4	73	1173	649	8	Local first, Offshore after 7	Both	Seeker	No	No
183	22	Philippines	Stu (b&e)	1	46	1758	1049	7	Local first, Offshore after 7	Both	Neutral	Yes	Yes
184	24	Philippines	Pro (emp)	3	0	1103	263	10	It was balanced	Economic	Seeker	Some	No
185	19	Philippines	Stu (b&e)	4	69	588	59	8	Local first, Offshore after 7	Both	Seeker	Some	Yes
186	19	Philippines	Stu (b&e)	2	0	1248	81	2	Always Local	Both	Seeker	Some	No
187	19	Philippines	Stu (b&e)	1	21	2154	929	5	Local first, Offshore after 7	Both	Neutral	Yes	Yes
188	21	Philippines	Stu (not)	1	51	1542	729	11	It was balanced	Both	Seeker	Some	No
189	19	Philippines	Stu (b&e)	3	86	2375	1291	10	Local first, Offshore after 7	Economic	Averse	Yes	Yes
190	19	Philippines	Stu (b&e)	4	49	2585	1312	10	Always Local	Economic	Averse	Some	No
191	22	Philippines	Stu (b&e)	3	4	1683	793	9	Always Local	Economic	Seeker	Some	Yes
192	19	Philippines	Stu (not)	3	39	1738	656	4	Local first, Offshore after 7	Both	Neutral	Yes	No
193	21	Philippines	Stu (b&e)	1	88	1999	363	10	Always Offshore	Both	Neutral	Yes	No
194	23	Philippines	Stu (b&e)	2	66	2293	992	6	Local first, Offshore after 7	Economic	Neutral	Some	Yes
195	21	Philippines	Stu (b&e)	1	99	2280	457	11	Local first, Offshore after 7	Economic	Averse	Yes	Yes
196	19	Philippines	Stu (b&e)	2	28	2586	1433	12	Always Local	Economic	Seeker	Yes	No
197	21	Philippines	Stu (b&e)	2	90	2510	724	13	Always Local	Economic	Averse	Yes	Yes
198	20	Philippines	Stu (b&e)	4	73	2221	774	7	Local first, Offshore after 7	Both	Neutral	Yes	Yes
199	21	Philippines	Pro (emp)	1	1	2355	723	3	Local first, Offshore after 7	Economic	Seeker	Some	No
200	21	Philippines	Stu (b&e)	4	94	2453	731	7	Local first, Offshore after 7	Both	Neutral	Yes	Yes

7) Bibliography

Abt, C. C. (1970). *Serious games*. University Press of America.

Annetta, L. A. (2010). The “I's” have it: A framework for serious educational game design. *Review of General Psychology, 14*(2), 105–113.

Arisha, A., & Tobail, A. (2013). Integrated Framework To Optimise Decisions: Supply Chain Serious Game (AUSUM). *Proceedings of the 20th International Annual EurOMA Conference, Dublin, Ireland.*

Arrow, K. J., Harris, T., & Marschak, J. (1951). Optimal inventory policy. *Econometrica: Journal of the Econometric Society, 19*, 250–272.

Asch, S.E. (1951). Effects of group pressure upon the modification and distortion of judgments. In H. Guetzkow (ed.) *Groups, Leadership and Men.* Carnegie Press.

Asch, S.E. (1955). Opinions and Social Pressure. *Scientific American, 193,* 31–35.

Autor, D., Dorn, D., Hanson, G. H., Pisano, G., & Shu, P. (2016). *Foreign competition and domestic innovation: Evidence from US patents* (p. w22879). National Bureau of Economic Research.

Baron, R. (1998). Cognitive mechanisms in entrepreneurship. *Journal of Business Venturing, 13*(4), 275–294.

Bascoul, G., Schmitt, J., Rasolofoarison, D., Chamberlain, L., & Lee, N. (2013). Using an experiential business game to stimulate sustainable thinking in marketing education. *Journal of Marketing Education, 35*(2), 168–180.

Biçer, I., Hagspiel, V., & De Treville, S. (2018). Valuing supply-chain responsiveness under demand jumps. *Journal of Operations Management, 61,* 46–67.

Blascovich, J., & Ginsburg, G. P. (1974). Emergent norms and choice shifts involving risk. *Sociometry, 37,* 205–218.

Blunt, R. (2009). Do serious games work? Results from three studies. *eLearn*, *2009(12)*, 1.

