Enhancing the Value Chain:

Three Essays Investigating Financial and Customer Flows

by

Jing Luo

Master of Science, Maastricht University, 2014

Submitted to the Graduate Faculty of

the Katz Graduate School of Business in partial fulfillment

of the requirements for the degree of

Doctor of Philosophy in Business Administration

University of Pittsburgh

2022

UNIVERSITY OF PITTSBURGH

KATZ GRADUATE SCHOOL OF BUSINESS

This dissertation was presented

by

Jing Luo

It was defended on

July 19, 2022

and approved by

Prakash Mirchandani, Professor, Business Administration

Jennifer Shang, Professor, Business Administration

Sera Linardi, Associate Professor of Economics, Graduate School of Public and International Affairs

León Valdés, Assistant Professor, Business Administration

Michael Hamilton, Assistant Professor, Business Administration

Dissertation Advisor: Prakash Mirchandani, Professor, Business Administration

Copyright © by Jing Luo
2022

Enhancing the Value Chain:
Three Essays Investigating Financial and Customer Flows

Jing Luo, PhD

University of Pittsburgh, 2022

This dissertation investigates special mechanisms for enhancing the value chain from both the supplier and customer perspectives. The first essay studies a new technology implementation to improve supply chain finance and hence reduce product costs. The second essay examines the costs associated with customers completing a queue before receiving goods and services. The third essay considers consumers' utilities in a queuing service system that they must travel to.

In the first essay of this thesis, we focus on the procurement, operations and receivables stages of the supply chain, and investigate how Blockchain Technology and deep-tier supply chain finance can enhance the supply chain value. Specifically, we explore three questions: (1) How can Blockchain Technology for Supply Chain Finance (BT-SCF) address the deep-tier suppliers' financial predicament and reduce their financial costs? (2) Should a brand retailer (the focal company) and its supply chain implement BT-SCF? If so, what is the impact of the BT-SCF implementation on the financial performance of each supply chain member? (3) What are the critical factors that determine the success of the BT-SCF implementation in a supply chain? Our results show that with a proper discount rate setting for each supply chain member, BT-SCF implementation is able to improve the profitability of all supply chain stakeholders and create higher value for consumers.

In the second essay of this thesis, we focus on the customer of the supply chain to study the impact of the experienced wait and prospective wait in queuing systems on consumers' utilities. We design an incentivized online experiment to study two research questions: how do (i) the experience of wait and (ii) the characteristics of the prospective wait influence people's completion costs in observable queues? We find that the wait experience induces subjects with negative affective attitudes towards waiting to exhibit greater completion costs for the remaining wait, while it increases commitment among subjects with positive attitudes.

Results also show that, in contrast to the prediction of rational models, the anticipated queue length and service time of the residual queue affect individuals' costs additively, not multiplicatively.

In the final essay of this thesis, we extend the value chain to customers who must travel to join the queue for services or products. Human-subject experiments are conducted to study the questions: (1) How do a customer's utilities before and after the travel differ from each other? (2) If there exists a difference in utilities before and after the travel, what is the mechanism that drives the result? (3) Whether the information-sharing levels of a queue impact an individual' utility? We find that subjects have a higher valuation of a queuing service system before than after traveling when queues are fast and long, while in slow and short queues, there is partial support that people value it more after than before traveling.

Overall, this thesis mainly contributes to the literature at the interface of supply chain finance, new disruptive technologies (i.e., Blockchain Technology and IoT) in operations management, behavioral operations, and queuing systems.

Table of Contents

List of Tables

List of Figures

Preface

First of all, I would like to thank my advisor, Professor Prakash Mirchandani. His unwavering support, guidance, and encouragement during past years were priceless, and he is a great example for my academic career in the future. I appreciate his support and freedom to conduct research in my interest. Besides the academic and research aspect, I would like to thank him personally. During this long Ph.D. journey as an international student, his help and suggestions on my life have meant a lot to me.

I would also like to thank my other thesis committee members. Throughout the years, my program mentor, Professor Jennifer Shang, has been a steadfast support for me, assisting me with my teaching, research, and personal life. She has affected and led me in ways that are beyond words. I will never forget her gentle guidance and edification. I want to express my deep gratitude to her for all of the help she has given me. I am very much grateful to Professor Sera Linardi for introducing me to the study of behavioral science in operations and supporting and guiding me in my academic research. Her passion and proficiency in research have always inspired me. I am deeply thankful to Professor León Valdés for guiding me patiently and opening my mind to conducting behavioral research. He is a wonderful mentor, teacher, and friend. I am very grateful for the enlightenment and encouragement he has shown me. His support and advice in my job search inspire me in many ways. I would also like to thank Professor Michael Hamilton for his insightful questions and suggestions. His great research and words of encouragement inspired me very much.

Similarly, I am also very thankful to all faculty members of business analytics and operations (BAO) at Katz school who have provided guidance and help during the past years as a Ph.D. student in BAO. Many other teachers and professors from the Katz Marketing department, and the Department of Statistics, and Swanson School of Engineering at the University of Pittsburgh have inspired me to grow in the academic field. I am very thankful for their instructions. I would like to thank Ms. Carrie Woods, Dr. Dennis Galletta, and all members of the doctoral office for their kindliness, consideration, and help during this memorable journey. I am also very grateful to all Ph.D. candidates at BAO (Krista, Mike, Joya,

Tiffany, Qian, and Titing) and other departments for being great colleagues and friends in the past years. The relevant discussions and personal support have created memories that will last a lifetime.

I would like to thank my parents and parents-in-law. Their visits to Pittsburgh, particularly during the pandemic, and their unconditional support brought us plenty of relaxation and happiness. Without their support and understanding, I could not have been so dedicated to studying and research during the past years. Most importantly, I would like to thank my wife, Xiaojing. Without her companionship and support, I could not have completed this dissertation. As my best friend and partner, she took care of our children and me in many ways, especially her encouragement and inspiration during my hard research times. I want to thank her for her love and care. Finally, I am also very grateful to my daughter, Rayna, and my son, Logan. My profound happiness over their births has inspired me in both my professional and personal life.

1.0 Introduction

I have always been passionate about real-world business problems, applications, and challenges. Under the scope of the value chain, my thesis lies in two fields: supply chain management & finance and behavioral operations management. I focus on providing practical insights into operations management using analytic modeling, experiments, and empirical methods. The explosion of new technologies and globalization has led to new ways to create worth in the value chain (Normann and Ramirez 1993). In this thesis, we focus on the production and service stages, where new disruptive technologies are making a dramatic change. The goal of this thesis is to enhance the value chain for all stakeholders.

Since the financial crisis in 2008, companies have been paying much attention to supply chain finance to reduce their financial pressure and supply chain risk. However, people suggest that the real risk originates from deep-tier suppliers, primarily small and medium enterprises (SMEs), in a supply chain, due to their lower credit rating. Motivated by a practical problem, my first essay, "Deep-Tier Supply Chain Finance through Blockchain: A Small and Medium-Sized Enterprises Perspective," studies how to reduce SMEs' financial costs by taking advantage of the focal company's preferred credit rating. We propose a new deep-tier supply chain finance framework capitalizing the Blockchain and IoT technologies to allow the deep-tier SMEs to get an endorsement from the focal company for lower discount rates. A game-theoretic method is used to model the difference between traditional supply chain finance (T-SCF) and Blockchain Technology based deep-tier Supply Chain Finance (BT-SCF). Results show that the new system does not always benefit all members in the supply chain, particularly the intermediate supplier, who is between the deep-tier supplier and the focal company. When implementing BT-SCF, the intermediate supplier is not always able to delay its payment to a deep-tier supplier and thus loses the opportunity to benefit from the extra cash on hand. We also investigate all supply chain members' profit changes between the two systems and propose an appropriate way to make BT-SCF benefit the entire supply chain. Namely, this research enables the focal company to determine whether to implement BT-SCF in a supply chain and how this new model could improve the value chain to benefit all members involved. This paper contributes to the theory of the interaction between supply chain finance and new disruptive technologies. In addition, it provides insights into Blockchain implementation for companies.

The following two essays investigate the value chain stage between a service provider and its customers. At this stage, when customers receive a service or product from the provider, we conduct human-subject experiments to understand consumer behavior and provide managerial implications for business. My second essay, titled "Experienced and Prospective Wait in Queues: A Behavioral Investigation", focuses on customers' completion costs when they are waiting in a queue. In this paper, we study how a perfectly informed customer in deterministic, visible queues forms her completion cost from (i) her position in line, (ii) the number of people that have been served since she joined the line, and (iii) the service speed. We also investigate how affective attitudes (emotional responses) towards waiting influence the cost. We conduct an online experiment in Prolific to address our research questions. In addition, we employ the Becker-DeGroot-Marshak (BDM) mechanism to elicit individuals' actual valuations at various positions in a queue. The experiment shows that the participants' wait experience has no impact at an aggregate level. However, at an individual level, we find that participants with a positive attitude toward waiting are more committed to wait in line after having waited for some time. In contrast, those with a negative attitude intend more to abandon the queue after waiting. In addition, our results show that participants focus on queue length and service time to evaluate the prospective wait. It explains why individuals' utility does not strictly follow total waiting time. Our study contributes to: (1) the theory about the impact of wait experience in the line, considering heterogeneity in attitude towards waiting; and (2) the practical insights on managing customer satisfaction in a queuing system.

In my last essay, we extend our analysis to a waiting dilemma. Contrary to past queuing literature, we consider a queue that customers must travel to. In this service system, we study the impact of travel on individuals' valuation of a queuing system. Research on this type of system is rare, but it is critical since service providers are sending more than ever online queuing information to provide better service to customers. To create value at this stage, we must not ignore how an individual's utility is related to the travel. We conduct a pilot study and observe interesting differences in utilities of individuals based on the characteristics of the queue. With identical waiting time, our study shows that individuals' utilities of the queuing system are higher before than after they have traveled in fast and long queues. Conversely, we find partial support for individuals' utilities being higher after rather than before traveling when queues are slow and short. We thus design a new study to investigate the fundamental mechanism and theory that drives an individual's change in utility. This research sheds light on both the theory and the practice for understanding how travel to a queue affects the value for the customers in the value chain.

Market competition is more fierce than it has ever been. This thesis focuses on the production and service stages to enhance value to the ecosystem. On the production side, there always exists risk in new technology implementation. As one of the most popular and disruptive technologies (Babich and Hilary 2019), Blockchain Technology, has received plenty of attention. However, companies should carefully examine this technology before implementation in a supply chain finance setting and use it with the proper discount rate setting policy for the supply chain members. On the consumer side, we understand how customers react to experienced wait, prospective wait, and travel to a queue. These findings help provide better service in queuing service systems, and benefit both consumers and businesses. Taken together, this thesis offers new ways to create value from both the production and service stages of a value chain.

2.0 Deep-Tier Supply Chain Finance through Blockchain: A Small and Medium-Sized Enterprises Perspective

Supply chain finance (SCF) is receiving increasingly greater managerial attention as businesses focus more on working capital management and strive to streamline their cash flow processes and reduce supply chain risk. However, the more severe financial risk to the supply chain (SC) often lies at deep-tier suppliers. Traditional supply chain finance cannot meaningfully help the deep-tier small and medium enterprises (SMEs), which often have difficulty receiving timely payments due to unfavorable terms stipulated by larger, more powerful downstream firms. SMEs need immediate and sufficient liquidity to run smoothly. The quicker the funds can be made available to the deep-tier SC members, the healthier and more financially viable the SC would be. However, current financial ledgers and ERP systems do not allow financial institutions, e.g., banks, to see information, inventory, and money flows. Without access to the relevant information, financial providers cannot link the transactions between the focal company and deep-tier suppliers. Fortunately, Blockchain Technology (BT) can help eliminate such blind spots to connect the entire SC by providing SC visibility and transparency, which are critical to building a trustworthy deep-tier SCF system. Motivated by the decisions facing a sporting goods retailer, we propose a Blockchain Technology based deep-tier SCF (BT-SCF) platform and develop analytic models to better serve the 1st tier and the deep-tier SMEs' needs. Through examining the impact of BT-SCF on each SC member's performance, we find that BT-SCF is not always beneficial to SC members and pinpoint when BT-SCF could benefit them and maximize the SC potential. Our findings indicate that companies should carefully consider invoice payment terms, early payment discount rates, deep-tier suppliers' previous financial cost rates, and the price elasticity of demand when contemplating BT-SCF implementation.

2.1 Introduction

Since the 2008 financial crisis, supply chain finance (SCF) has attracted much attention and is touted as a better way to finance a supply chain (SC). Conventionally, SCF focuses on the transactions between a focal company and its immediate suppliers (1st tier) to alleviate financial pressure and risk. However, Krishnan (2016) indicates that the real risk to the SC may not lie at the 1st tier supplier but rather at the 2nd or deeper-tier suppliers. Deep-tier SCF leverages business relations to unlock access to cheaper finance for all SC members, not just 1st tier suppliers. Namely, it affords the 2nd, 3rd, 4th, and even further upstream SC members, which are often small to mid-size enterprises (SMEs), the opportunity to secure funds expeditiously as is currently only available to 1st tier suppliers. Deep-tier finance enabled by Blockchain Technology has great potential to reduce the risk under disruptions in the SC (Wollenhaupt 2021). DBS bank Ltd in Singapore can price its financial product at lower risk and thus make it more affordable to SMEs. In general, deep-tier SCF allows the upstream SMEs to have more short-term cash on hand to meet their financial obligations, lower interest costs, and quicker payments, enhancing the SC's financial health and operational efficiency. In this research, we propose a Blockchain Technology based deep-tier SCF (BT-SCF) model, which enables SMEs to leverage the SC leader's strength. We then use the traditional SCF model as a benchmark to identify the benefit of the BT-SCF and offer strategies and managerial insights for improving multi-tier SCs.

This research is motivated by the situations encountered by a sport goods retailer. The retailer, which we name DSA for the sake of confidentiality, has more than 1600 stores in 57 nations. With 87,000 employees from 80 countries, DSA focuses on designing, procuring, distributing, and retailing sports goods and accessories. It offers more than 20 brands and private labels for more than 70 sports and registers 40 plus patents annually. Cognizant of the market and product price elasticity, DSA has been working closely with its suppliers and striving for "Everyday Low Price" to attract more customers. DSA dispatches its production managers to suppliers for quality assurance and process improvement to lower costs and boost sales. It aims to limit the markup rate at 5% and 15% in the production and retailing stages, respectively. Equipped with a global procurement team and substantial negotiation clout over suppliers, DSA judiciously controls its payment terms (e.g., invoice due date). Specifically, to improve liquidity and financial performance, DSA often sets its payment terms longer than its days in inventory (i.e., the time needed to turn inventory into sales). When facing a powerful retailer (e.g., DSA) and intense competition, many suppliers are compelled to accept the cost and payment terms dictated by the retailer. The manufacturers who supply DSA often turn to SCF to secure early payments from financial institutions at a discounted rate to meet their cash flow needs. Due to profit and liquidity concerns, these manufacturers predictably pass such costs to deeper-tier suppliers (often SMEs) by demanding harsher payment terms, which trigger additional financial pressure for the deep-tier suppliers. For example, HYQ, a DSA manufacturer that produces team-sports balls (e.g., soccer balls, basketball balls), would request early payment from the bank through SCF with DSA. Note that early payment is the cash that the bank pays the requester (e.g., HYQ). This amount paid before the payment due date is lower than the invoice amount due to the early payment discount (a.k.a. cash discount or prompt payment discount). To improve its cash flow position, HYQ would also lengthen payment terms with its vendors and suppliers. Thus, to improve its cash flow, HYQ would negotiate a much longer payment term with (say, its yarn supplier) FSM. However, with such longer payment terms, FSM would suffer from cash shortages. FSM must resort to a high-interest loan from an outside lender to support its operations, as its business volume and credit rating are low, and banks usually would not grant support. To build a more robust supply chain, DSA deemed it necessary to integrate the deep-tier suppliers (e.g., FSM) into its SCF system, leading to the reduction of financial costs and retail prices because the financial cost of suppliers is reflected in their product price eventually (Amberg et al. 2020). DSA seeks to treat the SC members' financial processes at the holistic level and aims to break down the silo mentality that only focuses on its own process. Namely, DSA wants to examine the supply chain's procure-to-pay cycle, working capital, and order-to-cash cycle processes. However, DSA does not have a direct partnership with the deep-tier suppliers; most importantly, like other financial ledgers and enterprise ERP systems (Gaur and Gaiha 2020), it lacks SC visibility and cannot see all the relevant information (e.g., inventory and financial flows) in the SC.

Current ERP systems cannot help DSA and other similar companies with their need for a new system to collaborate with the deep-tier suppliers. Fortunately, the emerging Blockchain Technology could potentially solve this problem by building a transaction sharing and inventory tracking platform to connect the blind parties (Gaur and Gaiha 2020) and provide visibility in the SC. Blockchain Technology is known for its applications in digital currencies and offers potential for crowdfunding, information tracking, and online games (Nakamoto 2008). It delivers a decentralized, transparent, and tamper-resistant system due to its immutable and translucent features. All these features, especially its traceability, are essential for SC efficiency and credibility (Hastig and Sodhi 2020) and can facilitate interaction among SC members. To complement the storage and sharing of transaction information using Blockchain Technology, we employ Internet of Things (IoT) devices for automatic information collection since SMEs in developing markets lack reliable methods to record the logistic and inventory flows. By employing IoT, manual mistakes can be avoided, and the transactions can be recorded on the Blockchain system in real-time. Financial institutions can thus access pertinent information of the SMEs with more confidence and trust. Subsequently, SMEs can take advantage of the focal company's financial strength and credit rating to increase the bank's willingness to finance their accounts receivable at a lower interest rate. Note that focal firms like DSA usually have a higher credit rating since they have sufficient financial transactions, better repayment history, a lower potential of default on the debt obligations, and a higher likelihood of making payments on time. Many financial institutions (e.g., Previs and Hitachi Capital) have started implementing deep-tier SCF due to the increasing need for deeper-tier SMEs. Yahsi (2017) found that besides banks (e.g., Deutsche Bank, C2FO, Orbian, CRXmarkets, Taulia, Ebury, Basware), FinTech firms such as Skuchain, Gatechain, and Hijro have also joined the competition and spread the capital benefit from the focal company (e.g., DSA) to deep-tier SC members through Blockchain Technology.

DSA and many similar firms are eager to understand the new system, especially in a SCF application. In this research, we focus on the financial issues most relevant to deep-tier suppliers, as they encounter the most difficulties in the SC. We develop two models: **T**raditional **S**upply **C**hain **F**inance (T-SCF) and **B**lockchain **T**echnology for **S**upply **C**hain **F**inance (BT-SCF). The main questions addressed in this research are:

1. How would BT-SCF address the deep-tier suppliers' (e.g., FSM) financial predicament and reduce their financial costs?
2. Should brand retailers (e.g., DSA) and their supply chains implement BT-SCF? If so, what is the impact of the BT-SCF implementation on the financial performance of each SC member?
3. What are the critical factors that determine the success of the BT-SCF implementation in a SC?

We propose an analytic model to predict each SC member's performance if BT-SCF is implemented. Firms like DSA often encounter difficulties in understanding whether their supply chain needs Blockchain Technology. Is it a must or a maybe to have BT-SCF? We find that BT-SCF does not always benefit SC members, and they can experience increased profit or loss under certain conditions. We pinpoint when and how BT-SCF could benefit all SC members, as well as increase their profits relative to the T-SCF case. Finally, we discuss the impact of expanding the BT-SCF to many deeper-tier SC members on SC performance.

The remainder of the paper is organized as follows. In Section 2.2, we review the related literature and position our research. Section 3 outlines the logic flow of BT-SCF and contrasts it with the timeline of T-SCF activities. In Section 4, we discuss the model setup and assumptions. Sections 5 and 6 examine the performance of SC members in T-SCF and in BT-SCF, respectively. In Section 7, we compare the profit differences between T-SCF and BT-SCF and discuss extensions to deeper tier suppliers. Section 8 presents the results of a numerical study and develops further insights. Finally, conclusions and future research directions are given in Section 9. All proofs are given in the Appendix.

2.2 Literature Review

Our research is related to three streams of literature: Blockchain Technology, smart contract, and supply chain finance. We contribute to the literature by proposing a Blockchain Technology based deep-tier supply chain finance model using a smart contract design.

2.2.1 Blockchain Technology

Blockchain Technology is a promising recent innovation (Babich and Hilary 2019). Any member on the platform can submit a transaction to the system and then broadcast it to the entire network such that all members see the transaction. Blockchain Technology allows all the untrusted members to reach a consensus under the same platform without any intermediary (Swan 2015, Morabito 2017). Various industries, especially financial institutions, have explored Blockchain Technology to build decentralized data storage systems (Kelly and Williams 2016). There are two types of Blockchain: permissioned and permissionless (Yaga et al. 2018). In permissionless Blockchain (a.k.a public Blockchain), all transactions are transparent, which may not be acceptable in all situations, as firms want to guard the confidentiality of their data and are unwilling to share private business information (Ma et al. 2019, Krishnan 2016). Due to privacy concerns, we propose using a permissioned Blockchain, which controls access and limits certain activities to specific members. Moreover, before joining a permissioned Blockchain platform, applicants need the approval of all platform members, including the external financiers (i.e., banks).

Financial institutions offering SCF services often employ the Know Your Customer (KYC) protocol, a set of standards in the financial industry, to verify customers and assess their risks (Jayachandran 2017). Weinberg (2019) pointed out that KYC is costly and time-consuming in the financing process. With the permissioned Blockchain platform, KYC approvals of SC members can be done more efficiently. In addition, Blockchain Technology can also increase information quality, lower transaction costs, and build a decentralized, tamper-proof, and efficient platform. Hackius and Petersen (2017) highlight that Blockchain-driven SCs can reduce paperwork, detect counterfeits, facilitate tracking and reduce fraud, advance safety and trust with the IoT devices. Tian (2016) confirms the value of transparency and traceability by showing an agri-food SC with Blockchain and RFID technologies. Chen et al. (2020) depict a Blockchain-driven financing system for auto retail business and show its promise in providing financing options for cash-strapped deep-tier suppliers.

Chod (2016) discusses the value of Blockchain transparency by comparing inventory signals with cash signals in a loan request. Dong et al. (2021) study how Blockchain Technology adoption impacts an agent's operational and financial decisions in a manufacturer-centric SCF facing two-tier suppliers with bankruptcy risk. In contrast to their study, we focus on the holistic view of a leading retailer and investigate how addressing the deep-tier supplier's financing concerns can save costs and improve SC competitiveness (i.e., lower retail price, higher sales volume, and profit) by taking advantage of the visibility and transparency provided by Blockchain Technology. Although few studies have shed light on Blockchain-based SCF, we believe tapping Blockchain Technology's potential can accurately and instantly validate transactions to help deep-tier suppliers boost credibility and lower financing costs. Such savings can then pass on to manufacturers and retailers and subsequently enhance the financial efficiency of the entire SC.

2.2.2 Smart Contracts

Smart contracts refers to a digitalized mechanism that triggers execution automatically when predetermined conditions are met. The concept of a smart contract was first introduced by Szabo (1997). However, smart contracts are not widely accepted due to a lack of trustworthy technology to execute the contract reliably and confidentially, and control physical assets to enforce agreements. Blockchain Technology enables smart contracts as computer-coded algorithms that run transactions automatically when the requisite conditions are met in different designed scenarios. Blockchain Technology provides a distributed trustworthy cloud data storage system, while smart contracts offer a distributed trustworthy judgment. For example, to build a decentralized market, OpenBazaar deploys its peer-to-peer application and executes business trade under an automatic and digitalized contract without intermediaries, which means no admission fees for the seller and buyer, and thus reduces the general cost. Smart contracting is more accurate, faster, trustful, and cost-saving when compared with traditional contracting (Naughter 2017). Rosic (2016) indicated that smart contract platforms (e.g., Ethereum) could apply to any services and make SCs transparent and act faster. Thus, the BT-SCF model proposed in this research assumes that Blockchain Technology will exploit smart contract capabilities to speed up transactions among SC members and execute through easy coding.

2.2.3 Deep-tier Supply Chain Finance

Deep-tier SCF is an extension of conventional SCF and requires closer collaboration among SC members. Although it can tap SC members' relationships to benefit more partners, it is not widely accepted, as the technology and mechanism involved are not well understood and designed. Like SCF, deep-tier SCF engages in short-term financing of working capital to lower costs and improve efficiency for upstream SC members.

Current research on SCF provides valuable insights for deep-tier SCF. Traditional SCF focuses on integrating financial flow in a two-echelon SC and maximizing profits by improving financial support, credit rating, discount rate. Although SCF has been accepted and implemented for years, Strom (2015), Prosser (2019) and Futures (2019) find that SCF mainly benefits large firms and makes operating SME businesses even harder. Moreover, Miller and Wongsaroj (2017) caution that an original equipment manufacturer as the focal company should not just dwell on its own profit, as its SME suppliers will eventually pass the negative impact of financial pressure, like a domino effect, to the entire SC. Dada and Hu (2008) proposed a non-linear schedule to maximize profit by deciding on a high loan rate. To minimize long-term costs, Vliet et al. (2015) optimize the financing rate and payment term for reverse factoring by combining the inventory level and financial constraints. Kouvelis and Zhao (2017) investigate the impact of various credit ratings of retailers and suppliers and the conditions when the internal or external financier should be chosen to finance the SC. Yang and Birge (2018) study the risk-sharing of trade credit by integrating operations decisions and financial constraints with multiple financing channels. Tong et al. (2019) discuss the importance of payment timing in multi-echelon SC and compared their findings between centralized and decentralized SCs. Overall, deep-tier SCF is an under-studied field desiring more attention.

2.2.4 The Uniqueness of Our Research

Our research makes use of the unique features of Blockchain Technology and smart contracts to offer a platform that integrates inventory, information, and financial information for SC members in need of financial backing. To enhance SC competitiveness, we investigate

Table 2.1: The Literature vs. Our Work

	Supply Chain Finance						Blockchain				Smart Contract	
Articles	Multi-echelon	Payment term	Outside financier	Rate setting	Sales Price change	Price elasticity of demand	Permissioned chain	Transaction endorsement	Credit sharing	IoT devices	Instant transaction	Rate update
Dada & Hu (2008)			✓	✓								
Tanrisever et al. (2012)		✓	✓	✓								
Vliet et al. (2015)		✓	✓	✓								
Kouvelis & Zhao (2017)			✓	✓								
Tong et al. (2019)	✓	✓			✓							
Chod et al. (2020)			✓	✓			✓	✓				
Chen et al. (2020)	✓		✓				✓	✓		✓	✓	
Dong et al. (2021)	✓		✓	✓			✓	✓	✓			
This research: BT-SCF	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

deep-tier financing to alleviate funding pressure at tier-1 and tier-2 suppliers (e.g., HYQ and FSM); determine the optimal order quantity for the retailer (e.g., DSA, the focal company in our study); and identify the conditions under which each SC member will benefit from a BT-SCF implementation.

By exploiting the focal company's high credit rating, current SCF literature examines the financial flow within SC and offers strategies for SC members and financiers. Research on Blockchain-based SCF is still in the early stages and mainly centers on conceptual design and software implementation. There is a dearth of studies on deep-tier SCF, particularly on the effect of cash-strapped deep-tier SMEs on SC competitiveness. Our research integrates Blockchain Technology, smart contract, and supply chain finance concepts with the aim of maximizing the potential of deep-tier SCF by offering the best operating settings.

Table 2.1 contrasts our research with the extant studies and shows the contribution of our work to the literature. We consider a three-echelon supply chain (a dominant retailer, 1st tier, and 2nd tier suppliers) and propose a BT-SCF platform within the smart contract framework to incorporate an outside financier (e.g., bank). The analytical model helps quantify how BT-SCF benefits SC members and improves SC competitiveness.

2.3 Financial Flow of the Blockchain-Based Supply Chain Finance

The reasons why SMEs have limited access to external finance relative to larger businesses are twofold (Lynn 2020). First, SMEs often lack accurate and complete records, e.g., business volume, credit information, and operating history. The second reason is that the time to receive the loan approval is too long to help the SMEs meaningfully. Fortunately, BT-SCF can resolve these problems, as under which deep-tier suppliers' business transaction information would be transparent and the approval procedure can be executed instantly. Thus, the reasons that SMEs have limited access to capital are primarily due to the unavailability and unreliability of the information, less owing to the production or operations issues. SC members having better information about the deep-tier SMEs' operations should vouch for their authenticity and endorse them for early bank payment to reduce SMEs' financial burdens.

Blockchain Technology affords deep-tier SCF with visibility and transparency between the focal company and the deep-tier suppliers. Combining information-, material- and financial- flow allows BT-SCF to exploit the SC leader's high credit rating to secure low-cost capital to benefit all SC members. Namely, BT-SCF helps the financier to extend SCF to deep-tier suppliers by taking advantage of the focal company's high credit rating instead. A more dependable (trustable) system enhances confidence and motivates cooperation, subsequently improves SC efficiency and competitive edges.

Figure 2.1 presents a BT-SCF framework for a 3-echelon SC using our motivating example, DSA, as a backdrop. In this framework, all information exchange is through the BT-SCF platform, and the transaction information of production, materials, and financial flows are visible to all SC members and the financier. IoT collects real-time information on inventory quality and compliance, which is recorded automatically on the Blockchain platform to enable fast process execution using smart contracts, prevent data tampering and avoid human errors (Chen et al. 2020). Thus, by integrating Blockchain Technology with the information recorded by IoT and following the rules stipulated beforehand to trigger actions, a fast and accurate new platform can be implemented to help financiers provide support for deep-tier suppliers.

Before the retailer places the order, the financier (e.g., bank) and the SC members need to agree on the terms (e.g., payment terms, early payment discount rate, lead time) to implement a smart contract in BT-SCF. There are six main activities involved in the BT-SCF system (see Figure 2.1). They are detailed below:

I The retailer (e.g., DSA) first places the purchase order on the BT-SCF platform (step 1a), which then automatically passes the order information to the tier-1 supplier (henceforth, manufacturer), like HYQ (step 1b) and the tier-2 supplier (henceforth, supplier), like FSM (step 1c).

II The supplier starts the production and then ships the output to the manufacturer (2a) and concurrently sends the invoice and early payment request to the platform (2b). At the same time, IoT devices track the delivery and share all the shipping information over the platform (the dashed line above 2a).

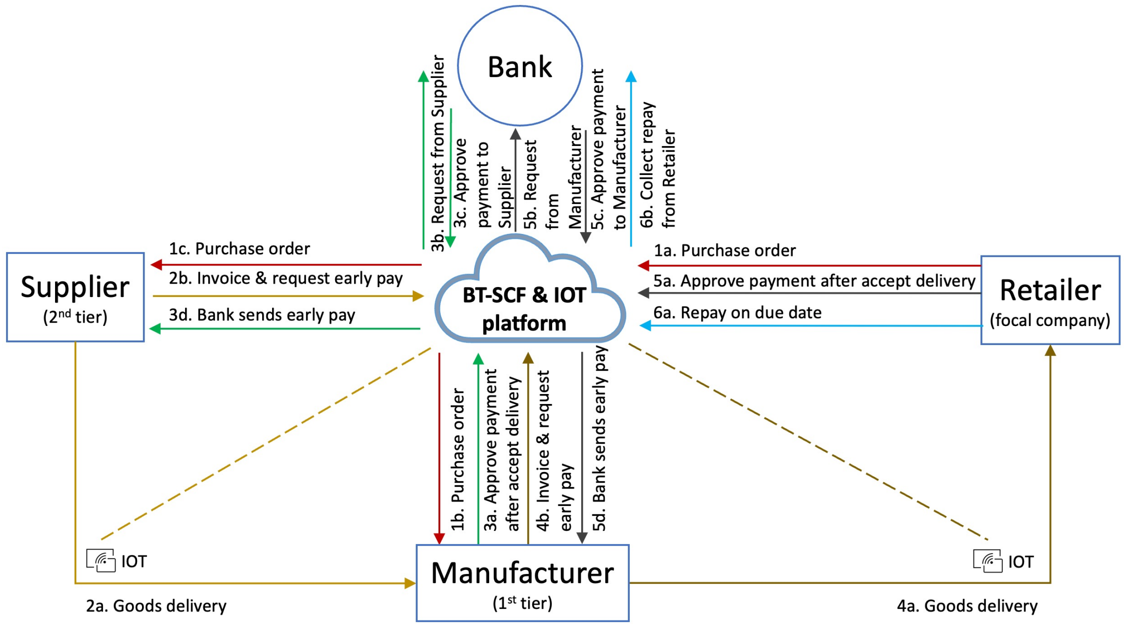
III When the supplier's output arrives at the manufacturer's warehouse, the platform receives the IoT signal, acknowledging the acceptance/rejection of the inventory (3a). If the delivery is accepted and invoice approved by the manufacturer, the platform sends the bank an early payment request to pay the supplier (3b). The bank evaluates the early payment request and informs the platform (3c). Subsequently, the bank sends the payment to the supplier (3d), with an early payment rate calculated automatically under the smart contract terms.

IV Likewise, the manufacturer follows the same procedure as the supplier by shipping the final product to the retailer (4a) and sending the invoice and payment request to the platform (4b).

V When the order is accepted and invoice approved by the retailer, the platform is informed (5a). The platform requests the bank to make the early payment (5b). The bank informs the platform (5c) and pays the manufacturer if the request is approved (5d).

VI Finally, after the product sales are completed (or on the pre-specified due date), the retailer informs the platform (6a) and repays the bank through the platform for the amount of early payment the bank has made to the supplier and the manufacturer earlier

Figure 2.1: BT-SCF Framework



(6b). Note that all transactions are carried out instantly as the smart contract enables fast execution whenever the pre-specified conditions are met.

We now compare the financial flows for BT-SCF and T-SCF. In our case, DSA is the retailer and the focal company with a high credit score; other SC members (i.e., HYQ and FSM) are not qualified for bank financing. In T-SCF, the manufacturer receives early payment under SCF with the retailer and the bank. However, the supplier cannot receive an early payment because the bank does not have visibility on the truthfulness of the information between the supplier and the retailer, and the manufacturer's credit rating is low. However, in the BT-SCF platform, all the transactions are visible and transparent. Blockchain Technology makes the information flow more reliable, traceable, immutable, and accessible to financial institutions.

2.4 Model Setup

To help the deep-tier SMEs in the SC, we study a 3-echelon SC as described in the DSA motivated case. We focus on SME suppliers as they make up the greater part of businesses globally and are critical players to job growth and economic development in most countries (Luo and Shang 2013). Currently, access to finance is a significant obstacle to SMEs' growth, especially in developing and emerging markets (Wang 2016). Blockchain Technology afford SMEs (the deep-tier suppliers) an opportunity to access a financier and unlock low-cost capitals to build a more sustainable and competitive SC. In this closely collaborative BT-SCF platform, the financier may be external (e.g., banks) or internal (e.g., other suppliers or retailers). In this research, we focus on an external financier and examine how SMEs could benefit from deep-tier supply chain finance. Banks often finance firms with high credit ratings at a low interest rate while funding low-credit firms at very high interest rates or giving no access to funds. Besides understanding the BT-SCF implementation issues, we also identify the success factors and how they influence members' profits. In the following, we discuss the sequence of SC events and the assumptions.

2.4.1 The Sequence of Events

Figures 2.2 and 2.3 show the timeline in chronological order of the events in the 3-echelon SC, including the lead time and payment term. The two timelines for T-SCF and BT-SCF respectively are similar, except for the differences discussed below.

1) At t_0, the process starts with the purchase order placed by the retailer (e.g., DSA). Upon receiving the order, the manufacturer (e.g., HYQ) submits the request to the supplier (e.g., FSM), who immediately starts production.
2) At t_1, the supplier completes and delivers her output to the manufacturer. The manufacturer's lead time is $L_M = (t_1 - t_0)$. Under BT-SCF, the supplier receives early payment from the bank at t_1 (see Figures 2.3). But under T-SCF, the supplier must wait until t_4 to receive the payment from the manufacturer (see Figures 2.2).

3) At t_2, the manufacturer completes and delivers his output to the retailer. The retailer's lead time is $L_R = (t_2 - t_0)$. At this time, the retailer can start selling the products, and the manufacturer is able to receive the early payment from the bank. The early payment amount for the manufacturer from T-SCF is often higher than from BT-SCF (to be explained in §6.2).

4) i Under T-SCF, at t_3 the retailer completes the sales and pays the bank for the early payment amount requested by the manufacturer. The retailer also pays the manufacturer the amount not paid early by the bank.

   ii Under BT-SCF, at t_3 the retailer completes the sales and pays the bank the full amount, which equals the total amount owed to the supplier and the manufacturer.

5) Under T-SCF, at t_4 the manufacturer pays the supplier.

Note that the payment term $T_M(= t_3 - t_2)$ represents the waiting time between when the manufacturer's delivery gets accepted and when he receives the payment from the retailer (e.g., HYQ's payment term is 72 days after DSA accepts the delivery). The supplier's payment term is $T_S(= t_4 - t_1)$ in T-SCF (e.g., FSM's T_S is 120 days which is the time between delivery to HYQ and receiving payment).

BT-SCF allows the supplier's working capital to be unlocked much earlier at t_1 instead of t_4 in T-SCF. However, this change incurs some loss to the manufacturer since his cash on hand under BT-SCF may be smaller. Relative to T-SCF, the manufacturer in BT-SCF is deprived of the chance to hold the cash (i.e., the amount to pay the supplier) from time t_2 to t_4. This brings out the question: how will the BT-SCF protect or enhance the profit of each SC member, especially the mid-tier SC member (e.g., manufacturer)?

2.4.2 Assumptions and Notations

In this research, the retailer (it), DSA, is the one with a high credit rating, while the manufacturer (he), HYQ, and the supplier (she), FSM, are financially strapped. The retailer needs to decide on the order quantities to maximize its profit. The manufacturer must choose an early payment amount to maximize his profit in T-SCF. However, in BT-SCF, he can only receive his own portion from the bank (i.e., the sales made to the retailer minus the amount

Figure 2.2: Chronological Sequence of Events for T-SCF

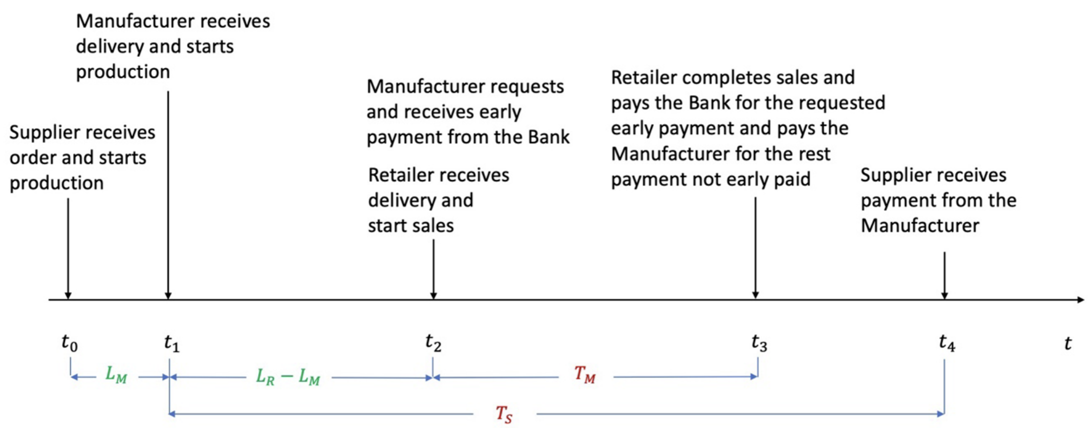
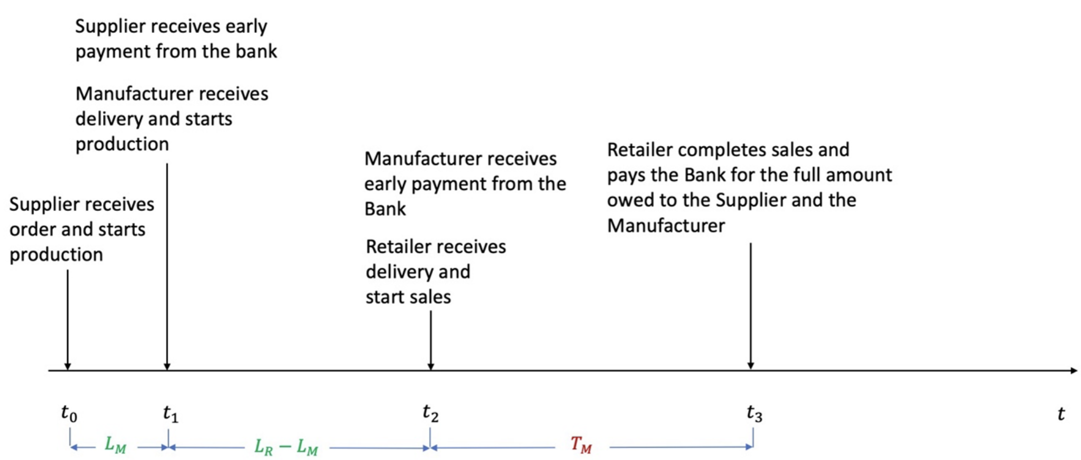


Figure 2.3: Chronological Sequence of Events for BT-SCF



he owes the supplier), as the supplier would deal with the bank directly. Namely, in T-SCF, the supplier has to wait for the manufacturer to pay her after he receives payment from the retailer. As she has no credit and no access to the bank, she would have to make a high-interest loan from other sources to maintain cash flow in her business. To avoid the trivial cases and focus on the advantage of Blockchain transparency and visibility, we assume that all SC members are risk-neutral, the order can be fulfilled as scheduled, and all SC members must and will resolve any production and quality issues. For ease of illustration, we assume there is no salvage value for the unsold final products.

Table 2.2 summarizes our notation. Assume customer demand D follows a stochastic distribution and is price sensitive. Given price p, the demand follows a probability density function (PDF), $f_p(\cdot)$; and cumulative density function (CDF), $F_p(\cdot)$, with a complementary CDF, $\bar{F}_p(\cdot) = 1 - F_p(\cdot)$. Like the literature, we assume the demand has an increasing generalized failure rate (IGFR) (Banciu and Mirchandani 2013). Thus, the corresponding demand is $\bar{F}_p(\cdot)$. Similarly, for the price p^B in BT-SCF, the demand distribution, D^B, can be denoted as $\bar{F}_{p^B}(\cdot)$. We assume the product has an increasing price elasticity (Chen et al. 2009), η, i.e., the % change in demand quantity is higher than the % decrease in price, and the retailer has a good knowledge of the product price elasticity.

2.5 Traditional Supply Chain Finance (T-SCF)

We model T-SCF in this section to serve as the benchmark for our research. In T-SCF, the supplier is unable to obtain SCF and must borrow from an alternate, more expensive source, while the manufacturer can receive early payment from the bank. The SC members' activities in T-SCF are modeled as follows.