Bösch, C., Erb, B., Kargl, F., Kopp, H. and Pfattheicher, S. (2016). Tales from the Dark Side: Privacy Dark Strategies and Privacy Dark Patterns. *Proceedings on Privacy Enhancing Technologies, 2016*(4), 237–254.

Buchanan, L., Wolanczyk, F., & Zinghini, F. (2011). Blending bloom's taxonomy and serious game design. *Proceedings of the International Conference on Security and Management, Las Vegas, Nevada USA, 2011*, 518–521.

Busenitz, L. and Barney, J. (1997). Differences between entrepreneurs and managers in large organizations: Biases and heuristics in strategic decision-making. *Journal of Business Venturing, 12*(1), 9–30.

Chaiken, S., & Trope, Y. (Eds.). (1999). *Dual-process theories in social psychology*. Guilford Press.

Coller, B. D., & Scott, M. J. (2009). Effectiveness of using a video game to teach a course in mechanical engineering. *Computers & Education*, *53*(3), 900–912.

Coller, B. D., & Shernoff, D. J. (2009). Video game-based education in mechanical engineering: A look at student engagement. *International Journal of Engineering Education, 25*(2), 308–317.

Croson, R., Schultz, K., Siemsen, E. and Yeo, M., 2012. Behavioral operations: The state of the field. *Journal of Operations Management, 31*(1-2), 1–5.

Das, T. K., & Teng, B. S. (1999). Cognitive biases and strategic decision processes: An integrative perspective. *Journal of Management Studies*, *36*(6), 757–778.

De Bondt, W. and Thaler, R. (1985). Does the Stock Market Overreact? *The Journal of Finance, 40*(3), 793–805.

De Treville S., Bicer I., Chavez-Demoulin V., Hagspiel V., Schuerhoff N., Tasserit C., Wager S. (2014). Valuing lead time. *Journal of Operations Management, 32,* 337–346.

De Treville S., Cattani K. ; Saarinen L. (2017). Technical note: Option-based costing and the volatility portfolio. *Journal of Operations Management, 49,* 77–81.

De Treville S., Schuerhoff N., Trigeorgis L., Avanzi B. (2014). Optimal Sourcing and Lead-Time Reduction under Evolutionary Demand Risk. *Production and Operations Management*, *23,* 2103–2117.

De Treville, S., Shapiro, R. D., & Hameri, A. P. (2004). From supply chain to demand chain: the role of lead time reduction in improving demand chain performance. *Journal of Operations Management*, *21*(6), 613–627.

De Treville, S., & Trigeorgis, L. (2010). It may be cheaper to manufacture at home. *Harvard Business Review, 88*(10), 84–87.

Donohue, K., Katok, E., & Leider, S. (Eds.). (2018). *The handbook of behavioral operations*. John Wiley & Sons.

Duke, R., & Greenblat, C. (1981). Principles and practices of gaming simulation. *Beverly Hills: Sage*.

Dunbar, N. E., Miller, C. H., Adame, B. J., Elizondo, J., Wilson, S. N., Lane, B. L., et al. (2014). Implicit and explicit training in the mitigation of cognitive bias through the use of a serious game. *Computers in Human Behavior, 37,* 307–318.

Ellington, H. (1981). *Games and Simulations in Science Education*. Nichols Publishing Company, PO Box 96, New York, NY 10024.

Forbes, D. (2005). Are some entrepreneurs more overconfident than others? *Journal of Business Venturing*, *20*(5), 623–640.

Flexner, S., 1970. *The Random House Dictionary Of The English Language*. New York: Random House.

Gardner, M., & Steinberg, L. (2005). Peer influence on risk taking, risk preference, and risky decision making in adolescence and adulthood: an experimental study. *Developmental Psychology, 41*(4), 625–635.

Gigerenzer, G. (1991). How to make cognitive illusions disappear: Beyond "heuristics and biases". *European Review of Social Psychology, 2*(1), 83–115.

Gigerenzer, G. (1996). On narrow norms and vague heuristics: A reply to Kahneman and Tversky. *Psychological Review, 103*(3), 592–596.

Gigerenzer, G. (2003). *Reckoning with risk: learning to live with uncertainty*. Penguin UK.

Gigerenzer, G., Todd, P. M., & The ABC Research Group. (1999). *Evolution and cognition. Simple heuristics that make us smart.* New York, NY, US: Oxford University Press.