2.5.1 Supplier in T-SCF

Without access to the bank's capital, the supplier in T-SCF has to finance her production and operations at a high-interest loan rate before receiving the payment from the manufac-

Table 2.2: Notation Summary

Parameters	
D	Stochastic demand in T-SCF
D^B	Stochastic demand in BT-SCF
L_i	Lead time of stage i. The time needed for stage i, $i = M, R$ (where denotes the manufacturer and R denotes the retailer) to receive an order after it is placed
T_i	Payment terms for stage i, $i = S, M$ (where S denotes the supplier and M denotes the manufacturer). This is the time needed for stage i to receive the payment after stage i delivers the order
c_i	Variable cost per unit (including production, inventory, delivery, etc.) of stage i, $i = S, M$
β_i	Stage $i's$ pre-specified markup rate, $i = S, M, R$
α_M	Manufacturer's ROI (return on investment) per unit time
r_S	Loan rate per unit time for the supplier in T-SCF
η	Price elasticity of demand for the final product
Intermediate Variables	
w_i	Wholesale price of stage i in T-SCF, $i = S,\ M$
w_i^B	Wholesale price of stage i in BT-SCF, $i = S,\ M$
p	Retail price to final customers in T-SCF
p^B	Retail price to final customers in BT-SCF
B_i^B	Early payment amount requested by stage i from the bank , in BT-SCF $i = S,\ M$
θ_M	Minimum sales quantity necessary for the retailer to fully repay the bank for the manufacturer's early payment in T-SCF
θ_M^B	Minimum sales quantity necessary for the retailer to fully repay the bank for the manufacturer's early payment in BT-SCF
θ^B	Minimum sales quantity necessary for the retailer to fully repay the bank for all early payment in BT-SCF

Table 2.2: Notation Summary (continued)

Intermediate Variables	
$\underline{q}_i^B$	Minimum order quantity that ensures stage i has the same profit in BT-SCF as in T-SCF, $i = S, M, R$
Decision Variables	
B_M	Early payment amount requested by the manufacturer in T-SCF
r_M	Manufacturer's early payment discount rate per unit time charged by the bank in T-SCF
q	Retailer's order quantity determined by the retailer in T-SCF
r_i^B	Stage $i's$ early payment discount rate per unit time charged by the bank in BT-SCF, $i = S,\ M$
q^B	Retailer order quantity determined by the retailer in BT-SCF

turer. Eq. 2.1 below shows the supplier's profit function, where c_S represents supplier's variable cost, while r_S denotes the supplier's loan rate per unit of time from an external source. Her profit and wholesale price, w_s, values are

$$\pi_S = -c_S q + (1 - r_S T_S) w_S q \tag{2.1}$$

$$w_S = c_S \frac{(1 + \beta_S)}{(1 - r_S T_S)} \tag{2.2}$$

The wholesale price comprises the product costs (e.g., fixed cost, variable cost, and markup for profit). Amberg et al. (2020) empirically show that a firm's financial conditions (e.g., higher SC finance cost) significantly impact its product price. We, therefore, assume that the financial cost impacts the supplier's product price and integrates her loan cost into the wholesale price. The supplier's effective loan rate is $r_S T_S$. From Eq. 2.2, we can see that $r_S T_S$ positively correlates to the supplier's wholesale price (w_S). The higher the $r_S T_S$, the higher the supplier's wholesale price (w_S). As $\beta_S > 0$ and $r_S T_S < 1$, π_S and w_s in Eqs. 2.1

and 2.2 are nonnegative.

2.5.2 Manufacturer in T-SCF

With the retailer's approval, the manufacturer can take advantage of the focal company's (retailer's) high credit rating to leverage with the bank. Given that the payment terms T_M and T_S are exogenously determined, Eq. 2.3 denotes the manufacturer's profit in T-SCF. Since he can delay the payment to the supplier until t_4 but must pay his operating expenses at t_2, the manufacturer can decide on the amount, B_M, to be paid early by the bank; this amount must be at least $(w_M - w_S)q$, and cannot exceed the invoice amount, $w_M q$. As shown in Figure 2a, the manufacturer gets the payment from the retailer at t_3 and pays the supplier at t_4. Like DSA's supply chain, the manufacturer (HYQ) receives retailer's payments, and the deep-tier supplier (FSM) typically lacks the negotiation power and has to accept the manufacturer's terms.

The manufacturer's profit function is given in Eq. 2.3. The first term is the early payment amount made by the bank, with the early payment discount rate per unit time r_M. The second term is the remaining payment received from the retailer. The following two terms represent the cost of production ($c_M q$) and payment to the supplier ($w_S q$). Finally, based on the manufacturer's ROI per unit time (α_M), the next term indicates the earning from the early payment amount beyond his share (i.e., belonging to the supplier) and adjusted for the early payment discount rate during T_M. The last term shows the earning of the delayed payment to the supplier. Eq. 2.4 shows the manufacturer's wholesale price to the retailer.

$$
\begin{aligned}
\pi_M = (1 - r_M T_M) B_M + (w_M q - B_M) - c_M q - w_S q + \\
\alpha_M T_M (1 - r_M T_M)(B_M - (w_M - w_S)q) + \alpha_M (T_S - T_M - L_R + L_M) w_S q, \\
where \;\; B_M \in [(w_M - w_S)q, w_M q]
\end{aligned} \tag{2.3}
$$

$$
w_M = (c_M + w_S)(1 + \beta_M) \tag{2.4}
$$

In T-SCF, the manufacturer gets early paid by the bank in SCF, while the supplier does not. The bank sets the early payment discount rate per unit time on the manufacturer's receivables at r_M based on the expected payoff, which is based on the uncertainty of the sale from the retailer. Eq. 2.5 shows the rules that the bank employs to decide the early payment discount rate in T-SCF.

$$(1 - r_M T_M) B_M = p \int_0^{\theta_M} x dF_p(x) + p\theta_M \bar{F}_p(\theta_M) \tag{2.5}$$

In the above equation, $\theta_M = \frac{B_M}{p}, \theta_M \geq 0$, is the *sales quantity threshold.*

Lemma 1: *The manufacturer's early payment discount rate ($r_M T_M$) depends on the demand distribution and is positively related to the sales quantity threshold (θ_M). Let $\bar{r}_M T_M$ be the early payment rate to the manufacturer when $B_M = w_M q$. Then, it would be profitable to push the supplier to join BT-SCF if $r_S T_S > \bar{r}_M T_M$. Otherwise, the supplier will have a higher financing cost in BT-SCF than in T-SCF and decline to join the BT-SCF. Thus, the retailer cannot help the supplier take advantage of its high credit rating and receive early payment from the bank.*

Lemma 2: *In T-SCF, the manufacturer can maximize his profit by optimizing the early payment amount, B_M. Given r_M in Eq. 2.5, a unique optimal value of θ_M^*, can be determined by Eq. 2.3.*

1) *If $\theta_M^* \leq \frac{(w_M - w_S)q}{p}$, the manufacturer's requested early payment amount does not include his payment to the supplier, and $B_M = (w_M - w_S)q$.*
2) *If $\frac{(w_M - w_S)q}{p} < \theta_M^* < \frac{w_M q}{p}$, the manufacturer's requested early payment amount includes part of his payment to the supplier, and $B_M = p\theta_M^*$.*
3) *If $\frac{(w_M q)}{p} \leq \theta_M^*$, the manufacturer requests full early payment amount from the bank which contains the amount he will pay the supplier later; and $B_M = w_M q$.*

2.5.3 Retailer in T-SCF

The retailer (e.g., DSA) can maximize its profit by identifying the optimal order quantity, given the retail price p, which is a markup over the unit wholesale cost (see Eq. 2.6). In T-SCF, the retailer's price is

$$p = (1 + \beta_R) w_M \tag{2.6}$$

$$\max_q \pi_R = p \int_0^q \bar{F}_p(x)dx - w_M q \tag{2.7}$$

After the sales, the retailer will pay the bank first and keep the rest as profit. With the IGFR demand function, $F_p(\cdot)$, we can find a unique order quantity, q^*, to maximize retailer's profit from Eq. 2.7, with $q^* = F_p^{-1}(\frac{\beta_R}{1+\beta_R})$ (Proposition 1 provides more details).

2.6 Blockchain-Technology based Supply Chain Finance (BT-SCF)

In T-SCF, the supplier cannot benefit from the retailer's high credit standing. But in BT-SCF, the deep-tier SCF's transactions are transparent and visible to the bank in the platform. Thus, the supplier can request and receive early payment at t_1, when the manufacturer accepts her delivery.

2.6.1 Supplier in BT-SCF

In BT-SCF, the supplier can benefit from unlocking working capital with a new rate by taking advantage of the retailer's credit. Eq. 2.8 shows the supplier's profit with deep-tier finance, where the second term denotes the early payment amount received from the bank with an early payment discount rate of $r_S^B(T_M + L_R - L_M)$. Note that in T-SCF, the supplier is paid at t_4 and needs to find an external loan by herself for the period T_S, from t_1 to t_4. But in BT-SCF, the supplier can instantly receive early payment from the bank when her shipment is accepted under smart contract design. The bank finances the supplier during $(T_M + L_R - L_M)$, i.e., from t_1 to t_3. We thus have:

$$\pi_S^B = -c_S q^B + (1 - r_S^B(T_M + L_R - L_M))w_S^B q^B \tag{2.8}$$

$$w_S^B = \frac{c_S(1 + \beta_S)}{1 - r_S^B(T_M + L_R - L_M)} \tag{2.9}$$

The supplier's wholesale price to the manufacturer is defined in Eq. 2.9 given the new early payment discount rate per unit time r_S^B from the bank in BT-SCF. Eqs. 2.2 and 2.9 together indicate that if $r_S^B(T_M + L_R - L_M) < r_S T_S$, the wholesale price will be lower in BT-SCF. If not, the supplier will have a higher financing cost and have no incentive to join BT-SCF.

2.6.2 Manufacturer in BT-SCF

The manufacturer is the key member of the BT-SCF because he is directly connected with the supplier and the retailer, linking the SC. For example, DSA needs to get support from HYQ to include FSM in the new platform for a stable and integrated SC relationship. Unlocking the supplier's working capital earlier reduces the supplier's financing cost, which can pass on to lower the manufacturer's wholesale cost and final product's cost. Eventually, a lower price can increase sales quantity and improve SC competitiveness.

However, in T-SCF, a critical but often overlooked issue is the manufacturer's profit. The focal companies usually pay little attention to the manufacturer's profitability, and the traditional SCF often makes SMEs worse off (Strom 2015, Futures 2019, Prosser 2019). This negative impact could also occur in BT-SCF and hinder its implementation if the SMEs are not taken seriously. The manufacturer's potential profit loss stems from the bank's direct payment to the supplier when switching from T-SCF to BT-SCF. This problem cannot be ignored and needs to be addressed in the smart contract design, as BT-SCF implementation needs the approval of all SC members. To motivate SC members to collaborate and join BT-

SCF, we need to address the problem regarding SC members' profit changes when employing BT-SCF.

In BT-SCF, the manufacturer seeks his share of the early payment amount, $(w_M^B - w_S^B)q^B$. Eqs. 2.10 and 2.11 show the manufacturer's profit and wholesale price to the retailer. The manufacturer's wholesale price will be lower if the supplier joins BT-SCF and takes advantage of the retailer's high credit rating to lower its w_S^B. We have

$$\pi_M^B = -c_M q^B + (1 - r_M^B T_M)(w_M^B - w_S^B)q^B \tag{2.10}$$

$$w_M^B = (w_S^B + c_M)(1 + \beta_M) \tag{2.11}$$

The manufacturer's profit consists of the order production cost and the discounted early payment from the bank. His profit functions in Eq. 2.3 and Eq. 2.10 differ in that the $w_S^B q^B$ portion goes to the supplier directly from the bank, and the manufacturer cannot request more than his share, $\frac{(w_M - w_S)q}{p} < \theta^* < \frac{(w_M q)}{p}$ (see Lemma 2). Thus, he cannot gain from keeping the extra potion of the early payment request like that in T-SCF. Also, the manufacturer loses the opportunity to profit from the delayed payment to the supplier. Namely, in T-SCF, he can hold the payment, $w_S^B q^B$, until t_4. Thus, the manufacturer's profit may become lower in BT-SCF. However, with the decreasing of supplier's financial cost, a lower wholesale price will lead to a lower final sales price and a higher sales quantity. The manufacturer, as an intermediary, is a key actor to implement BT-SCF. The more important the mid-tier member (e.g., manufacturer) is, the more effort is necessary to convince him to join the BT-SCF platform by ensuring that the manufacturer's profit increases in BT-SCF.

Lemma 3: *The manufacturer will join BT-SCF when $\pi_M^B \geq \pi_M$. From Eqs. 2.3 and 2.10, we find that there is a lower bound of order quantity, $\underline{q}_M^B$. Namely, if the new order quantity is lower than $\underline{q}_M^B$, he will not be incentivized to join BT-SCF.*

2.6.3 Rate Setting for BT-SCF

Under BT-SCF, the bank approves the early payments and expects a return at a rate of $r_S^B(T_M + L_R - L_M)$ from the supplier and return at a rate of $r_M^B T_M$ from the manufacturer. These two rates are functions of the demand uncertainty associated with the retailer, who has a high credit rating and can obtain low-cost financing from the bank. After sales, the retailer's repayment to the bank at t_3 includes the early payments to the supplier at t_1 and to the manufacturer at t_2. Since the repayment to the bank will only be made by the retailer at t_3 (neither by the manufacturer nor by the supplier), we assume the discount rate per unit time r_M^B and r_S^B to be equal, which is fair in DSA's case as all SC members get the same financial support.

In BT-SCF, B_M^B is the early payment amount to the manufacturer, and B_S^B is the amount to the supplier, where $B_M^B = (w_M^B - w_S^B)q^B$ and $B_S^B = w_S^B q^B$. Let θ_M^B and θ_S^B be the respective sales quantity thresholds for the manufacturer's and supplier's early payment amount in BT-SCF, where $\theta_M^B = (B_M^B)/p^B$ and $\theta_S^B = (B_S^B)/p^B$, and θ^B is the sales quantity threshold for total early payments, with $\theta^B = \theta_M^B + \theta_S^B$.

Then, the early payment discount rates per unit time for the manufacturer and the supplier can be derived from Eq. 2.12 with $r_M^B = r_S^B$. Eq. 2.12 shows the bank's decision rule to determine the early payment discount rates per unit time for the manufacturer and the supplier, that the left-hand side represents the early payments paid and right-hand side denote the expected payoff.

$$B_M^B(1 - r_M^B T_M) + B_S^B(1 - r_S^B(T_M + L_R - L_M)) = p^B(\int_0^{\theta^B} x dF_{p^B}(x) + \theta^B \bar{F}_{p^B}(\theta^B)) \quad (2.12)$$

Lemma 4: *The supplier will join BT-SCF when $w_S^B \leq w_S$. In other words, her early payment rate is lower than the loan rate. From Eqs. 2.2 and 2.11, we find that there is a lower bound of ordering quantity, $\underline{q}_S^B$, with early payment rate derived from Eq. 2.12. That is, when q^B is lower than $\underline{q}_S^B$, the supplier will not have a low early payment rate to benefit from and thus will not join BT-SCF.*

2.6.4 Retailer in BT-SCF

In BT-SCF, the retailer will maximize its profit, Eq. 2.14, subject to order quantity.

$$p^B = (1 + \beta_R) w_M^B \tag{2.13}$$

$$\max_{q^B} \pi_R^B = p^B \int_0^{q^B} \bar{F}_{p^B}(x)dx - w_M^B q^B \tag{2.14}$$

Eqs. 2.6 and 2.13 show that the retailer has different final sales prices since the wholesale prices of the manufacturer, w_M^B, and the supplier, w_S^B, in BT-SCF will be lower than those in T-SCF. Thus, we have $p > p^B$ and the lower sales price will lead to a higher sales quantity. Similarly, the retailer maximizes the profit by finding the best order quantity, given the early payment discount rates per unit time r_S^B and r_M^B from Eq. 2.12. In Eq. 2.14, we find that the optimal order quantity is $q^{B*} = F_{p^B}^{-1}(\frac{\beta_R}{1+\beta_R})$. As in Proposition 1, the retailer, e.g., DSA, is eager to lower its final prices to boost sales since its sales quantity is drive by the price-sensitive demand distribution.

Lemma 5: *In BT-SCF, the retailer joins BT-SCF when $\pi_R^B \geq \pi_R$. According to Eqs.2.7 and 2.14, there exists a lower bound of the order quantity, $\underline{q}_R^B$, which can be determined by solving: $p^B \int_0^{\underline{q}_R^B} \bar{F}_{p^B}(x)dx - w_M^B \underline{q}_R^B = p \int_0^q \bar{F}_p(x)dx - w_M q$. When the new order quantity is lower than $\underline{q}_R^B$, it will not benefit from BT-SCF.*

Proposition 1: *For a given price, there exists a corresponding optimal order quantity for the retailer (risk-neutral) to maximize its profit. Under both T-SCF and BT-SCF, the optimal order quantity q^* equals $F_p^{-1}(\frac{\beta_R}{(1+\beta_R})$, indicating that q^* depends on the retailer's markup rate and the price-induced demand distribution.*

2.7 SC Profit and BT-SCF Extension

As the retail price is lower in BT-SCF, the SC members' profits will differ from those in T-SCF. Below we will investigate the profit change of each SC member and decipher when and how BT-SCF benefits them.

For the supplier, when BT-SCF allows a lower financial rate, $r_S^B(T_M + L_R - L_M)$, she has a lower wholesale price, w_S^B. Relative to T-SCF, the manufacturer has a potential loss in profit. He can no longer request more early payment than his own share and lose the opportunity to hold his payment to the supplier for longer. As the key player in BT-SCF implementation, he needs $q^B \geq \underline{q}_M^B$.

The retailer will have a more competitive (lower-priced) product in the market in BT-SCF. We use the point elasticity method to calculate the price elasticity of the demand, η, in the market (Allen and Lerner 1934). We have $\eta = \frac{p(E(D^B)-E(D)}{(p-p^B)E(D)}$ with $E(\cdot)$ being the expected demand. The retailer will need to determine how BT-SCF will benefit itself and the entire SC. The retailer's benefit comes from higher sales quantity due to cost reduction stemming from the deep-tier supplier's lower early payment discount rate in BT-SCF than her loan rate in T-SCF. The improvement of the retailer's profit from T-SCF to BT-SCF is defined as $\Delta\pi_R$. Similarly, we let the profit change for the manufacturer as $\Delta\pi_M$ and the supplier as $\Delta\pi_S$.

Proposition 2: *From Lemmas 3-5, we find there exists a lower bound of the order quantity $\underline{q}^B$, which ensures none of the SC members will be worse off after the BT-SCF implementation, where $\underline{q}^B = \max\{\underline{q}_R^B, \underline{q}_M^B, \underline{q}_S^B\}$. Let $\underline{\eta}$ be the lower bound of price elasticity, which corresponds to the expected demand $E(D^B) = (1 + \frac{p-p^B}{p}\underline{\eta})E(D)$, given price p^B. From Proposition 1, we see the order quantity only depends on the demand distribution since the markup rate β_R is a constant by assumption, which implies that*

(1) *When $\eta \geq \underline{\eta}$, all SC members in BT-SCF under the new price, p^B, will generate no less profit than in T-SCF.*

(2) *When $\eta < \underline{\eta}$, we cannot guarantee that all SC members will generate higher profit by joining BT-SCF.*

Note that the profits between T-SCF and BT-SCF for each SC member are calculated simultaneously. We thus sum them up to show the SC profit change.

Proposition 3: *The supplier's loan rate in T-SCF (r_S), payment term (T_S), and price elasticity (η) are positively correlated with the SC profit change from T-SCF to BT-SCF. This implies that BT-SCF has sufficient room to reduce the supplier's financial cost (r_S and T_S) and price cut has a significant effect on demand. However, the manufacturer's ROI (α_M) has a negative impact on the manufacturer since it induces more sacrifice for the manufacturer to implement BT-SCF.*

In addition, we examine the above 3-echelon model extension to deeper tiers with the approvals of the existing SC members in BT-SCF (e.g., DSA's SC has six tiers). When the new tier i member joins, the impact on the system performance is twofold: the financing rates of tier i and tier $i-1$ change, and all downstream members' wholesale prices change. Under our proposed rate setting in section 2.6.3, the new tier i member entering BT-SCF allows tier i and tier $(i-1)$ members to have new and lower early payment discount rates, $r_i^B(T_M + L_R - L_M) < r_i T_i$, like in Lemma 4. The corresponding new rates per unit time are $r_(i-1)^B$ and r_i^B. For simplicity, we assume that there is only one supplier in one tier and supplier i chooses to request invoice amount of loan (in T-SCF), or early payment from the bank (in BT-SCF).

Subsequently, we can see the final price change following a new tier i member joining BT-SCF. Let w_i be the wholesale price of tier i member in the supply chain, where $i \in [1, 2, 3, ..., n]$ and $w_i = \frac{w_{i+1}(1+\beta_i)}{1-r_i T_i}$ in T-SCF. Each SC member has a variable cost c_i, markup rate β_i, payment term, T_i, and L_0 denotes the retailer's lead time.

Proposition 4: *When $r_i^B(T_1 + L_0 - L_(i-1)) < r_i T_i$, the deeper tier, i, the BT-SCF can accommodate, the lower the new retail price will be. Namely, the retailer will have a lower price and become more competitive in the market to get a higher sales quantity when BT-SCF implementation is extended to deeper tiers.*

Table 2.3: Parameters for Numerical Analysis

c_S	c_M	β_S	β_M	β_R	T_M	T_S	L_M	L_R	α_M (APR)	r_S (APR)	r_f (APR)
0.1	0.1	0.4	0.4	0.4	72	120	7	14	0.6	0.9	0.01

2.8 Numerical Analysis

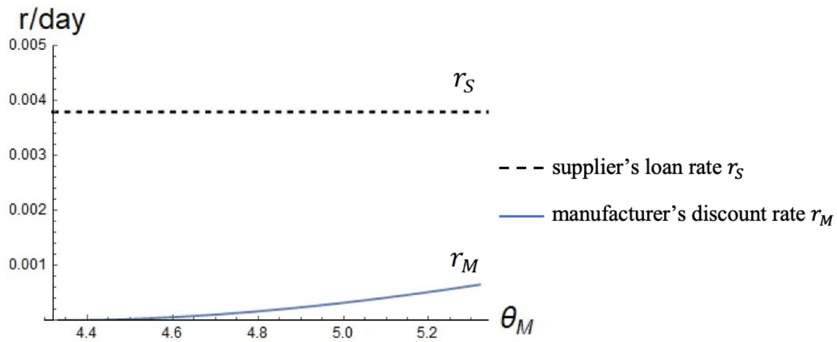
To validate our model and understand the performance of each SC member, we reference the DSA data to set the parameter values and assume the demand is uniformly distributed for our numerical study. Similar to Chen et al. (2009), we assume customer demand D is additive and price-dependent, with $D = d(p) + X$, where X is the demand uncertainty. The price determines the scale of the demand distribution, $d(p)$, which is strictly decreasing, non-negative, twice differentiable on a closed interval, and has an increasing price elasticity. We set $d(p) = \frac{1}{p-0.4}$ and X, the random price-independent component, is uniformly distributed with $X \in [L, U](L < 0, U > 0)$, $L = -d(p)$ and $E(X) = 0$. The numerical results are discussed below.

2.8.1 The Performance of T-SCF

Lemma 4 suggests that for BT-SCF to outperform T-SCF, the early payment discount per unit time rate (r_M) for the manufacturer's full early payment amount ($B_M = w_M q$) should be lower than the supplier's external loan per unit time rate (r_S) in T-SCF. Figure 2.4 shows that in T-SCF, regardless of θ_M (i.e., sales quantity threshold), the early payment discount rate per unit time (r_M) is always lower than the supplier's loan rate per unit time (r_S) in T-SCF.

Figure 2.4 shows how the manufacturer's profit changes with supplier's loan rate per unit time (r_S), and the threshold of sales quantity (θ_M), given manufacturer's early payment amount ($BM = \theta_M p$). For a given r_S, there exists a specific θ_M that maximizes the manufacturer's profit. For example, when r_S is high (e.g., 0.002), the manufacturer would choose

Figure 2.4: Early Payment Discount Rate in T-SCF



a low θ_M (of 1.44) to achieve the maximum profit (of 0.42). In addition, the manufacturer's optimal profit is negatively correlated with r_S, which indicates that lowering the supplier's financing rate per unit time would improve his profit, which can be achieved by implementing BT-SCF.

Figure 2.6 shows the retailer's profit functions under T-SCF and BT-SCF, respectively. For a given product price (p), the retailer would choose the best order quantity (q) to maximize its profit. From the figure, we can see that the profit of the BT-SCF is higher than that of the T-SCF at the optimal order quantity.

Figure 2.5: Manufacturer's Profit

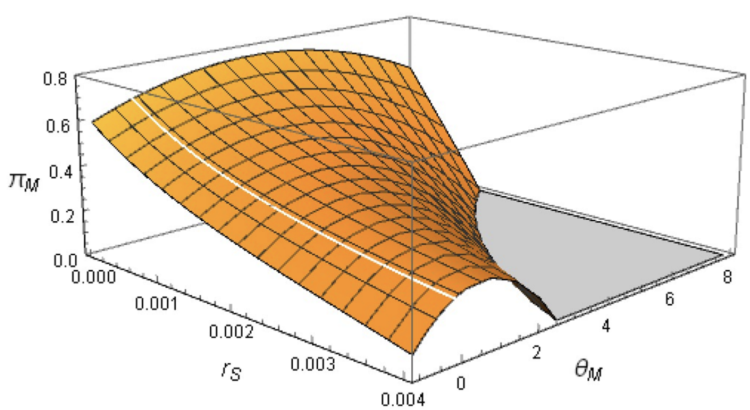
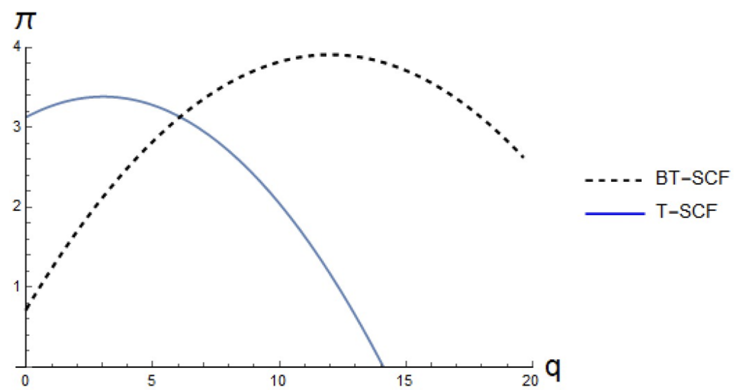


Figure 2.6: The Retailer's Profit Under T-SCF and BT-SCF



2.8.2 The Impact of Parameters on the Performance of BT-SCF

We first explore how T_S (payment terms for suppliers in days) impacts the profit change from T-SCF to BT-SCF. Figure 2.7 verifies Proposition 3 and shows that when T_S changes from 30 to 120, the BT-SCF profits increase. BT-SCF benefits the supplier the most, followed by the manufacturer and then the retailer. As the manufacturer's profit can still improve even though he lost the opportunity to hold the supplier's cash (from accounts receivable), the manufacturer is thus incentivized to implement BT-SCF.

Figure 2.8 examines the relationship between the supplier's early payment discount per unit time rate (r_S) and the SC members' profit changes from T-SCF. We find the profit gaps among the members of the BT-SCF increase with r_S. A higher r_S would create more room for BT-SCF profit improvement, with the supplier receiving the most benefit. We also find (not shown here) that increasing α_M (manufacturer's ROI) will increase the manufacturer's profit gap between the T-SCF and BT-SCF, making BT-SCF more attractive when the profits of every member can be guaranteed.

In Proposition 2, we find there exists a threshold of price elasticity, $\eta = \frac{p(E(D^B)-E(D))}{(p-p^B)}E(D)$. A higher means that when the product price drops, customers are strongly incentivized to make a purchase, leading to higher demand. Figure 2.9 shows that the retailer would be worse off in BT-SCF if $\eta < 5$. Namely, when customers are insensitive to price cuts (lower η), a lower price may not sufficiently increase demand, leading to a reduction in the retailer's

Figure 2.7: Profit Change from T-SCF to BT-SCF given T_S

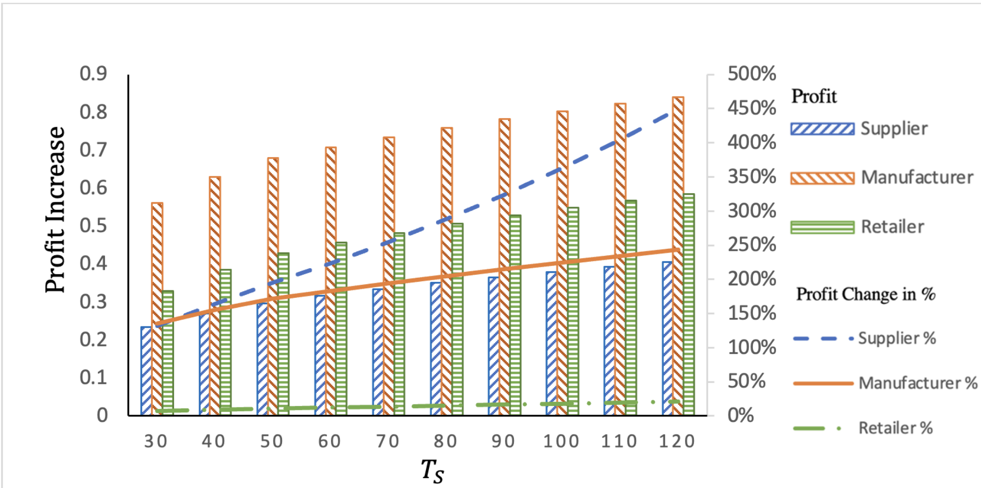


Figure 2.8: Profit Change from T-SCF to BT-SCF given r_S

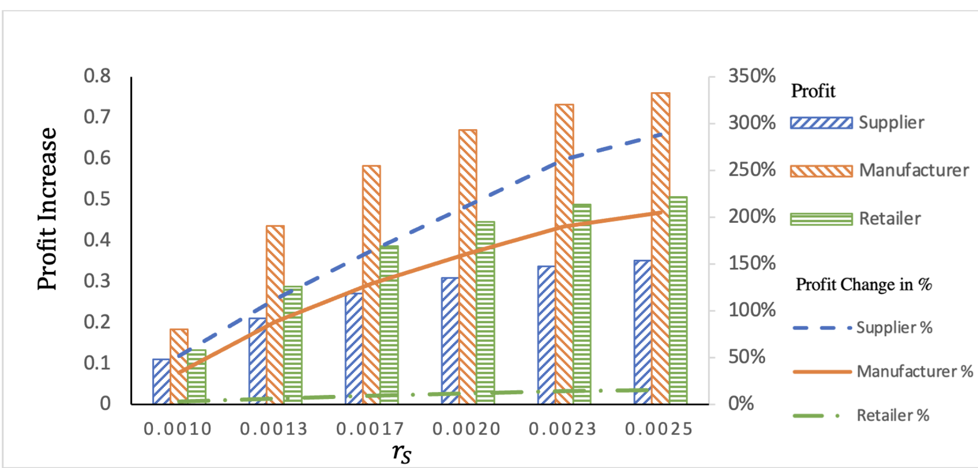
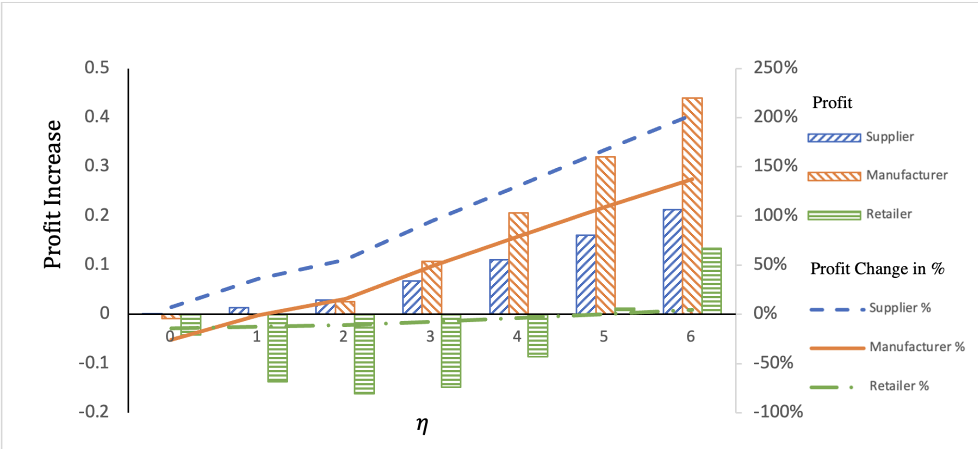


Figure 2.9: Profit Change from T-SCF to BT-SCF with Price Elasticity



profit. Similarly, the manufacturer will also lose profit in BT-SCF when $\eta < 1$.

2.8.3 Managerial Insights

The numeric study in this section has verified our propositions. It helps managers to understand the conditions under which BT-SCF will benefit the SC and which SC members would benefit or be worse off. An effective collaboration scheme can be developed from such findings to benefit all SC members.

Implications for Suppliers

Suppliers should know that they can reduce financing costs and derive higher profit with deep-tier SCF, and explore the opportunity to join the BT-SCF platform. However, such benefits can only be realized when the early payment discount rate with BT-SCF is lower than her external loan rate in T-SCF, and the final product demand has an increasing price elasticity.

Implications for Manufacturers

The manufacturer should evaluate T-SCF and BT-SCF carefully, as the manufacturer may not benefit from joining BT-SCF due to the reduction of his cash on hand. Their loss may be exacerbated when the manufacturer has a very high ROI.

The manufacturer can improve his profit in BT-SCF if the product's price elasticity is sufficiently high. Also, the higher the supplier's loan rate per unit time (r_S) and payment terms (T_S) in T-SCF, the more it will improve the manufacturer's profit from T-SCF to BT-SCF. Under such conditions, the manufacturer should aggressively advocate for BT-SCF implementation.

Implications for Retailer

The retailer in our study is the SC leader and needs to evaluate the potential benefit of BT-SCF to reduce the SC's financing cost. In evaluating BT-SCF, the retailer should attend to the supplier that has the potential to lower financial cost and the manufacturer to ensure that he is not worse off.

In addition, the retailer needs to have good knowledge about the price elasticity of the demand in the market since the profitability of the BT-SCF is highly dependent on the price elasticity. Only when the price elasticity is higher than a threshold (e.g., $\underline{\eta} = 5$ in Figure 2.9) will all SC members benefit from the BT-SCF implementation.

2.9 Conclusion

Blockchain Technology, together with IoT and smart contracts, provides a new opportunity for deep-tier finance to support often financially strapped SMEs and increase the competitiveness of the entire SC. Through the proposed BT-SCF model, we identify its differences with T-SCF and caution that companies need to carefully design and evaluate the BT-SCF platform before employing it (referring to DSA's problem). Appropriate mechanism design among business alliances is needed to motivate SC members, especially the mid-tier members, to commit to a BT-SCF implementation. By identifying the agreeable early payment rates, we find deep-tier financing can benefit the SC with lower financing costs and competitive retail prices. Finally, we discuss the impact of BT-SCF if it is implemented in deeper-tier (four or more levels) SCs.

We identify the issues that hinder BT-SCF implementation and find that privacy and SC members' profit shift are the main concerns. To address these concerns, we show the value of Blockchain visibility and transparency in SCF and its ability to help deep-tier SMEs. The current literature lacks the mechanism necessary to carry out deep-tier SCF. The limited studies focus on the conceptual model of implementing SCF using Blockchain Technology. They did not discuss how to incorporate deep-tier SC members into the SCF framework using new technologies like Blockchain and IoT to increase SC competitiveness. The new Blockchain platform requires the approval of all SC members. The literature has thus far not discussed the necessary mechanism to quantify and share the benefit of the new platform with all SC members. Most importantly, the issue of intermediary (mid-tier) SC members is not defined and taken into account before implementation.

We contribute to the literature by studying the potential of deep-tier SCF and pinpoint the important roles the mid-tier members play in a stable and sustainable SC. From the insights derived in this study, firms can better understand the SC members' profit changes, especially in the mid-tier SMEs, after switching from T-SCF to BT-SCF. Our results provide helpful guidance for BT-SCF implementation and improving long-term relationships among SC members, such that a win-win situation is attainable in a competitive market.

We have discussed whether SCF should extend to deep-tier SC or not and how BT-SCF with appropriate rate-setting impacts SC profitability. There are limitations to our study within the scope of our theoretic model. For example, in practice, there may be multiple suppliers in each tier, and trade credit is often used in SCF besides invoice financing. Also, a deeper-tier member may be the one with the highest credit rating rather than the retailer. Our models are motivated by the DSA case, whose manufacturers and suppliers are SMEs in developing countries (e.g., HYQ, FSM) and often ignore the time value of money in the contract. In the future, when applicable, it will be essential to include the present value in the analysis.

3.0 Experienced and Prospective Wait in Queues: A Behavioral Investigation

Problem definition: The cost of completing a line—a continuous variable—is typically studied indirectly through customers' decisions to balk or renege from a queue—binary variables. However, these decisions only tell us whether a customer's completion cost is above some (unknown) personal threshold; we do not have a good understanding of individuals' *precise* completion costs, V. In this paper, we study how a perfectly informed customer in deterministic, visible queues forms her completion cost from (i) her position in line, (ii) the number of people that have been served since she joined the line, and (iii) the service speed. We also investigate how affective attitudes (emotional responses) towards waiting influence V.

Methodology/results: Using a controlled experiment, we introduce the use of the Becker-DeGroot-Marschak (BDM) method (Becker et al. 1964) to *directly* measure V. We find two important deviations from rational predictions. First, completion costs are not independent from subjects' experienced wait (i.e., the wait they had to endure to get to their current position)—but the direction of this effect depends on subjects' affective attitudes. Second, regarding the prospective queue, we find that length and service speed influence V additively, not multiplicatively. That is, subjects use heuristics; the completion cost is not directly proportional to the prospective waiting time.

Managerial implications: Companies and organizations regularly offer customers paid options to shorten their waiting time, present them with alternatives to waiting in line, or use incentives to manage queuing congestion. Our results can help them by providing a granular metric of completion costs—measured in monetary terms—and by shedding light on how these costs are affected by the experienced wait (and hence the timing of the offer or incentive) and the characteristics of the prospective queue. Our clean experimental framework can also be easily extended to a wide array of queuing settings.

3.1 Introduction

Consider the following situation: a customer is standing in a queue of length l that moves at a speed of s seconds per customer. To get to this point, the customer has already waited for w persons to be served. How does she feel about the experienced and prospective wait? Specifically, how do they impact the cost that the customer assigns to staying in line and completing the queue? Interestingly, the answer to this question remains unclear. Most studies analyze customers' decisions whether to quit waiting (e.g., Janakiraman et al. 2011, Batt and Terwiesch 2015, Akşin et al. 2020), but few have elicited customers' moment-to-moment expected cost for completing the queue, V. The two are not the same: the decision to leave only shows that V has risen above a certain threshold, at which point it is too late for the service-provider to intervene. Furthermore, subjects that had a negative experienced wait but still complete the queue can harm a business if they share their negative wait experience publicly (such as on Yelp). Similarly, several studies investigate whether people will join or balk from a queue (e.g., Pazgal and Radas 2008, Hannigan and Flicker 2020), but this only tells us whether V is above a customer's threshold for the cost of joining and completing the queue. Moreover, whether and how the characteristics of the prospective wait—in particular, l, s, and their interaction, waiting time—may change the value of V is not well understood.

Our study is also motivated by the fact that, as part of their congestion management strategies, several organizations present individuals with alternatives to joining a (or staying in) line. For example, Disneyland recently launched Genie+, a paid option to access some of their parks' attractions using faster lanes (Pallotta 2021). Similarly, call centers regularly offer customers the option to receive a call-back at a later time, or to submit requests online. These options may sometimes be less preferable than immediately speaking with an agent, but they offer the benefit to the customer of not having to wait on the phone (Elliott 2019). In such situations, understanding the *actual cost* that people assign to completing a queue is a necessary first step to assess how likely individuals are to choose between the regular queue and the alternative. To illustrate, consider a group of customers waiting for a table at a restaurant. To manage the queue, the restaurant manager offers the group the alternative to instead sit at the bar—without needing to wait for a table, but with less comfortable chairs, less privacy, etc. In this scenario, the manager would benefit from knowing the cost the group attributes to waiting in line, which in turn affects how likely they are to prefer the bar option. Similarly, the manager would benefit from knowing how this cost depends on whether the group has been waiting for some time, on the number of customers ahead, etc.

In this paper, we introduce the use of the Becker-DeGroot-Marschak (BDM) method (Becker et al. 1964) to *directly* measure individuals' completion costs, V, in queuing experiments. We define completion cost as the difference between the reward that can be obtained from completing the queue, and the utility that a person assigns to staying in line (i.e., after accounting for both the reward *and* the cost or disutility of the associated wait). Unlike survey questions (such as ratings about wait satisfaction),[1] the BDM provides an incentive-compatible method to translate what was an individual's subjective expectation of the cost of waiting into monetary units. This paper aims to provide a first, simple framework to use the BDM to study V, stripping away some of the complexity found in previous studies (e.g., uncertainty, dynamic changes in queues). We focus on how a perfectly informed customer in a deterministic, visible queue forms her completion cost from the customer's position in line (l), the number of people that have been served since she joined the line (w, including the case $w = 0$), and the service speed (s). We also investigate how the customer's affective attitudes (i.e., emotional responses) towards waiting, which we measure with questions from the widely validated Framingham Type-A scale (Haynes et al. 1978), influence V.

Our results show evidence of sunk cost fallacy with regards to experienced wait. The BDM reveals that the experienced time (i.e., the product of places moved, w, and service time, s) has a significant effect on completion costs. The direction of this effect, however, depends on participants' affective types. Controlling for the characteristics of the prospective wait, customers that self-identify as having negative affective attitudes towards wait (i.e., who get upset when having to wait) exhibit a *higher* cost of completing the queue, V, after a long experienced time. Conversely, those not reporting negative affective attitudes report

[1]For example, participants in Buell (2021) are asked to complete the statement "Please rate your overall satisfaction with the length of your wait"—or "It was worth my time to wait in the line I just experienced"—with one of seven possible answers ranging from extremely unpleasant to extremely pleasant.

a lower cost V—i.e., become more committed—after experiencing a long wait. Our results also show that subjects evaluate prospective wait—the remaining queue ahead of them—using heuristics, rather than the rational computation of waiting time. While both l and s impact the values elicited for V, they do so *additively*, not multiplicatively as the rational theory would predict. In other words, an increase in l (s) is accompanied by an increase in V that is independent of the value of s (l). After accounting for the main effects of l and s, their interaction—waiting time—does *not* significantly affect the completion cost. This is surprising, as in our study subjects are fully informed about the queue characteristics.