Gilboy, M. B., Heinerichs, S., & Pazzaglia, G. (2015). Enhancing student engagement using the flipped classroom. *Journal of Nutrition Education and Behavior, 47*(1), 109–114.

Gosen, J., & Washbush, J. (2004). A review of scholarship on assessing experiential learning effectiveness. *Simulation & Gaming, 35*(2), 270–293.

Gray, J., Esenduran, G., Rungtusanatham, M. and Skowronski, K. (2017). Why in the world did they reshore? Examining small to medium-sized manufacturer decisions. *Journal of Operations Management, 49-51*(1), 37–51.

Hafenbrädl, S., Waeger, D., Marewski, J. N., & Gigerenzer, G. (2016). Applied decision making with fast-and-frugal heuristics. *Journal of Applied Research in Memory and Cognition, 5*(2), 215–231.

Hahn, E. D., Doh, J. P., & Bunyaratavej, K. (2009). The Evolution of Risk in Information Systems Offshoring: The Impact of Home Country Risk, Firm Learning, and Competitive Dynamics. *Management Information Systems Quarterly, 33*(3), 597–616.

Hambrick, D., 2007. The Field of Management's Devotion to Theory: Too Much of a Good Thing? *Academy of Management Journal, 50*(6), 1346–1352.

Hartley, J. & Cameron, A. (1967). Some observations on the efficiency of lecturing. *Educational Review, 20*(1), 30–37.

Hevner, Alan & R, Alan & March, Salvatore & T, Salvatore & , Park & Park, Jinsoo & , Ram & , Sudha. (2004). Design Science in Information Systems Research. *Management Information Systems Quarterly, 28,* 75–105.

Hilbert, M. (2012). Toward a synthesis of cognitive biases: How noisy information processing can bias human decision making. *Psychological Bulletin, 138*(2), 211–237.

Huber, G. P., & Power, D. J. (1985). Retrospective reports of strategic-level managers: Guidelines for increasing their accuracy. *Strategic Management Journal, 6*(2), 171–180.

Jones, K. (1998). Simulations: Reading for action. *Simulation & Gaming, 29*(3), 326–327.

Kahneman, D. (2003). A perspective on judgment and choice: Mapping bounded rationality. *American Psychologist, 58*(9), 697–720.

Kahneman, D., & Frederick, S. (2002). Representativeness Revisited: Attribute Substitution in Intuitive Judgment. *Heuristics and Biases*, 49–81.

Kahneman, D., & Tversky, A. (1984). Choices, values, and frames. *American Psychologist, 39*(4), 341–350.

Kapur, M., & Lee, J. (2009). Designing for productive failure in mathematical problem solving. *Proceedings of the Annual Conference of the Cognitive Science Society, Austin, Texas USA, 31,* 2632–2637.

Karahanna, E., Benbasat, I., Bapna, R., & Rai, A. (2018). Editor's comments: opportunities and challenges for different types of online experiments. *Management Information Systems Quarterly, 42*(4), 3–10.

Keller, J. M. (1987). Development and use of the ARCS model of instructional design. *Journal of Instructional Development, 10*(3), 2–10.

Keren, G., & Schul, Y. (2009). Two is not always better than one: A critical evaluation of two-system theories. *Perspectives on Psychological Science, 4*(6), 533–550.

Klein, G. (2001). *Sources of Power: How People Make Decisions.* MIT Press.

Knight, F. H. (1921). *Risk, uncertainty and profit* (Vol. 31). Houghton Mifflin.

Kolb, D. A. (2014). *Experiential learning: Experience as the source of learning and development*. FT Press.

Kornell, N., Hays, M. J., & Bjork, R. A. (2009). Unsuccessful retrieval attempts enhance subsequent learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 35*(4), 989–998.

Kruglanski, A. W., & Gigerenzer, G. (2011). Intuitive and deliberate judgments are based on common principles. *Psychological Review, 118*(1), 97–109.

Lamm, H., Trommsdorff, G., & Rost-Schaude, E. (1972). Self-image, perception of peers' risk acceptance and risky shift. *European Journal of Social Psychology, 2*(3), 255–272.

Lang, J. M. (2016). *Small teaching: Everyday lessons from the science of learning*. John Wiley & Sons.

Larsen, M., Manning, S. and Pedersen, T. (2012). Uncovering the hidden costs of offshoring: The interplay of complexity, organizational design, and experience. *Strategic Management Journal, 34*(5), 533–552.

Little, J., & Bjork, E. (2011). Pretesting with multiple-choice questions facilitates learning. *Proceedings of the annual meeting of the cognitive science society, 33,* 294–299.

Lonati, S., Quiroga, B., Zehnder, C. and Antonakis, J., 2018. On doing relevant and rigorous experiments: Review and recommendations. *Journal of Operations Management, 64*(1), 19–40.

Long, X. and Nasiry, J., 2015. Prospect Theory Explains Newsvendor Behavior: The Role of Reference Points. *Management Science, 61*(12), 3009–3012.

Machuca, J. A. (2000). Transparent-box business simulators: An aid to manage the complexity of organizations. *Simulation & Gaming, 31*(2), 230–239.

MacManaway, L. A. (1970). Teaching methods in higher education–innovation and research. *Higher Education Quarterly, 24*(3), 321–329.

Marewski, J. N., Gaissmaier, W., & Gigerenzer, G. (2010). Good judgments do not require complex cognition. *Cognitive Processing, 11*(2), 103–121.

Meesters, K., & Van de Walle, B. (2013). Disaster in my backyard: a serious game introduction to disaster information management. *Proceedings of the 10th International ISCRAM Conference, Baden-Baden, Germany, May 2013,* 145–150.

Mitgutsch, K., & Alvarado, N. (2012). Purposeful by design?: a serious game design assessment framework. In *Proceedings of the International Conference on the Foundations of Digital Games, Raleigh, North Carolina USA, May 2012,* 121–128.

Mizuyama, H., Nonaka, T., Yoshikawa, Y., & Miki, K. (2016). ColPMan: a serious game for practicing collaborative production management. *Simulation and Gaming in the Network Society, 9,* 185–197.

Mousavi, S., & Gigerenzer, G. (2014). Risk, uncertainty, and heuristics. *Journal of Business Research, 67*(8), 1671–1678.

Mousavi, S., & Gigerenzer, G. (2017). Heuristics are tools for uncertainty. *Homo Oeconomicus, 34*(4), 361–379.

Musteen, M. (2016). Behavioral factors in offshoring decisions: A qualitative analysis. *Journal of Business Research, 69*(9), 3439–3446.

Ncube, L. B. (2010). A simulation of lean manufacturing: The lean lemonade tycoon 2. *Simulation & Gaming, 41*(4), 568–586.

Osterwalder, A., & Pigneur, Y. (2013). Designing Business Models and Similar Strategic Objects: The Contribution of IS. *Journal of the Association for Information Systems, 14,* 237–244.

Osterwalder, A., Pigneur, Y., Bernarda, G., & Smith, A. (2014). *Value proposition design: How to create products and services customers want*. John Wiley & Sons.

Pasin, F., & Giroux, H. (2011). The impact of a simulation game on operations management education. *Computers & Education, 57*(1), 1240–1254.

Petit, O., & Bon, R. (2010). Decision-making processes: The case of collective movements. *Behavioural Processes, 84*(3), 635–647.

Prensky, M. (2001). *Digital Game based learning.* McGraw-Hill, New York.

Prince, M. (2004). Does active learning work? A review of the research. *Journal of Engineering Education, 93*(3), 223–231.

Proctor, M. D., Bauer, M., & Lucario, T. (2007). Helicopter flight training through serious aviation gaming. *The Journal of Defense Modeling and Simulation, 4*(3), 277–294.

Ribeiro, C., Fernandes, J., Lourenço, A., Borbinha, J., & Pereira, J. (2012). Using serious games to teach business process modeling and simulation. *Proceedings of the International Conference on Modeling, Simulation and Visualization Methods (MSV), Las Vegas, Nevada USA, July 2012,* 1–7.

Richland, L. E., Kornell, N., & Kao, L. S. (2009). The pretesting effect: Do unsuccessful retrieval attempts enhance learning? *Journal of Experimental Psychology: Applied*, *15*(3), 243–257.

Rothkopf, E. Z. (1966). Learning from written instructive materials: An exploration of the control of inspection behavior by test-like events. *American Educational Research Journal, 3*, 241–249.