These findings have implications for both theory and practice. From a theoretical standpoint, a rational queuing model (e.g., Naor 1969, Hassin and Haviv 1995, Cui et al. 2018) would suggest that individuals compute their opportunity costs of time and compare it against the value that can be derived from completing a queue. Thus, all that should matter is the time that it takes to complete the wait: the value of V should be independent of w, and should be negatively correlated *only* with the prospective waiting time—the product of l and s. Our results challenge both of these assumptions. From a practical perspective, our findings suggest that, when offering alternatives to customers who are waiting in line, organizations need to take into account the timing of the offer; but the response to timing is heterogeneous and depends on customers' attitudes towards waiting. In addition, we observe that for long and/or slow queues (short and/or fast queues), an increase in length or service time impacts a person's completion cost less (more) than anticipated by the rational model. This result has implications for the design and management of queuing systems. For example, while pooling queues can reduce overall waiting time, it could backfire due to our observed response to queue length. A similar observation is made by Lu et al. (2013) in a setting with uncertainty in waiting time; however, we find that this may be the case even when subjects are *perfectly informed* about the length, speed, and waiting time of the queue.

3.1.1 Related Literature and Contributions

This paper draws from and contributes to two streams of work within the behavioral queuing literature (for an excellent review, see Allon and Kremer 2018). First, regarding the *experienced wait* in queues, several studies analyze how reneging (i.e., abandonment) decisions are influenced by characteristics of the elapsed wait (e.g. Batt and Terwiesch 2015, Webb et al. 2017, Akşin et al. 2020). Close to our work, Janakiraman et al. (2011) suggest that people experience two opposing forces while waiting: an increasing disutility for the remaining wait and an increasing commitment to complete the queue successfully due to the time already spent waiting, resulting in an inverse U-shaped curve in reneging probability. In an unobservable-queue setting, the authors find experimental support for this conjecture. This result is linked to the effect of sunk time costs (Soman 2001), which have also been found to influence the amount that people spend after waiting in line (Ülkü et al. 2020). Relatedly, the affect-based literature hypothesizes that as the time spent waiting increases, a customer experiences increasing negative emotions from waiting: e.g., due to boredom, anxiety, and annoyance (e.g., Maister 1984, Larson 1987). For example, Carmon and Kahneman (1995) find evidence in a laboratory experiment that participants' affective states worsen during periods of idle wait, and improve when they make progress in line.

We contribute to this first stream of work by studying the effect of experienced wait in an observable queue, where the length and service time of the remaining wait are perfectly known. In unobservable queues, the experienced wait can be used by individuals to update their beliefs about the remaining wait—which constitutes reasonable, rational behavior. Conversely, our setup allows us to (i) isolate the effect of experienced wait on completion costs by controlling for the (known) remaining wait and (ii) thanks to this approach, rule out that such an effect could be fully explained by rationality. In addition, our results highlight heterogeneity in affective attitudes as a key mechanism that helps to explain *when and how* the sunk cost fallacy may change individuals' responses in a queuing environment. While Janakiraman et al. (2011) hypothesize that two opposing forces occur within-person, our experiment suggests that the net effect may depend on a customer's affective type. This result relates to the observation that there is considerable heterogeneity in the degree to which people are susceptible to decision biases in queues (Conte et al. 2016).

A second stream of literature in behavioral queuing studies how the characteristics of the *prospective wait* influence people's joining decisions and utility. In particular, authors have found that, in addition to the waiting time, the length (e.g., Lu et al. 2013, Conte et al.

2016) or speed (e.g., Batt and Terwiesch 2015, Bolandifar et al. 2019) of a queue may also and separately impact people's joining decisions. In a related experiment, Hannigan and Flicker (2020) use conjoint analysis to measure participants' utility based on their stated preferences over a series of virtual queues. They find that, in addition to the total expected waiting time of a queue, participants' utility is also impacted by the variance of the service time, as well as by the length of an observable queue.

Our contributions to this second stream of work are twofold. First, to the best of our knowledge we are the first to *simultaneously* study the effects of length, service time, *and* waiting time on completion costs. By omitting one (or more) of these queue characteristics, the extant literature provides an incomplete understanding of their effects on people's decisions. For instance, a study indicating that waiting time and length influence subjects' completion costs leaves unanswered whether either of the two effects could be attributed instead to subjects' reactions to the omitted variable—in this example, service time. Understanding the three factors' relative contributions to completion costs is important as this may impact, e.g., how people decide whether to join a queue, or how much they would be willing to pay to avoid a queue, and therefore have implications for the management of queuing systems. Second, by considering a setting where length and speed are known and deterministic, we study participants' responses when our three factors of interest are either known or easy to evaluate, and hence comparable. Thus, in our setting, the effect of queue length cannot be attributed to subjects (rationally) using it as a proxy for waiting time, as has been suggested in the literature (e.g., Lu et al. 2013). Even in this simple deterministic queue, with perfectly informed subjects, we find that people use heuristics instead of behaving according to the rational-model prediction.

Finally, we contribute to the behavioral queuing literature by proposing a novel methodological approach to measure the utility that individuals assign to queues. Thanks to the BDM mechanism, our experimental framework provides a measure that is more granular than what can be observed from balking or reneging decisions, as we observe an exact value of utility (and therefore V) for each individual. In addition, our utility measure is expressed in monetary terms, which can be useful for decision-makers as they offer alternatives to manage congestion. Lastly, we find that the dollar estimates that we derive from subjects through the BDM mechanism are consistent with subjects' opportunity costs of time—measured both through an additional control task and the online platform's (Prolific's) suggested payment to participants. This provides further support for both the internal and external validity of our metric.

The rest of the paper is organized as follows. In Section 3.2, we introduce our experimental design and procedures. In Section 3.3, we discuss the hypotheses development. Section 3.4 presents our main experimental results and findings. Finally, conclusions and implications are discussed in Section 3.5.

3.2 Experimental Design

Our experiment consists of three parts: the queuing task (hereafter referred to as QT), which is the main part of our study; two control tasks to measure subjects' risk preferences and value of time; and an exit survey. In what follows, we discuss our experimental design and procedure in detail.

3.2.1 The Queuing Task

The QT consists of a single-player queuing game, where each participant interacts with a computer-simulated queuing environment. Before joining the queue, participants see the following information: (i) the number of (virtual) customers waiting in line (l); (ii) the time that it takes to serve each customer (s); and (iii) the reward, in experimental tokens, that they can receive from the virtual store upon completing the line—which we keep constant and equal to 100 tokens. Thus, our setting captures an *observable queue*, where participants have complete information about the queuing system states. After learning about the queue, participants must join it and start to wait in line, moving forward each time a virtual client is served.

Sometime after joining the queue and before completing it, each participant (she) is asked to state the minimum number of experimental tokens, M, such that she would rather receive a payment of M tokens than continue to wait in line for the store's reward. We hereafter refer to this step as the *elicitation question*. After a participant states the value of M, Nature randomly selects a value X from a uniform distribution between 1 and 100 tokens. If X is greater than the participant's stated value of M, then she immediately leaves the queue and receives X tokens without any additional wait. Otherwise, if X is less than or equal to M, then she continues to wait in line for the store's reward. Participants also learn that stating M equal to 0 (100) ensures that they leave (stay) in line for certain. The approach of comparing a participant's stated value against a randomly selected value to determine the participant's payoff is the Becker-DeGroot-Marschak (BDM) mechanism (Becker et al. 1964). This mechanism is commonly used in experimental economics to elicit individuals' *truthful* valuations of a product or service (Klos et al. 2005, Plott and Zeiler 2005, Halevy 2007). The value of M corresponds to the utility that an individual assigns to staying in line and earning the store's reward. Thus, based on the value of this reward (constant and equal to 100 tokens) and M, we define an individual's *completion cost* as $V := 100 - M$.

In addition, we measure participants' heterogeneity in affective attitudes towards waiting (i.e., feelings and emotions that they experience when confronted with a waiting situation) with two questions from the Framingham Type-A scale (Haynes et al. 1978): (1) "In comparison to others, are you a person who is generally willing to give up something today in order to benefit from that in the future or are you not willing to do so?" (5-point Likert scale with 1 = strongly willing and 5 = strongly unwilling); and (2) "Do you get upset when you have to wait for anything?" (binary options Yes/No). This scale has been widely used and validated in the behavioral sciences' literature to measure people's sense of time urgency and self-control (e.g. Gambetti and Giusberti 2012, Falk et al. 2016, Neff 2017, Loewenthal and Lewis 2018). In our study, these questions allow us to investigate whether and how individuals' affective attitudes towards waiting moderate their responses to the experienced wait and the characteristics of the prospective queue. Furthermore, there is empirical evidence that suggests these attitudinal questions may play a role in our context. For example, Hernandez-Maskivker and Ryan (2016) find that in theme parks, customers with negative attitudes towards waiting are more likely to pay for a "fast pass" to avoid long lines.

Before continuing, we note three key aspects of our experimental design. First, we make joining the queue mandatory and do not allow participants to freely renege (except when they receive the elicitation question). In practice, decision-makers would only be able to observe, and potentially take actions to mitigate, the completion costs of people who voluntarily join and choose to stay in line. However, one of our main goals is to compare individuals' completion costs in the presence versus absence of experienced wait. To achieve this, we must be able to compare the cost of a participant who just joined a queue (i.e., $w = 0$), with that of another participant who is confronted with the *same prospective queue* at the time of the elicitation question, but who has already been waiting (and moved) in line (i.e., $w > 0$). Allowing participants to decide whether to join, or to freely renege from, the queue would introduce self-selection biases that would make these two situations not directly comparable. To illustrate, consider i and j to be two indices, both of which represent the entire population. In this case, we can calculate the effect of having waited for K customers, when the queue has a current length l and service time s through the difference $E[\,V_i(l, s, w = K)\,] - E[\,V_j(l, s, w = 0)\,]$—which is the approach we follow in this paper. However, this would no longer be true if i represented instead the population that *chose* to join a line of length $l + K$ (and subsequently decided to *stay* in line after waiting for K customers to be served), and j represented the population that chose to join a line of length l. To reduce the effect of any potential difference between our experimental approach and practice, we calibrate our queuing parameters so that most people would choose to join and voluntarily stay in our virtual queues (i.e., they state a utility $M > 0$, or equivalently, a completion cost $V < 100$; see §3.4).

Second, all customers that a participant sees waiting in line are virtual clients, as opposed to other (human) participants. This allows us to analyze our participants' responses to queue characteristics and the experienced wait while controlling for any interpersonal or strategic considerations, which are outside the scope of this study. Finally, after participants join the queue, no virtual client joins behind them. This design choice allows us to avoid introducing differences in customers' completion costs that could be due to, e.g., last place aversion (Buell 2021); or to the fact that, as the number of people behind increases, consumers have been found to be more committed to staying in line (Zhou and Soman 2003). Thus, excluding new client arrivals allows us to study the effect of experiencing wait while controlling for such confounding factors.

3.2.2 Manipulations

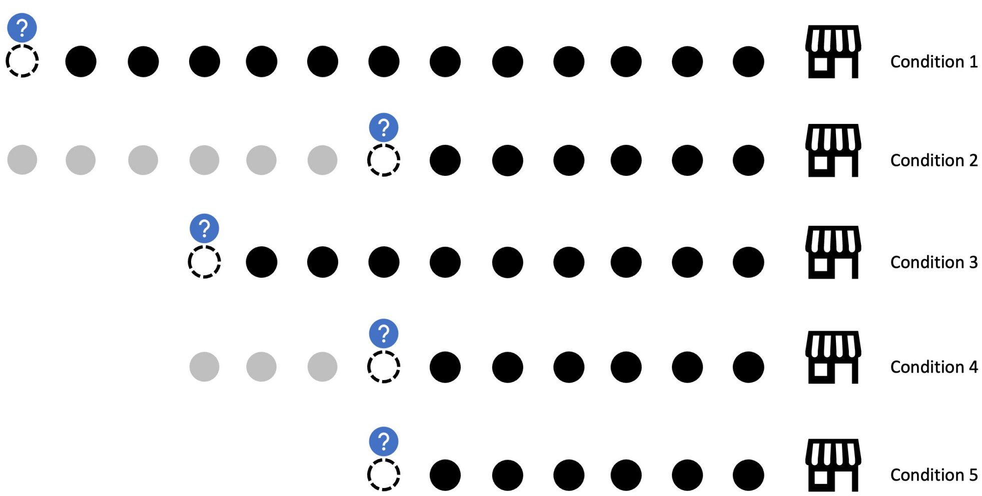
We manipulate the QT along three dimensions: prospective length (l), service time (s), and experienced length (w). First, the prospective length corresponds to the total number of clients that a participant needs to wait for before receiving the store's reward, which includes the virtual clients ahead plus the participant herself. We consider three levels of prospective length: 7, 10, and 13 clients. Second, the service time is defined as the number of seconds that it takes to serve each customer, and it therefore determines the speed of the queue: a higher (lower) service time corresponds to a slower (faster) queue. We consider three levels of service time: 5, 10, and 20 seconds/customer. Finally, we vary the experienced length, which we define as the number of places that a participant has moved in line before receiving the elicitation question; i.e., before they state the value, M, that they attribute to staying in line. We account for three experienced lengths: 0, 3, and 6 places. In the case of an experienced length of 0 places, participants are presented with the elicitation question immediately upon joining the queue.

Based on these dimensions, we consider a set of key combinations to obtain a total of 15 experimental conditions, shown in Table 3.1. This design allows us to investigate the impact of (i) the experienced wait and (ii) the characteristics of the prospective wait on subjects' completion cost. Figure 3.1 helps to illustrate this using the conditions with service time equal to 5 secs./client. In each condition, the dashed circle denotes a participant's position in line when they receive the elicitation question. For example, comparing participants' responses between conditions 2, 4, and 5 helps us to address whether experienced length influences completion cost. On the other hand, comparing participants' responses between conditions 1, 3, and 5 helps us to study the effect of prospective length, absent any experienced wait. Similarly, repeating these analyses across our three service times allows us to not only study the effect of service time on completion cost, but also to investigate whether a significant interaction exists between prospective length and speed (i.e., prospective waiting time), or between experienced length and speed (i.e., experienced time).

Table 3.1: Summary of Experimental Conditions

Condition	Prospective Length (l) (clients)	Service Time (s) (secs./client)	Experienced Length (w) (places)
1	13	5	0
2	7	5	6
3	10	5	0
4	7	5	3
5	7	5	0
6	13	10	0
7	7	10	6
8	10	10	0
9	7	10	3
10	7	10	0
11	13	20	0
12	7	20	6
13	10	20	0
14	7	20	3
15	7	20	0

Figure 3.1: Experimental Conditions ($ServTime = 5$ secs./client)



Note. The dashed circles denote a participant's position when they receive the elicitation question (represented by the question mark). Each black dot represents a virtual client ahead, and the gray dots are the places that the participant has moved in line.

Note that in our study we do not introduce any uncertainty in service time. We make this design choice for two reasons. First, uncertainty in waiting time would introduce a confound to experienced wait: participants who received the elicitation question after moving a (non-zero) number of places would not only experience wait, but also observe—and hence learn from—realizations of the (random) service time. Conversely, these realizations would not be observed by participants who receive the elicitation question immediately after joining the queue. Thus, in the presence of uncertainty, we would not be able to know the extent to which differences between the two situations (e.g., conditions 2 and 5 in Figure 3.1) could be attributed to experienced wait, versus differences in learning. Second, regarding the prospective queue, one of our main goals is to disentangle the impacts of speed, length, and waiting time on subjects' completion cost. Uncertainty in service time would also introduce uncertainty in waiting time, while the queue's length would be known with certainty. Thus, our three main factors of interest would not be directly comparable by participants; and disentangling the impacts of average of, versus uncertainty in, service time (waiting time) would require us to consider several levels of uncertainty, considerably increasing our number of experimental conditions.

3.2.3 Control tasks and Exit Survey

We include two control tasks where we study participants' value of time and risk preferences. The value-of-time task allows us to measure the value that participants attribute to a two-minute wait (which is similar to the average waiting time of the QT). The risk-preference task is included as people's attitudes towards risk may have an impact on participants' decisions in the QT, since the randomly-generated values from the BDM mechanism help to determine whether someone stays or leaves a queue. Thus, we include these tasks to control for heterogeneity in the outside value of time (i.e., opportunity cost in a non-queue-related setting) and risk preferences of our participants.

In the value-of-time task, we employ the BDM mechanism to elicit participants' cost of opportunity for a two-minute wait (for a similar approach, see Eckel and Grossman 2002). Specifically, each participant is first required to state the minimum number of tokens, Z, that they are willing to accept as payment for a two-minute wait. Then, Nature randomly selects a number, Y, from a uniform distribution between 1 and 150 tokens. If Y is larger than Z, then the participant receives a payment of Y tokens after waiting for two minutes. Otherwise, if $Y < Z$, then the participant skips the two-minute wait and does not receive any tokens from the task. Participants also learn that stating Z equal 0 (150) ensures that they wait (do not wait) for two minutes for certain. Note that, by designing the value-of-time task with a similar waiting time but a larger range of possible random payments than in the QT, we can have a more general understanding of people's value of time. This is particularly the case given that, in the QT, there is no reason for a participant to require a payment of more than 100 tokens to leave the queue, since the store's reward is equal to 100 tokens. However, such a natural upper limit does not exist in the case of the control task.

To measure participants' risk preferences, we follow a similar approach to Gneezy and Potters (1997) and design an investment game in which each participant receives an endowment of 15 tokens and must decide how many tokens to put into a risky investment. Then, Nature randomly determines whether the participant wins or loses the game, with equal chances. If the participant wins, then they get a return of 2.5 times the investment, plus the rest of the initial endowment (i.e., the amount out of the 15 tokens that were not invested). Otherwise, the participant loses the investment and receives only the non-invested portion of the initial endowment. Therefore, a participant's investment captures a measure of risk tolerance: less (more) risk-averse participants are expected to invest more (fewer) tokens in the game.

After participants finish the QT and control tasks, they proceed to the exit survey. The survey consists of three sections: (1) questions about their decisions in the QT; (2) a demographic questionnaire; and (3) the questions from the Framingham Type-A scale described in §3.2.1.

3.2.4 Experimental Procedures

Our experiment was conducted in Prolific, an online laboratory platform (Palan and Schitter 2018). Compared with other online subject pools (e.g., Amazon Mechanical Turk), Prolific has been found to provide a higher quality of data collected (Peer et al. 2021, Gupta et al. 2021). An online platform provides a good environment to evaluate people's valuations of waiting experiences, as subjects are free to leave the platform as soon as the study is completed. Thus, a shorter (longer) wait in the experiment directly and precisely translates into shorter (longer) time spent in the study, which is more difficult to implement in an in-person laboratory setting. All sessions followed the same procedure for all subjects: (1) four rounds (i.e., queues) of the QT, (2) the risk reference and value of time tasks, and (3) the exit survey.

The experiment began with a series of instruction screens to inform participants about the QT, in general, and the BDM mechanism, in particular (the instructions are available in the Online Appendix). Participants also saw two examples of the BDM mechanism, one where the realization of randomness was such that a participant would leave the queue, and another one where they would stay in line. Then, participants were given three attempts to pass a comprehension quiz to ensure that they understood the BDM mechanism. Participants who passed the quiz proceeded to a practice session, where they became familiar with the procedures to move forward in line, and learned firsthand what waiting in line felt like in the experiment. The practice session was followed by four rounds of the QT. In each round, participants encountered a queue and elicitation question with different characteristics; i.e., one of the experimental conditions presented in Table 3.1. To reduce the potential impact of order effects, we prespecified a set of random sequences of conditions that ensured diversity in service time, length ahead, and experienced length, as well as similarity in the total time that it took a participant to complete the four queues.

To help participants better understand the BDM mechanism, we asked them to select the minimum value (in tokens) that an "alternative product" should be worth so that they would prefer receiving this product over waiting in line for the store's product. In both cases, we chose to refer to "products" (compared to, e.g., the more abstract concept of reward) so that participants could easily relate to them. Similarly, we used the notion of an alternative product to (i) make the two payment sources (i.e., from completing the line or being paid to leave) more easily and directly comparable, and (ii) better approximate one of the motivations for our study, namely, that companies may present people with alternatives to waiting in line.

In order to introduce wait in our online study, and to prevent the performance of other activities while in line, participants had to click a button on the screen to move forward whenever a virtual client was served. Participants were given 10 seconds to click this button, and failure to do so resulted in exiting the QT and not receiving *any payment* for any of the queues in the QT (for a similar implementation of queues in an online environment, see, e.g., Hannigan and Flicker 2020, Buell 2021, Rodriguez et al. 2021). A similar strategy was employed in the value-of-time control task, where participants had to click on a button that showed up on their screens every 10 seconds.

We implemented our experiment with oTree, an experimental software (Chen et al. 2016). Participants were not allowed to go back to the previous page to change their decisions or take the experiment more than once. A total of 299 participants started our experiment and 259 of them passed the comprehension quiz. We removed from our analyses the observations from 15 participants who failed to click to move forward on time in the QT (and therefore did not complete this task); and from 2 participants who stated a valuation of $M = 0$ for all queues. We followed these steps to reduce the chance that our results may be due to participants who did not pay attention to the QT (and/or were not waiting for the virtual customers to be served); or to participants who would not voluntarily join or stay in *any* of our virtual lines (and whose evolution of completion cost we would thus not observe in practice, see the discussion in §3.2.1).[2] Thus, our analyses are based on a total of 242 participants and 968 observations. Of these participants, 50% identified as female and the average age was 29.3 years old, with a standard deviation of 8.06 years. Participants' earnings depended on all rounds of the QT and the two control tasks. Every 150 tokens were worth one U.S. dollar. Total earnings averaged \$6.65 per participant, with a minimum of \$3.83 and a maximum of \$7.65. It took participants 35 minutes on average to complete the study.

[2]We confirm that our main results remain unchanged if we consider all observations. See Table 3.4.

3.3 Hypotheses

In this section, we discuss our study's hypotheses. For ease of exposition and in light of our main research questions, we separately formulate hypotheses for how an individual's completion cost is influenced by (i) experienced wait and (ii) characteristics of the prospective queue (i.e., l, s, and $l \times s$). In addition, given the relative lack of studies regarding how experienced wait may impact completion costs, we restrict ourselves to the comparison of having ($w > 0$) versus not having experienced wait ($w = 0$), rather than the characteristics of such wait; i.e., we do not formulate specific hypotheses for the (more detailed) effects of experienced length, experienced time, etc.

3.3.1 Experienced Wait

In the canonical queuing theory (e.g., Naor 1969), an individual's completion cost is commonly modeled as depending only on residual wait (the queue that is still *ahead*), instead of elapsed wait (the queue that has been completed). Indeed, Akşin et al. (2013), Afeche and Sarhangian (2015), Batt and Terwiesch (2015) provide some evidence that an individual's utility and abandonment behavior may not be related to her elapsed time in line. Pazgal and Radas (2008) study the effect of notifying subjects of elapsed time through a clock and find that it does not influence their queue abandonment. Akşin et al. (2020) conduct lab experiments to study individuals' balking and reneging behaviors while controlling for total waiting time. They indicate that in most scenarios (except for queues with a fast start), there is no evidence of sunk cost bias: an individual's reneging decision is not impacted by her experienced wait. These studies show that individuals' queuing behavior often follows the rational assumption that their abandonment decision is based on the remaining wait instead of their elapsed wait. Thus, we make the following hypothesis.

Hypothesis 1a (H1a): *Controlling for the characteristics of the prospective queue, the experienced wait has no impact on subjects' completion cost.*

However, other behavioral research suggests that more may be going on; in particular, that waiting results in two opposing forces within an individual. The first strand of studies indicates that experiencing queuing wait increases people's completion costs. Psychology and marketing scholars find that an idle-wait experience leads to an increase in anxiety, unpleasantness, and stress, which could thus raise their completion costs (Maister 1984, Osuna 1985, Carmon and Kahneman 1995). On the other hand, the literature also suggests that over time, a second competing force—completion commitment—pushes subjects to continue to stay in line, i.e., decreasing their disutility over time. For example, Webb et al. (2017) find that, the longer customers spend waiting in unobservable queues, the less likely they are to renege. Janakiraman et al. (2011) propose a model that combines both forces within an individual, and experimentally show how such a model can help explain reneging decisions in unobservable queues. Based on this evidence, we make the following competing hypothesis.

Hypothesis 1b (H1b): *Controlling for the characteristics of the prospective queue, the experienced wait has a significant impact on subjects' completion cost.*

3.3.2 Prospective Queue

Next, we address the potential impact that the characteristics of the prospective queue may have on subjects' completion cost. In particular, we explore the roles of waiting time ($l \times s$), queue length (l), and service time (s). To the best of our knowledge, we are the first to concurrently study all three factors, and thus to disentangle whether and to what extent subjects' completion cost may be separately impacted by each of them. Most experimental studies include only the effect of waiting time, or measure the additional effect of queue length *or* service time—but not both. Nevertheless, we next build on the existing literature to formulate hypotheses regarding the potential effect of each of these factors on completion costs.

We first focus on prospective waiting time ($l \times s$). People treat time as a valuable resource and are averse to time losses (Leclerc et al. 1995). Thus, it is widely accepted that, all else equal, people prefer a shorter waiting time (Naor 1969, Mandelbaum and Shimkin 2000, Shimkin and Mandelbaum 2004, Cui et al. 2018). In experimental and empirical studies, total waiting time is also found to significantly impact people's decisions. For example, Hannigan and Flicker (2020) conduct a conjoint-analysis study where subjects are systematically asked to choose among pairs of queues with different characteristics, and find that subjects prefer queues with shorter average waiting time. Similarly, studies show that people are more likely to join lines with smaller waiting times in observable queues (Pazgal and Radas 2008). We thus formulate the following hypothesis.

Hypothesis 2a (H2a): *Controlling for the effects of experienced wait, prospective queue length, and service time, completion cost is increasing in the waiting time of the prospective queue.*

Traditionally, under perfect rationality assumptions, individuals' cost of waiting is expected to depend only on prospective waiting time, regardless of whether such time is due to, e.g., a long and fast queue or a short and slow queue (Hassin and Haviv 1995, Afeche and Sarhangian 2015). However, a number of studies show that individuals' behaviors deviate from this assumption. For example, Conte et al. (2016) note that participants tend to focus more on queue length than other characteristics when making joining decisions with time limitation. Lu et al. (2013) suggests that this may be due to the fact that queue length is a visual cue, easier to perceive than, e.g., service time. Similarly, even after controlling for waiting time, Akşin et al. (2020) suggest that a shorter length leads to less reneging. Based on this evidence, we hypothesize that a greater queue length (l) increases subjects' completion cost.

Hypothesis 2b (H2b): *Controlling for the effects of experienced wait, prospective waiting time, and service time, completion cost is increasing in the length of the prospective queue.*

The last queue characteristic that we study is service time (s). Compared to waiting time and queue length, the effect of service time on completion cost remains understudied, and its effect is hence less clear. Some studies find no significant impact of speed on people's queuing decisions. For example, Conte et al. (2016) indicate that some people do not incorporate server speed when making joining decisions. Similarly, Lu et al. (2013) study purchase incidence and find that customers do not react enough to the speed in line. However, other studies find a significant effect of service time. Batt and Terwiesch (2015) and Bolandifar et al. (2019), for example, find that emergency-room patients choose a queue with faster speed, as it influences their perception of waiting time. Thus, in our setting, service time may also play a role in influencing people's completion cost. This is particularly the case given that we consider a setting where, contrary to Lu et al. (2013) and Conte et al. (2016), the service time is known with certainty.

Hypothesis 2c (H2c): *Controlling for the effects of experienced wait, prospective waiting time, and queue length, completion cost is increasing in the service time of the prospective queue.*

Finally, we also investigate whether and how individuals' affective attitudes towards waiting moderate their responses to experienced wait and/or the characteristics of the prospective queue. Several studies assume that impatience—and in particular, heterogeneous levels of it—drive individuals' reneging behavior in queues (e.g., Mandelbaum and Shimkin 2000, Akşin et al. 2013, Su 2007). Similarly, Durrande-Moreau and Usunier (1999) show that impatience has a negative impact on individuals' satisfaction with a waiting experience. Thus, it is reasonable to expect that subjects with negative affective attitudes towards waiting may exhibit a greater level of completion cost. However, it is not clear whether such a difference may manifest itself as an overall higher level of cost; whether it may arise only after the experienced wait; or whether it may change how individuals respond, for example, to only one or some of the factors of a prospective queue. To the best of our knowledge, none of the existing studies provide a direct measure of how impatience influences completion cost in a manner that would allow us to answer these questions. Moreover, impatience is typically assumed in the operations management literature to be equivalent—by construction—to willingness to continue to wait in line, which is different from our measure based on psychological traits (e.g., Webb et al. 2017, model patience as an individual's survival time in a queuing setting). Therefore, we do not formulate specific hypotheses for the impact of affective attitudes on our results. Instead, we investigate this as an open question in our empirical analyses.

3.4 Experimental Results

In this section, we discuss our experimental results. In particular, we use our experimental data to address our main research questions, namely, how do: (i) the *experienced wait* and (ii) the characteristics of the *prospective* queue influence completion costs? In addition, we explore whether and how the answers to these questions depend on participants' *affective attitudes* towards waiting.

Table 3.2 presents summary statistics of completion cost by experimental condition. First, rows 1–3 present participants' average completion cost for different values of experienced length (w), given the same prospective length ($l = 7$ customers) and varying service time (s). At the aggregate level, i.e., without distinguishing by affective attitudes, we do not observe any consistent effect—positive or negative—on completion cost as experienced length increases. A two-way ANOVA test, with interaction between service time and experienced length, corroborates this observation: completion cost is only correlated with service time ($p < 0.01$), but neither experienced length nor its interaction with service time are significant ($p > 0.1$). Conditional on $l = 7$, this main effect of service time on completion cost is also confirmed with a nonparametric test (Kruskal-Wallis test, $p < 0.001$). Second, rows 3–5 in Table 3.2 summarize participants' completion cost as a function of service time and prospective length, given experienced length $w = 0$ (i.e., before any wait has occurred). We observe an overall increasing trend in average completion cost as service time or prospective length increase. Through a two-way ANOVA test, we confirm that their main effects are significant ($p < 0.01$), though surprisingly, their interaction is not ($p = 0.496$). We also confirm these results with nonparametric tests: conditional on $w = 0$, we find significant main effects of prospective length and service time on completion costs (Kruskal-Wallis test, $p = 0.01$ and $p < 0.001$, respectively).

In addition, as discussed in §3.2.1, we calibrate the parameters of the virtual store and queue so that most participants, if they were given the option, would voluntarily join and then choose to stay in the experimental queues. Indeed, we find that the completion cost is equal to 100 (or equivalently, the utility M is equal to 0) in only 3.20% of the observations. In other words, in almost 97% of the cases, subjects assign a positive value to staying in line;

Table 3.2: Summary Statistics of Participants' Completion Cost

Prospective Length (l) (clients)	Experienced Length (w) (places)	Service Time (s) (5 secs./client)	(10 secs./client)	(20 secs./client)
7	6	20.74 (25.61) N=72	34.84 (29.44) N=61	33.68 (30.94) N=56
7	3	27.05 (29.09) N=64	29.73 (27.10) N=70	34.64 (31.26) N=64
7	0	20.67 (28.31) N=69	29.59 (28.46) N=68	36.59 (30.93) N=61
10	0	25.57 (30.25) N=67	32.43 (29.76) N=67	45.40 (33.12) N=63
13	0	32.49 (31.83) N=73	35.53 (31.62) N=57	44.84 (27.36) N=56

Note: Mean (standard deviation) of completion cost. N denotes the number of observations in each cell.

i.e., in the absence of an alternative offer, they would choose to join and/or stay in line.

To formally investigate our hypotheses, we consider the following random-effects Tobit regression:

$$V_{ij}^* = Intercept + \beta_W \cdot ExpLength_{ij} + \beta_S \cdot ServTime_{ij} + \beta_L \cdot Length_{ij} + \beta_{WS} \cdot ExpLength_{ij} \cdot ServTime_{ij} + \beta_{LS} \cdot Length_{ij} \cdot ServTime_{ij} + \beta_j \cdot Round_j + \mu_i + \epsilon_{ij} \tag{3.1}$$

We use a Tobit model because the value of V is bounded between 0 and 100, with 18.08% (3.20%) of all observations corresponding to $V = 0$ ($V = 100$). Thus, a Tobit model is recommended (Wooldridge 2002, pp. 517–542). Similarly, we include participant-level random effects because we have four observations for each participant, one for each round. The dependent variable V_{ij}^* denotes the Tobit model's latent variable for participant i in round j. $ExpLength$, $ServTime_{ij}$, and $Length_{ij}$, are the experienced length (in number of places moved), service time (in seconds per person), and prospective length (in number of customers) of the queue that participant i observes when receiving the elicitation question in round j. $ServTime_{ij}$ and $Length_{ij}$ are centered around their median values, i.e., 10 seconds per person and 10 customers ahead, respectively.[3] We control for round effects with the dummy variables $Round_j$, equal to 1 in round j and 0 otherwise (with round 1 as the baseline level). Finally, μ_i is the individual error term and ϵ_{ij} is the independent error across participants' responses in the QT.

In addition to the model in Equation (3.1), we also consider variations of it where we explore whether our results are moderated by participants' affective attitudes towards waiting. In particular, we define the dummy variable $NegAffect_i$ as equal to 1 if participant i responded Yes to the question "Do you get upset when you have to wait for anything?", and equal to 0 otherwise. Participants with $NegAffect_i = 1$ ($NegAffect_i = 0$) are hereafter referred to as having (not having) *negative affective attitudes*, and they correspond to 28.9% (71.1%) of all observations. As discussed in §3.2, we also asked participants their agreement with the statement "In comparison to others, are you a person who is generally willing to give up something today in order to benefit from that in the future, or are you not willing to do so?" However, only 9.5% of participants indicate that they are unwilling or strongly unwilling to do so, versus 80.6% of them indicate that they are willing or strongly willing. The skewness of these responses makes it difficult to use them for moderation purposes. Nevertheless, we note that participants' level of agreement with the two affective-response questions is highly correlated (χ^2 test, $p < 0.05$). Thus, participants with $NegAffect = 1$ are also significantly more willing to "give up something today" than those with $NegAffect = 0$.

In what follows, we discuss our main results separately by the effects of experienced wait (Hypotheses 1a–1b) and prospective queue characteristics (Hypotheses 2a–2c).

[3] Since the interaction between $ServTime_{ij}$ and $Length_{ij}$ is also included in Equation (3.1), centering ensures that the main effect of service time (length) is evaluated at a meaningful level of length (service time)—as opposed to when the non-focal variable takes the meaningless value of 0. Moreover, centering helps to reduce the correlation between single variables and interaction terms, *without* influencing either the estimate or statistical significance of the latter (Jaccard et al. 1990, Dalal and Zickar 2012, Iacobucci et al. 2016). Indeed, we confirm that multicollinearity is not a serious concern in our analyses: the greatest coefficient of correlation (in absolute terms) between our coefficients is less than 0.6; and the variance inflation factor (VIF) that we obtain with an OLS-specification (where our results continue to hold) is less than 3.3 for all terms, including interactions.

3.4.1 Results: Experienced Wait

Table 3.3 summarizes our results under different model specifications. First, Column (1) presents the results of Equation (3.1), i.e., without considering affective attitudes or additional control variables. We find that the variable $ExpLength$ is not statistically significant, and neither is its interaction with service time. Thus, at the aggregate level and controlling for the characteristics of the prospective queue, we do not find a significant effect of experienced wait (either as number of places moved, $ExpLength$, or as experienced time in line, $ExpLength \cdot ServTime$) on completion cost.

However, the apparent lack of effect of experienced wait at the aggregate level masks a significant moderation effect based on participants' affective attitudes towards waiting. Column (2) in Table 3.3 shows the regression results when we include the interactions of $ExpLength$, $ServTime$, and $ExpLength \cdot ServTime$ with the dummy variable $NegAffect$. With these added variables, we find that $ExpLength \cdot ServTime$ is significant and negative; i.e., conditional on participants <u>not</u> having negative affective attitudes (i.e., when $NegAffect = 0$, the baseline level), a long experienced time leads to a *lower* disutility, compared to those who have not experienced wait. Conversely, we find that $ExpLength \cdot ServTime \cdot NegAffect$ is statistically significant and positive. As a result, conditional on participants having negative affective attitudes (i.e., when $NegAffect = 1$), a long experienced time leads to a *greater* disutility.[4]

The above result is driven, and hence best illustrated, by participants' behavior in slow queues (i.e., when $ServTime = 20$ secs./client). In this service-time condition—where the experienced times are the longest—we observe (i) clear trends for the effects of experienced wait on participants' completion costs, and as a result, (ii) the biggest differences between having vs. not having experienced wait. Figure 3.2 depicts these costs, conditional on $Length = 7$ and $ServTime = 20$, separately by affective attitudes and experienced length. Consistent with the regression results, we find that as experienced length increases, completion costs decrease (increase) among participants without (with) negative affective attitudes. As a result, when $NegAffect = 0$, the average completion cost decreases from 37.7 tokens

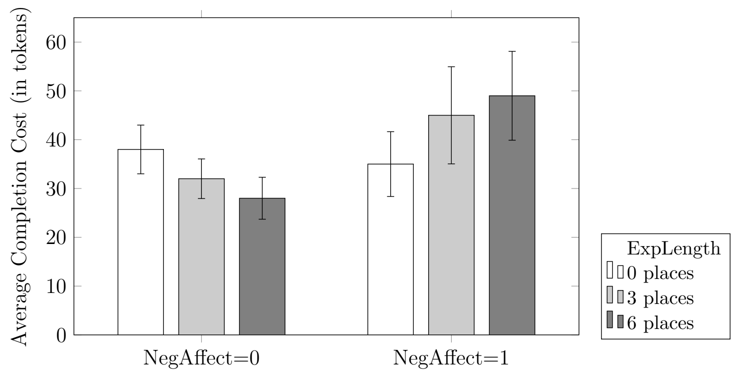
[4]The sum of the regression coefficients for $ExpLength \cdot ServTime$ and the triple-interaction $ExpLength \cdot ServTime \cdot NegAffect$ is equal to 0.215, which is significantly greater than zero (z test, $p < 0.1$)

Table 3.3: Random-effects Tobit Model Results for Completion Cost

	(1)	(2)	(3)	(4)
Intercept	34.55***	34.57***	34.73***	24.18**
	(2.45)	(2.77)	(2.77)	(8.00)
ExpLength	0.20	0.15	0.34	0.39
	(0.45)	(0.50)	(0.52)	(0.52)
ServTime	1.29***	1.38***	1.37***	1.36***
	(0.17)	(0.20)	(0.20)	(0.20)
NegAffect		1.18	1.09	1.75
		(4.47)	(4.48)	(4.34)
ExpLength · ServTime	-0.08	-0.19*	-0.21*	-0.20*
	(0.07)	(0.08)	(0.08)	(0.08)
ExpLength · NegAffect		0.09	-0.71	-0.70
		(0.82)	(1.01)	(1.00)
ServTime · NegAffect		-0.27	-0.27	-0.26
		(0.36)	(0.36)	(0.36)
ExpLength · ServTime · NegAffect		0.40**	0.50**	0.48**
		(0.13)	(0.16)	(0.16)
Length	1.64***	1.64***	1.98***	2.02***
	(0.45)	(0.45)	(0.52)	(0.52)
Length · ServTime	0.03	0.02	-0.02	-0.01
	(0.07)	(0.07)	(0.08)	(0.08)
Length · NegAffect			-1.36	-1.35
			(1.01)	(1.01)
Length · ServTime · NegAffect			0.15	0.14
			(0.15)	(0.15)
Round = 2	-8.49***	-8.66***	-8.78***	-8.75***
	(2.24)	(2.23)	(2.22)	(2.23)
Round = 3	-7.51***	-7.69***	-7.76***	-7.76***
	(2.24)	(2.23)	(2.23)	(2.23)
Round = 4	-9.10***	-9.70***	-9.83***	-9.84***
	(2.24)	(2.23)	(2.23)	(2.23)
Risk				0.78
				(0.49)
TimeValue				0.14***
				(0.04)
Male				3.52
				(3.85)
Age				-0.17
				(0.24)

Note. Standard errors in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 3.2: Effects of Experienced Length on Completion Costs, by Affective Attitudes towards Waiting ($ServTime = 20$ secs./client)



Note. All cases have equal prospective length at 7 clients. The error bars correspond to standard errors of the mean.

at $ExpLength = 0$, to 28 tokens at $ExpLength = 6$ (one-tailed Wilcoxon rank-sum test, $p < 0.1$). Conversely, when $NegAffect = 1$, the average completion cost increases from 34.6 tokens at $ExpLength = 0$, to 49.1 tokens at $ExpLength = 6$ (one-tailed Wilcoxon rank-sum test, $p < 0.1$). Interestingly, as a result of these opposite effects, we observe that the completion costs of the two affect-types are statistically similar before the experience of wait (two-tailed Wilcoxon rank-sum test, $p = 0.7$), but they are significantly different from each other after moving 6 places in line (two-tailed Wilcoxon rank-sum test, $p < 0.05$).[5]

Following the suggestion by Janakiraman et al. (2011) that two opposing forces are at play while waiting in line, we conjecture that the net effect of experienced time on participants without negative affective attitudes is dominated by a sense of *commitment* (ibid, p. 971) to complete the line; whereas it is dominated by an increasing sense of *displeasure* (ibid, p. 973) among participants with negative affective attitudes. We summarize these observations

[5] Figure 3.5 shows the effect of experienced length on completion costs when $ServTime = 5$ and when $ServTime = 10$. In the latter case, we do not observe significant differences by $ExpLength$. When $ServTime = 5$, we continue not to observe significant differences among participants with $NegAffect = 1$, but find a small increase in completion cost among participants with $NegAffect = 0$ after the experience of wait (from 20 tokens when $ExpLength = 0$, to 23.6 tokens when $ExpLength = 6$, one-tailed Wilcoxon rank-sum test, $p < 0.05$). Following Janakiraman et al. (2011), we conjecture that among these participants, the experience of wait may have a nonlinear effect, with completion costs slightly increasing following a short wait, before decreasing for longer waits. The study of potential nonlinear effects of experienced time on completion costs is beyond the scope of this paper.

in the following result:

Result 1: *The effect of experienced wait on completion cost depends on participants' affective attitudes towards waiting. Controlling for the characteristics of the prospective queue, a long experienced time is associated with an increase (decrease) in completion costs among participants who have (do not have) negative affective attitudes. Thus, we find support for H1b.*

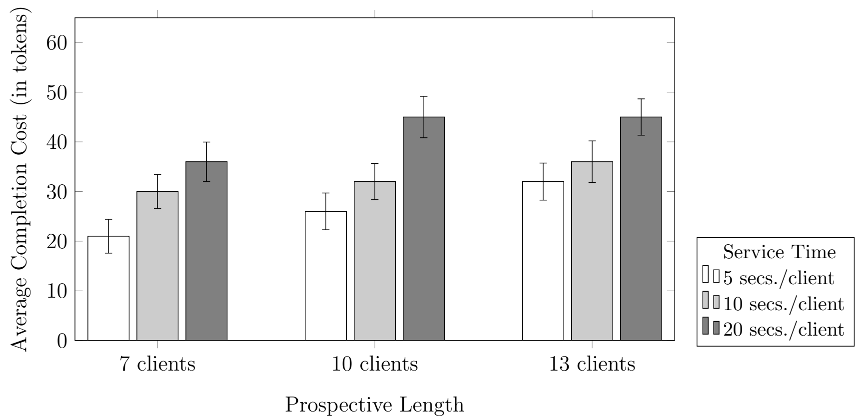
Before continuing, we make the following observation. Since participants' affective attitudes are self-reported and measured at the end of the study, it is possible for this attitudinal question to be used by participants to rationalize their responses in the QT. In other words, participants who state a high (low) completion cost may explain their choices by indicating that they have (do not have) negative affective attitudes. However, we do not find evidence to support this conjecture. First, we observe in Table 3.3 that the variable $NegAffect$ is not statistically significant, i.e., it does not have a main effect on completion costs. Similarly, we find that the average completion cost (averaged across rounds for each participant) is not significantly different between participants who have versus do not have negative affective attitudes (34.26 vs. 30.91 tokens, respectively; Wilcoxon rank-sum test, $p = 0.29$).