Saethang, T., & Kee, C. C. (1998). A gaming strategy for teaching the use of critical cardiovascular drugs. *The Journal of Continuing Education in Nursing*, *29*(2), 61–65.

Sauvé, L., Renaud, L., Kaufman, D., & Marquis, J. S. (2007). Distinguishing between games and simulations: A systematic review. *Journal of Educational Technology & Society*, *10*, 247–256.

Schoenherr, T., Rao Tummala, V. and Harrison, T. (2008). Assessing supply chain risks with the analytic hierarchy process: Providing decision support for the offshoring decision by a US manufacturing company. *Journal of Purchasing and Supply Management, 14*(2), 100–111.

Schweitzer, M. E., & Cachon, G. P. (2000). Decision bias in the newsvendor problem with a known demand distribution: Experimental evidence. *Management Science*, *46*(3), 404–420.

Schwenk, C. H. (1986). Information, cognitive biases, and commitment to a course of action. *Academy of Management Review, 11*(2), 298–310.

Schwenk, C. R. (1984). Cognitive simplification processes in strategic decision-making. *Strategic Management Journal, 5*(2), 111–128.

Schwenk, C. R. (1995). Strategic decision making. *Journal of Management, 21*(3), 471–493.

Simon, H. (1955). A Behavioral Model of Rational Choice. *The Quarterly Journal of Economics*, *69*(1), 99–118.

Simon, H. (1956). Rational choice and the structure of the environment. *Psychological Review, 63*(2), 129–138.

Simon, H. (1979). Rational Decision Making in Business Organizations. *The American Economic Review, 69*(4), 493–513.

Simon, H. (1996). *The Sciences of the Artificial*. MIT Press, Cambridge.

Simon, M., Houghton, S. and Aquino, K. (2000). Cognitive biases, risk perception, and venture formation. *Journal of Business Venturing, 15*(2), 113–134.

Soderstrom, N. C., & Bjork, R. A. (2014). Testing facilitates the regulation of subsequent study time. *Journal of Memory and Language, 73*, 99–115.

Sterman, J. D. (1989). Modeling managerial behavior: Misperceptions of feedback in a dynamic decision making experiment. *Management Science, 35*(3), 321–339.

Tantan, O. C., Lang, D., & Boughzala, I. (2015). Quid d'apprendre le Business Process Management à travers l'utilisation d'un Serious Game spécifique? *Proceedings of the 20ème Conférence de l'Association Information et Management (AIM), Rabat, Maroc, May 2015.*

Thaler, R., & Sunstein, C. (2008). *Nudge*. Yale University Press, New Haven.

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science*, *185*(4157), 1124–1131.

Van der Zee, D. J., & Slomp, J. (2009). Simulation as a tool for gaming and training in operations management—a case study. *Journal of Simulation*, *3*(1), 17–28.

Vanhoucke, M., Vereecke, A., & Gemmel, P. (2005). The project scheduling game (PSG): simulating time/cost trade-offs in projects. *Project Management Journal*, *36*(1), 51–59.

Von Neumann, J., & Morgenstern, O. (1947). *Theory of games and economic behavior*. Princeton University Press.

Wong, W. L., Shen, C., Nocera, L., Carriazo, E., Tang, F., Bugga, S., & Ritterfeld, U. (2007). Serious video game effectiveness. *Proceedings of the International Conference on Advances in Computer Entertainment Technology, Salzburg, Austria,* June 2007, 49–55.

Wouters, P., Van Nimwegen, C., Van Oostendorp, H., & Van Der Spek, E. D. (2013). A meta-analysis of the cognitive and motivational effects of serious games. *Journal of Educational Psychology*, *105*(2), 249–265.

Yin, Y., Stecke, K. E., Swink, M., & Kaku, I. (2017). Lessons from seru production on manufacturing competitively in a high cost environment. *Journal of Operations Management*, *49*, 67–76.

Yordanova, L., Angelova, N., & Kiryakova, G. (2015). Interactive models of e-learning for active learning. *Applied Researches in Technics, Technologies and Education*, *3*(4), 336–343.

Zyda, M. (2005). From visual simulation to virtual reality to games. *Computer*, *38*(9), 25–32.

Zyda, M., Mayberry, A., McCree, J., & Davis, M. (2005). From Viz-Sim to VR to games: How we built a hit game-based simulation. *Organizational Simulation: From Modeling & Simulation to Games & Entertainment,* Wiley Press, 553–590.