3.4.2 Results: Characteristics of the Prospective Wait

Next, we study how the characteristics of the prospective queue impact participants' completion cost. In particular, based on the model formulation in Equation (3.1), we are interested in understanding the effects of $Length$, $ServTime$, and their interaction, where the latter corresponds to (prospective) waiting time. Even though the regression results include observations from participants who have and have not experienced wait, it is worth noting that: (i) since the variable $ExpLength$ is also included in the regression model, the three aforementioned coefficients are evaluated in the baseline level where $ExpLength = 0$; and (ii) our results remain unchanged if we only include observations from participants who have not experienced wait.

First, we observe in Column (1) of Table 3.3 that the main effects of service time and length are positive and statistically significant; i.e., participants' completion costs increase

Figure 3.3: Effects of Prospective Length and Service Time on Completion Cost



Note. All cases have no experienced length (i.e., they correspond to conditions where experienced length is equal to 0). The error bars correspond to standard errors of the mean.

with them. Surprisingly, though, waiting time—captured by the coefficient estimate for $Length \cdot ServTime$—is *not* statistically significant. Figure 3.3 helps to illustrate these results. For each combination of prospective length and service time, it shows participants' average completion cost when $ExpLength = 0$. Thus, it provides a graphical representation of rows 3–5 in Table 3.2. As previously noted, a two-way ANOVA test confirms that the main effects of length and service time are significant ($p < 0.01$), but their interaction is not ($p = 0.496$). Controlling for prospective length, the difference in average completion cost between queues with 20 and 5 secs./client is approximately equal to 12.32, 19.83 and 12.35 tokens when the prospective length is equal to 7, 10, and 13 clients, respectively. Similarly, controlling for service time, the difference in average completion cost between queues with 7 and 13 clients in prospective length is approximately equal to 11.8, 5.9, and 8.3 tokens when the service time is 5, 10, and 20 secs./client, respectively. Thus, we find that increasing service time (length) has a similar effect on completion costs *regardless* of the prospective length (service time).

These results are consistent with participants' responses to the exit survey regarding how they determined the utility M of the queue. Specifically, we ask three 5-point Likert scale agree/disagree questions regarding how they determined this value: (i) "I estimated the total time that it would take me to complete the line"; (ii) "I considered how long it took to serve each customer"; and (iii) "I considered the number of customers waiting ahead of me." We find that participants agree significantly more with using service time and queue length to determine the value of M, compared to using an estimate of waiting time (one-tailed paired Wilcoxon rank-sum tests, $p < 0.01$).

Next, column (3) in Table 3.3 introduces interaction terms between the dummy variable $NegAffect$ and all variables in Equation (3.1), i.e., with respect to both experienced and prospective wait. Interestingly, we find that affective responses to waiting do not moderate the effect of either service time or prospective length on participants' completion cost. In addition, similar to column (2), $NegAffect$ also has no significant main effect on completion cost. Thus, combined with Result 1, we conclude that participants' affective attitudes have an impact on completion cost *only* after participants have experienced wait. This observation suggests that our affective measure captures how participants react to the experience of wait, but that they do not seem to anticipate these emotional reactions when evaluating prospective wait. Finally, Column (4) confirms that our results continue to hold when we control for participants' control-task responses and demographic characteristics. We find that the variable $TimeValue$, which corresponds to the minimum amount that a participant needs to be paid to accept a two-minute wait, has a positive and significant effect on completion cost. Across all model specifications, we also find that the dummy variables for rounds > 1 have a significant negative effect, i.e., completion cost is lower in rounds 2–4 than in round 1 (the baseline level).

To summarize, we find the following result regarding the effect of the prospective queue characteristics on participants' completion cost:

Result 2: *Participants' completion cost increases with both the length and service time of the prospective queue. Surprisingly, however, the interaction between length and service time—prospective waiting time—is not statistically significant. Thus, we find support for Hypotheses 2b and 2c, but not for 2a. These results hold regardless of participants' affective responses to waiting.*

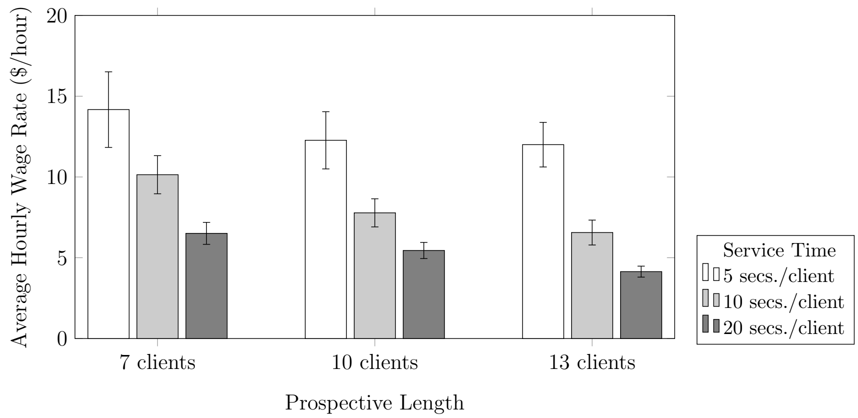
Note that this result does not mean that participants do not care about how long they have to wait in line. In our experiment, participants correctly anticipate that an increase in service time or queue length increases the total time that it will take for them to complete a queue.[6] However, our results demonstrate that this response is *not directly proportional* to the waiting time that an extra person or an extra second-per-person adds to the wait. This result is all the more striking when we consider that in our experiment, there is no uncertainty in service time, which makes the computation of waiting time trivial.

3.4.3 Additional Results: Wage Rate

Finally, we discuss two additional results regarding participants' wage rate, i.e., the amount of money that participants earn per unit of time. This measure is widely used in the economics literature as a measure of a subject's opportunity cost (e.g., Soman 2001, Okada and Hoch 2004). First, we validate that in our experiment, different sources of wage rate yield similar results. In particular, we have three sources of information to compute a participant's wage rate: the QT, the value-of-time control task, and the suggested pay rate from Prolific. In the QT, we compute a participant's wage rate as their completion cost divided by the time remaining to complete the queue, averaged over the four rounds of the game. In the value-of-time task, we similarly compute a participant's wage rate as the minimum amount that the participant needs to be paid to accept a two-minute wait, divided by two minutes. Finally, we consider the suggested pay rate from Prolific to be equal to \$9.60/hour, which was the minimum amount that Prolific encouraged researchers to pay their participants when our study was conducted (ProlificTeam 2022). To compare these measures, we transform each of them to dollars/hour. We observe that the three measures are similar to each other, equal to \$9.89/hour, \$11.46, and \$9.60, respectively. Furthermore, the average wage rate from the QT is statistically comparable to that from the control task (Wilcoxon rank-sum test, $p = 0.33$) and Prolific (Wilcoxon signed-rank test, $p = 0.45$). In other words, participants' opportunity costs are consistent when we compare the BDM procedure in a queuing versus simple-wait situation, as well as between the QT and payments

[6] In our post-experiment survey, we ask the following 5-point agree/disagree Likert questions: "When I estimated the total time that it would take me to complete the line, I considered how long it took to serve each customer;" and "When I estimated the total time that it would take me to complete the line, I considered the number of virtual customers waiting ahead of me." We find that 87.60% (83.88%) of the participants somewhat or strongly agree that they use service time (queue length) to estimate waiting time.

Figure 3.4: Effects of Prospective Length and Service Time on Wage Rate



Note. All cases have no experienced length (i.e., they correspond to conditions where experienced length is equal to 0). The error bars correspond to standard errors of the mean.

in Prolific. This finding suggests that the BDM mechanism is a promising and appropriate way to measure individuals' completion costs in queuing systems.

Second, we note that Result 2 has important implications for our understanding of individuals' wage rates. In particular, since participants' completion costs are *not* directly proportional to prospective waiting time, our results suggest that—contrary to rational-behavior predictions—individuals do not exhibit a constant wage rate. Instead, in a queuing setting, the monetary value that individuals assign to time depends on the characteristics of the queue. Figure 3.4 illustrates this observation by showing how the characteristics of the prospective wait affect participants' average wage rates. Using a two-way ANOVA test, we find that the wage rate is significantly impacted by length and service time ($p < 0.01$), while not impacted by their interaction ($p = 0.72$). In particular, we observe a tendency of the average wage rate to *decrease* in queue length and service time; i.e., individuals adjust their cost of waiting so that, for each unit of time, they demand a lower pay when the queue is longer or slower. A similar result is observed by Leclerc et al. (1995), who find that participants' opportunity costs depend on the waiting situation, and the marginal value of time is higher in a short wait than in a long wait. However, to the best of our knowledge, we are the first to find evidence of and quantify this behavior in an incentivized, observable queuing setting.

3.5 Conclusions

In this study, we conduct an incentivized human-subject experiment to investigate how (i) the experienced wait and (ii) the characteristics of the prospective wait influence individuals' completion costs in queues. Contrary to past studies that rely solely on binary balking or reneging decisions, we introduce the use of the BDM mechanism to directly measure participants' completion costs at different points in time and with varying queue characteristics. Thanks to this approach, we not only obtain a more granular measure, but can also compare the completion cost of participants who have versus have not experienced wait while controlling for the (perfectly known) prospective queue. As a result, we are the first to isolate the impact that waiting has on individuals' completion costs. Similarly, our methodology and experimental design allow us to measure the effects that the length, service time, and waiting time of a prospective queue have on individuals' utility. To the best of our knowledge, our study is the first to disentangle the impact of these queue characteristics.

Our results challenge two important rationality assumptions that are common in queuing theory. First, we find that the experienced wait cannot always be ignored; i.e., completion costs may not depend only on the prospective queue. Though a similar observation has been made in the literature regarding within-subject differences over time (e.g., Janakiraman et al. 2011), our results show that there are important *between-subject* differences as well. Given the same wait and prospective queue, the experienced wait may change participants' completion costs in opposite directions—and we identify affective attitudes towards waiting as a key moderator of this effect. Second, our results also challenge the assumption that, when it comes to the prospective queue, all that matters is the total time that it takes to complete it. By concurrently evaluating the effects of queue length, service time, and waiting time, we find that length and speed have *additive* effects; i.e., they are not proportional to the impact that an extra person in line or an additional second/person have on waiting time. This result echoes past findings that suggest people's perceptions of wait are driven by heuristics (e.g., Conte et al. 2016), such as the easily observable queue length, rather than by a rational calculation of the total time ahead. Interestingly, however, we observe both of these deviations from rational behavior in a context where the length and service time of the queue are *perfectly known*, and hence the waiting time can be easily estimated. Therefore, the effect of experienced wait cannot be attributed to learning about the prospective wait; and the additive effects of length and speed cannot be attributed to the difficulty of estimating waiting time. In other words, we find evidence of *behavioral* responses to experienced wait, length, and service time, with an experimental design that minimizes rational alternative explanations for our observations.

From a practical standpoint, our methodology allows us to assign a monetary value to individuals' perceived cost of completing a queue. This can be particularly helpful to decision-makers who are increasingly offering monetary incentives and other forms of alternatives to individuals to manage congestion in queues. For example, transit agencies have offered rewards for people to change their commuting routes and/or departure times, particularly by leveraging big data from mobile phones (Greene-Roesel et al. 2018, Sun et al. 2020a). Or, in a healthcare setting, patients in Ontario who need to test for sexually transmitted infections have the option to "pay to skip the line" to see a provider at public clinics, and instead provide samples at private testing labs (MacKinnon et al. 2021). In this context, our results suggest that subjects' willingness to accept such incentives, or willingness to pay for wait-reduction options, may be impacted by perceptions of queue length and service time in a manner that is not necessarily proportional to the waiting time of the queuing situation. Regarding *when* to make such offers, we identify under which conditions decision-makers should pay special attention to whether individuals have been waiting in line (when service speed is slow); and that individuals' responses to experienced wait—and thus their likelihood to accept or reject alternative offers—is likely to depend on their affective attitudes towards wait.

Finally, the additive nature of the effects of length and speed on people's completion costs have important implications for the optimal allocation of resources in a queuing system. For example, a decision to pool multiple queues can reduce overall waiting time, but it may backfire due to the associated increase in queue length—and to what we observe are customers' behavioral responses to it. Similarly, our results suggest that in very long and/or very slow queues, an additional person or additional delay in service time may not change customer completion costs as much as predicted by the rational model. Conversely, the opposite is true for very short and/or very fast queues, where participants may react to an additional person or an increase in service time *more* than predicted by the rational model—even when the increase in waiting time is small.

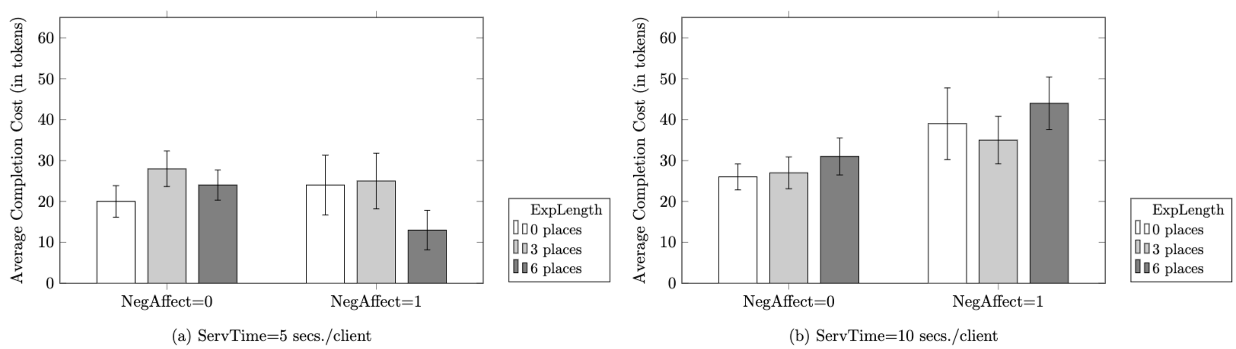
We believe that the framework we introduce in this study is easy to extend to analyze people's completion costs, and utility more broadly, in more complex queuing settings. Thus, we identify several interesting future research directions. For example, researchers can use the BDM mechanism to study a context featuring uncertainty. This would allow them to analyze both the main effect of uncertainty on completion costs, as well as whether and how it impacts the roles of experienced wait, length, and service time identified in the present study. Similarly, this incentivized mechanism could be used to evaluate completion costs throughout a queue to get a more detailed representation of how these costs evolve over time. Our study could also be extended to incorporate additional factors that were considered outside the scope of our present work, such as the the effect of having people waiting behind the focal subject, or the value of the product or service, to name a few. Finally, it would be interesting to investigate whether there are any significant non-linear effects of experienced time, prospective length, or service time on completion costs. We hope that our work will help other researchers to continue to investigate behavioral deviations from rationality in queuing settings, and that it may help lay the groundwork for future research on the management of queues through incentives and alternative offers.

Table 3.4: Random-effects Tobit Model Results for Completion Cost with All Observations

	(1)	(2)	(3)	(4)
Intercept	34.81***	34.48***	34.64***	28.13***
	(2.43)	(2.76)	(2.76)	(8.08)
ExpLength	0.13	0.13	0.30	0.34
	(0.44)	(0.49)	(0.51)	(0.51)
ServTime	1.24***	1.29***	1.28***	1.28***
	(0.17)	(0.20)	(0.20)	(0.20)
NegAffect		2.20	2.11	2.44
		(4.46)	(4.46)	(4.37)
ExpLength · ServTime	-0.06	-0.16*	-0.19*	-0.18*
	(0.07)	(0.08)	(0.08)	(0.08)
ExpLength · NegAffect		-0.03	-0.80	-0.80
		(0.80)	(0.99)	(0.99)
ServTime · NegAffect		-0.16	-0.15	-0.13
		(0.36)	(0.36)	(0.36)
ExpLength · ServTime · NegAffect		0.38**	0.47**	0.45**
		(0.13)	(0.16)	(0.16)
Length	1.52***	1.52***	1.84***	1.88***
	(0.45)	(0.44)	(0.52)	(0.52)
Length · ServTime	0.02	0.02	-0.01	-0.01
	(0.07)	(0.07)	(0.08)	(0.08)
Length · NegAffect			-1.31	-1.31
			(1.00)	(1.00)
Length · ServTime · NegAffect			0.14	0.14
			(0.15)	(0.15)
Round controls	YES	YES	YES	YES
Additional controls	NO	NO	NO	YES

Standard errors in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 3.5: Effects of Experienced Length on Completion Costs, by Affective Attitudes towards Waiting ($ServTime$ = 5 and 10 secs./client)



Note: All cases have equal prospective length at 7 clients. The error bars correspond to standard errors of the mean.

4.0 On Joining Decisions When Customers Travel to a Queue: An Experimental Study

Traditional queuing systems assume that people join a queue immediately after they decide to join. However, in practice, it is common that people need to spend time and effort going to a store for a service or product. In this study, we focus on a queuing system in which customers have to travel to wait. That is, customers first need to decide whether to travel to a store and then start to wait after arrival. We conduct an experiment to study how travel impacts individuals' valuations of a queuing system that they must travel to. In addition, we investigate what mechanisms and theories drive people's behavior. With the Becker-DeGroot-Marshak (BDM) mechanism, our pilot experiment shows that the difference in how people value a service system before and after traveling is based on the characteristics of the queue. Interestingly, we observe that individuals' utility is significantly higher before than after traveling to the queue when queues are fast and long. However, when queues are slow and short, we find partial support for their utilities being higher after than before traveling. From a rational point of view, the value of queues should be the same, controlling for total waiting time. To explain this phenomenon, we refer to the mechanism of the "cold-to-hot" empathy gap with respect to the pain associated with waiting (Read and Loewenstein 1999). Our next step is to use a new experimental study to investigate the difference in affective states (momentary emotion) before and after traveling to a queue. In addition, we plan to investigate whether the difference in individuals' utility valuations and affective states before and after travel relates to the information-sharing level (i.e., basic, sufficient, and complete waiting information) of a queuing service system in which people must travel to. In other words, we will determine whether customers' gaps in utilities and affective states before and after traveling are reduced when they are provided with a higher information-sharing level about waiting time, thus impacting their queuing decisions.

4.1 Introduction

Service providers nowadays are providing more online queuing information (e.g., waiting time forecast) than ever to serve customers better and improve their wait experience. For example, Google offers real-time "Popular Times" information, which is about service providers' relative busyness compared to their historical data. The trend of sharing queuing information happens both in unobservable settings (e.g., call centers (Yu 2020)) and in observable settings (e.g., restaurants on the Yelp waitlist (Hu et al. 2021)). This information helps people better anticipate a queuing system and decide whether to join the wait in line remotely before traveling to a store (Hassin and Roet-Green 2020).

Though they realize the importance of travel to a queue, these studies do not focus on the impact of the travel itself and ignore the time and effort that customers spend to travel to the remote queuing system. That is, whether people's joining decision to visit a store that requires travel differs before and after traveling is unclear. It is a critical question since, in practice, a customer checks the online queuing information to decide whether to travel and then she determines whether to join the queue at the store. She has to make two decisions in tandem to queue for the service output. Therefore, our study aims to investigate customers' behavior before and after traveling to a queue.

Our research is also motivated by a practical question in Smart City. To mitigate transportation congestion during rush hours, social planners often use incentives to nudge passengers' traveling decisions to smooth the traffic (Spielman 2017, Greene-Roesel et al. 2018). The question is thus whether to send incentives when customers are at home or when they are at transportation stations. The program's effectiveness depends on the difference in people's utility before and after the travel to a queue. Without knowing this difference, it is impossible to know when to send incentives to customers economically and effectively.

In this chapter, we attempt to fill the gap by conducting a human-subject experiment. In particular, we study the following questions: (1) How are customers' utilities different before and after traveling to a queuing system, controlling for the total waiting time? (2) If there is a difference between before and after traveling, what mechanism drives the customer's behavior? (3) Does the information-sharing level of a queue before traveling impact a customer's valuation? Besides the traditional literature that studies customers' valuations indirectly through balking, we also measure individuals' utilities by employing the Becker-DeGroot-Marshak (BDM) mechanism. This incentive-compatible method helps us to elicit people's actual evaluations truthfully and directly. By controlling the queuing characteristics and the timing of our BDM elicitation questions, our pilot study allows us to (i) compare participants' utilities with the same prospective waiting time between before and after traveling to a queue; and (ii) measure the effects of queue length and service time on individuals' joining decisions and utilities.

4.2 Literature Review

In this paper, we investigate the impact of travel to a queue on people's joining decisions by conducting a human-subject experiment to measure people's valuation before and after the travel. The valuation of a queuing system is determined by individuals' estimation of the wait and the travel before obtaining service. We also apply behavioral theory to investigate individuals' psychological changes regarding travel. Thus, our research contributes to two streams of literature on the queuing system.

4.2.1 Joining Decisions in Queues

People's decision about whether to join or balk a queue is one of the most commonly studied research questions in the queuing literature. Since Naor (1969)'s work, researchers have started incorporating human decision-making into queuing systems. It is then widely assumed in the following studies that a customer joins a queue to maximize her utility. Our study falls into this stream of literature by extending inquiry into the impact of travel to a queue on people's utilities and joining decisions.

Assuming that people join a queue instantly, Naor (1969) first models a customer's joining strategy using a utility function with homogeneous waiting costs in queues. The customer's joining decision thus depends on the remaining waiting time. In an observable setting, it is widely assumed in theoretical modeling research that individuals incorporate service speed for each customer and queue length before service to calculate the total remaining waiting time for balking decisions (Wang et al. 2010, Afeche and Sarhangian 2015, Cui et al. 2018). This rational assumption is also supported by multiple empirical studies, which find that individuals' balking decisions are determined by total waiting time (Hui and Tse 1996, Hannigan and Flicker 2020).

However, other empirical and experimental studies show that people do not strictly follow rational assumptions. Instead, it is how individuals estimate total waiting time that determines their decisions (Donohue et al. 2018). In other words, individuals' expectation of the total waiting time relates to the queuing characteristics (i.e., service time and queue length). Pazgal and Radas (2008) find that participants' balking strategies depend solely on queue length in a postal office queuing setting. Conte et al. (2016) and Lu et al. (2013) find that people focus more on queue length than service speed to form their estimation of total waiting time and accordingly to make balking decisions. In addition, other studies show that in hospital emergency departments, balking decisions of patients are impacted by both queue length and service speed (Batt and Terwiesch 2015, Bolandifar et al. 2019). Similarly, Chapter 3 of this dissertation finds that controlling for the length of time spent in the queue, people's completion cost of a queue is driven by the main effects of service time and queue length instead of their interaction (i.e., the total waiting time).

To the best of our knowledge, only two papers investigate people's joining decisions in a queuing system that people must travel to. Hassin and Roet-Green (2020) is the first paper that discusses a queuing system that considers travel. They focus on an order-onsite model in that customers first decide whether to travel to a store with or without queuing information and then decide whether to join the queue for the service or not. Their study finds that to maximize system-performance evaluation, the service provider should conceal its queue-length information at low system congestion and disclose it at high congestion. Instead of an order-onsite model, Sun et al. (2020b) study an order-ahead model that remote customers can order before arriving at the facility. Namely, the traveling and the waiting happen simultaneously. Different from these two pioneering studies that theoretically model a queuing system that requires travel, our research focuses on the behavioral impact of the travel to an observable queue, as well as the mechanism that drives individuals' behavior. That is, we investigate how individuals' joining decisions and utilities differ at home before travel and at the service location after travel.

4.2.2 Psychological Change in Queues

Researchers have long studied people's psychological changes in the queuing literature. People hate waiting, as waiting generates anxiety and stress (Osuna 1985). During waiting in a queue, the idle wait worsens people's affective responses (Carmon and Kahneman 1995) and lengthens their feeling of wait (Maister 2005). Janakiraman et al. (2011) investigate individuals' abandonment decisions while waiting in line. The experienced long wait in line leads to a sunk cost that increases people's consuming amount (Ülkü et al. 2020). In addition, Chapter 3 studies the effects of experienced and prospective wait on individuals' utilities in queues. Different from these studies that focus on the psychological change in queues that customers can join instantly, this study extends to a queuing system for customers before they travel to the queue and is the first to investigate the psychological perspective of the travel to a queue.

From a rational point of view, people's value of a queue is determined by the waiting time ahead. In other words, an individual's valuations are the same between two waits with the identical waiting time. However, in the perspective of psychological cost, people may endure a sunk cost after experienced wait (Soman 2001). That is, in our scenario, an individual would have a higher utility after the travel. On the other hand, being at home and being at the store are different for individuals due to the change in environment, which would cause a difference in human behavior. To explain this phenomenon, we refer to the mechanism of "cold-to-hot" empathy gaps with respect to the pain of wait (Read and Loewenstein 1999). The theory states that people would have various affective states in different stages of a task, which eventually impact their evaluation and decision-making. Similarly, in our scenario, people in "cold" states (i.e., at home) would mispredict their tendency in future "hot" states (i.e., at the store). They may regret their decision, made before travel (i.e., in "cold" states), by overestimating their utility and valuation at the store. Namely, "cold-to-hot" empathy gaps would impede self-control (Loewenstein 2005) and could make an individual's utility higher before than after travel.

Research on people's behavior in a queuing system that people must travel to is rare (Sun et al. 2020b, Hassin and Roet-Green 2020). Different from their theoretical research, this study contributes to behavioral aspects of travel in both theory and practice. As complementary to the current behavioral queuing literature, our study enlarges the queuing behavior research by discussing the impact of travel on queuing decisions and the theory that drives people's behavior. In addition, it is valuable and critical for the service providers in practice. Our study sheds light on customer queuing system management before and after store travel.

4.3 Hypotheses

This section discusses our main hypotheses in this paper. To address our main research questions, we formulate separate hypotheses to investigate (1) the effect of travel on people's utilities, (2) how affective states connect to people's utilities before and after traveling, and (3) whether information level alters people's affective states.

4.3.1 The Travel to a Queue

With the benefit of online queuing information, customers are able to check the prospective wait at a store before traveling. It is common in daily life for customers to travel to a store. However, how travel impacts individuals' joining decisions is unclear. To the best of our knowledge, we are the first to study the impacts of travel on people's utility related to a queuing system. Based on the relevant literature on people's psychological cost in time, travel may lead to a higher utility after traveling due to the sunk cost fallacy (Soman 2001). In other words, the effort and time spent on the travel may increase people's intention to wait in line for the service. Therefore, we first hypothesize that individuals' utilities regarding a queuing service system become higher after traveling to the queue.

Hypothesis H1a (H1a): *Controlling for total waiting time, subjects' utility is higher after* *than before traveling to a queue.*

On the other hand, considering the change of location due to the travel, we refer to the findings of Loewenstein (2005) that people's decisions may vary, depending on self-reported discrepancy in a "cold to hot" scenario (i.e., from home to store). At home, a customer's utility of the remote service system depends on her expectation and imagination of the wait, which may change when she observes the queue. We refer to the home as the "cold" scenario and the store as the "hot" scenario. That is, people's utility becomes lower at the store, since they underestimate the cost and pain of waiting (Read and Loewenstein 1999, Loewenstein 2005) when they are at home. We thus make a competing hypothesis based on this theory that people's utilities are higher when they are at home than when they are at the store.

Hypothesis H1b (H1b): *Controlling for total waiting time, subjects' utility is higher before than after traveling to a queue.*

4.3.2 Affective States in Queues

Next, we study the affective state (i.e., momentary emotional state) before and after the travel to a queue. Compared with an unknown wait at a store, people would be more familiar with the home environment and are thus in a calmer emotion (i.e., a "cold" state). In other words, individuals are in a relatively hotter state when they observe the queue at the store. Read and Loewenstein (1999) suggest that, due to empathy gaps, people in a "cold" state would value more the utility of a service system and underestimate their pain and the cost of waiting that they will experience. In other words, after travel, observing the queue and being in the actual queue would remind people of the pain of the remaining wait and change their affective state from "cold to hot". Thus, we hypothesize that subjects would have a more negative affective state after than before travel.

Hypothesis H2 (H2): *Controlling for total waiting time, subjects' affective states are more positive before than after traveling to a queue.*

4.3.3 Information-Sharing Level of Queues

In addition, to help an individual make better decisions and to reduce the potential regrets experienced when they travel but balk at the store, we also investigate ways to reduce the gaps in individuals' affective states and valuation before and after travel. Considering the gap in affective states before and after travel, we believe that a higher information-sharing level about the store queue would help reduce people's underestimation at home. Similar to other behavioral queuing research, the sharing of queuing information allows individuals to form better expectations and increase the system efficiency (Hassin and Roet-Green 2020). That is, providing more details of queues before traveling increases transparency and could help individuals better estimate the wait in the store, leading to a smaller difference in affective states. Therefore, we hypothesize that a higher information-sharing level about the queue leads to a smaller gap in affective state before and after travel.

Hypothesis H3 (H3): *Controlling for total waiting time, subjects' gap in affective states before and after travel becomes smaller with a higher level of queuing information sharing.*

4.4 Pilot Experimental Study

Our pilot experiment contains three parts: the joining task and two control tasks. The joining task is the main focus of the study that investigates the participants' queuing behavior. We also consider two control tasks to measure individuals' risk preferences and value of time. In this pilot, we focus on participants' utilities before and after traveling. The pilot experimental design and result are discussed in the following sections.

4.4.1 The Joining Task

Our main component of the study is the joining task (JT), which is a computer-simulated queuing game at a single-player level. That is, the participants only interact with the experimental application. Before heading to a store, participants are initially given the following details to consider when deciding to join: (i) the number of virtual clients waiting in line at the store; (ii) the distribution of the service time for each client; and (iii) the number of experimental tokens as the reward (constant as 100 tokens) that participants get if they complete waiting at the store.

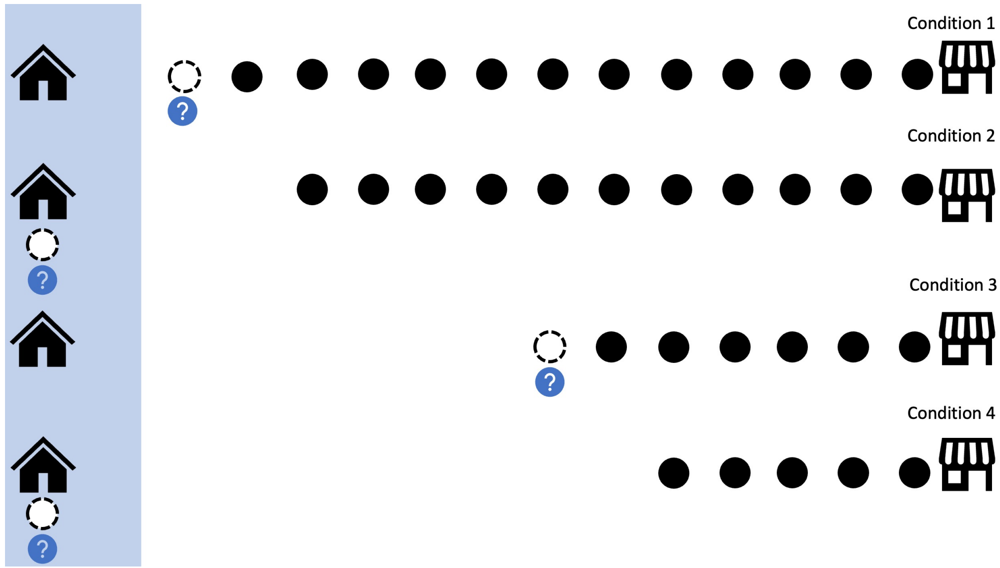
After a participant (she) decides to leave home and travel to the store, she may be required to state the minimum value of experimental tokens, U, such that she prefers to receive U tokens rather than completing the line for the store's reward. This step is referred to as the *elicitation question*. We use the same Becker-DeGroot-Marschak (BDM) mechanism (Becker et al. 1964) to elicit participants' utilities as in Chapter 3 (see detail in section 3.2.1). Therefore, given the store's reward (constant at 100 tokens), we can refer to U as a subject's utility of the queuing service system that she must travel to.

Remark: To address our research questions, we consider two aspects of our experimental design. First, the participants only interact with virtual clients in our study instead of any human subjects. By doing so, we are able to remove any interpersonal and social concerns that may change individuals' behavior. Second, our pilot experiment provides complete waiting information (i.e., service time, queue length and queuing interface) before traveling to a queue. By clearly defining and comparing the scenarios (i.e., before and after traveling), it enables us to focus on the effects of the travel.

4.4.2 Manipulation

The JT is manipulated along three dimensions: queue length, service time, and elicitation question timing. Firstly, the queue length refers to the total number of virtual clients at the store that participants need to wait until receiving the store's reward. That is, the total wait of the queuing system includes the travel to the queue, and the waiting for both the virtual clients and the participant herself to be served at the store. In the pilot study, we consider two levels of queue length: short and long. Secondly, we manipulate the service time as the average time to serve each client at the facility. It is considered at two levels: fast (10 sec./client) and slow (20 sec./client). Thirdly, we separate the conditions when the elicitation question is presented either before or after traveling to a queue. That is, the elicitation question occurs either when participants are about to leave home (after deciding

Figure 4.1: Pilot Experimental Conditions



Note. The dashed circles denote a participant's position when they receive the elicitation question (represented by the question mark). Each black dot represents a virtual client ahead, and the light blue area denotes that the participants are before the travel and on a different screen.

to travel to the store) or just as they arrive at the queue. We also control the total waiting time to ensure that the condition before and the condition after travel are equivalent. In other words, traveling from home to a store takes the same amount of time as serving a customer at the store. For example, as shown in Figure 4.1, condition 1 and 2 allows us to compare subjects' utilities before and after traveling with identical total residual wait time. That is, participants would see a queue length of 12 (6) after arriving at a store or 11 (5) at home before leaving when they observe the elicitation question in the fast (slow) service time condition.

As shown in Table 4.1, we consider a total of four experimental conditions in the pilot experiment. The design of combinations mainly focus on the comparison of individuals' utilities before and after travel with two levels of queue length and service time, respectively. In addition, the four conditions have identical total waiting time (120 seconds), including travel time. The design allows us to investigate the impact of travel on people's utilities before and after travel, controlling for the total remaining waiting time.

Our pilot study is developed in Otree, an experimental software (Chen et al. 2016), and

Table 4.1: Summary of Pilot Experimental Conditions

Condition	Queue Length (clients)	Service Time (sec./client)	Travel Time (sec.)	Elicitation Question Timing	Total Waiting Time (sec.)
1	11	10	10	Before	120
2	12	10	10	After	120
3	5	20	20	Before	120
4	6	20	20	After	120

is conducted in Amazon Turk, a crowdsourcing platform for online experiment (Paolacci et al. 2010). All participants follow the same procedure: (1) four rounds of the JT, (2) a risk preference task and a value of time task, and (3) an exit survey. Note that, within the four rounds of the JT, we keep the second round as a reset round, in which no elicitation question is included. This design aids in preventing the scenario when individuals join on purpose in order to receive any amount of tokens from the elicitation question but would actually prefer not to join. In sum, a total of 250 participants played our experiment and 217 of them voluntarily decided to travel and join the line. Of these 250 participants, 43% were female and the average age was 38.17 years old, with a standard deviation of 11.32 years. Participants' final payment depended on all rounds of the JT and the two control tasks. Every 100 tokens were worth one U.S. dollar. Total earnings averaged \$4.98 per subject, with a minimum of \$1 and a maximum of \$6.74. It took 23 minutes on average to complete the entire study on Amazon Turk.

4.4.3 Pilot Study Result

In this section, we discuss our main results from the pilot study. In particular, the pilot study allows us to address our first research question mainly about the impact of travel on individuals' utility valuations.

First, we model participants' decisions to join a queuing system with a random-effects Logit model:

$$\begin{aligned} Prob(Join_{ij} = 1) = &Intercept + \beta_T \cdot Travel_{ij} + \beta_S \cdot ServTime_{ij} + \beta_{TS} \cdot Travel_{ij} \cdot ServTime_{ij} \\ &+ \beta_j \cdot Round_j + \mu_i + \epsilon_{ij} \end{aligned} \tag{4.1}$$

The variable $Join_{ij}$ denotes participant i's decision to join a queue or not in round j. $Travel_{ij}$ is a dummy variable equal to 1 if participant i receives the elicitation question after traveling to the store in round j, and 0 otherwise. $ServTime_{ij}$ is a dummy variable equal to 1 if participant i observes service time equal to 20 sec./client in round j, and equal to 0 otherwise. $Round_j$ is a control variable for round j. Note that queue length is not included in our model because it is perfectly correlated with $ServTime$ and $Travel$ in our pilot study. In other words, with the main effect of $ServTime$ and $Travel$, and their interaction, we can include all four experimental conditions, as shown in Table 4.1. Lastly, μ_i denotes the individual error term, and ϵ_{ij} represents independent error across subjects' responses in the JT.

Table 4.2 shows our results of Equation 4.1. In the pilot study, there are two service time levels. We, therefore, consider service time a discrete variable. We find that the variable $ServTime$ is statistically significant. That is, compared to fast and long queues, people prefer to join slow and short queues, controlling for the total waiting time. Our research thus supports the findings from Conte et al. (2016) and Lu et al. (2013) that individuals prioritize queue length above wait time when making decisions and would choose to join a shorter queue, even if the service time is greater. Importantly, neither $Travel$ nor $Travel \cdot ServTime$ are statistically significant. This indicates that, for a given service time, the joining rates in our study are similar regardless of when the elicitation question is asked.

After participants decide to travel to join a queue, the elicitation question allows us to elicit their utilities of the service system in tokens. Table 4.3 summarizes the individuals' utilities, U, by experimental conditions. As a reminder, participants' utility U considers the store's reward and the wait in the queuing system. Shown in Figure 4.2, we find that there exists a significant difference in utilities before and after traveling when the service time is 10 sec./client (one-tail Wilcoxon rank-sum test, $p < 0.05$). Conversely, when service time is 20 sec./client, we observe that participants' utility is directionally greater after travel than before travel, but the difference is not statistically significant (Wilcoxon rank-sum test, $p = 0.36$). That is, people value the service system more before than after traveling when the queue at the store is fast and long. As noted earlier, when the queue is fast and long, we do not observe any statistically significant differences in participants' joining rates before vs.

Table 4.2: Random-effects Logit Model Results for Joining Decision

	(1)
Intercept	0.84
	(1.80)
ServTime	2.19**
	(0.98)
Travel	0.07
	(0.54)
Travel · ServTime	-1.18
	(0.99)
Round	-0.33
	(0.21)
Risk	0.14
	(0.10)
TimeValue	-0.00
	(0.01)
Male	0.32
	(0.70)
Age	0.07
	(0.04)

Standard errors in parentheses
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

after travel (85.85% vs. 85.58%, respectively; two-sample Proportion test, $p = 0.96$). Thus, the difference in utility in both scenarios cannot be attributed to differences in joining rates.

Next, we use a random-effect Tobit regression to model participants' utilities:

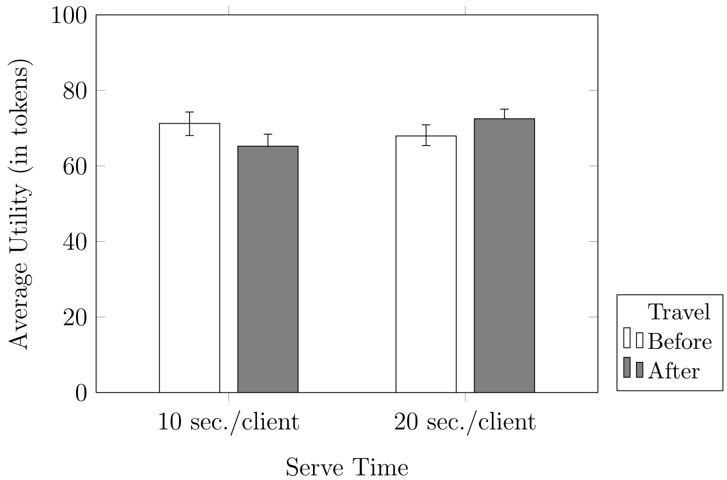
$$\begin{aligned} U_{ij} =& Intercept + \beta_T \cdot Travel_{ij} + \beta_S \cdot ServTime_{ij} + \beta_{TS} \cdot Travel_{ij} \cdot ServTime_{ij} \\ &+ \beta_j \cdot Round_j + \mu_i + \epsilon_{ij} \end{aligned} \tag{4.2}$$

The variable U represents participant i's utility of the queuing service system, given a constant store reward at 100 tokens. Table 4.4 summarizes the Tobit model results from Equation 4.2. We find that the dummy variable $Travel$ is statistically significant, as well as

Table 4.3: Utility Summary in Pilot Experimental Conditions

Condition	Average Utility (Standard Error)
1	71.25 (3.03)
2	65.22 (3.20)
3	67.94 (2.94)
4	72.49 (2.55)

Figure 4.2: Effects of Travel on Uitlity



Note: The error bars correspond to standard errors of the mean.

its interaction with $ServTime$. It denotes that, with fast queues (10 sec./client), people value the queuing system less after traveling, but they value it more after traveling when the service time is slow. That is, conditional on slow queues (i.e., when $ServTime$ = 20 sec./client), H1a is partially supported since participants' utilities are higher after than before traveling (the sum of the aforementioned main effect and two-way interaction terms is equal to 5.57, t test, p = 0.047). Also, H1b is supported due to the statistical significance of the dummy variable $Travel$ when $ServTime$ = 10 sec./client. This finding is interesting, especially that the impact of travel on people's utilities relates to various queuing settings. In what follows, we discuss the design of a follow-up study (Study 1) to better understand (i) how our results may depend on the relative cost of travel (relative to the total waiting time) and (ii) the behavioral reasons behind individuals' valuations.

4.5 Study 1 Experimental Design

Based on the results of the pilot study, we conclude that the JT's fundamental design guarantees that participants join decisions are made voluntarily in accordance with the

Table 4.4: Random-effects Tobit Model Results for Utility

	(1)
Intercept	87.25***
	(12.32)
ServTime	-2.14
	(5.04)
Travel	-6.60*
	(2.88)
Travel · ServTime	12.18**
	(4.02)
Round	-0.15
	(0.89)
Risk	-0.26
	(0.70)
TimeValue	-0.07
	(0.05)
Male	0.19
	(5.09)
Age	-0.22
	(0.21)

Standard errors in parentheses
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

queuing parameters. The BDM mechanism helps us elicit their valuation of the service system. Therefore, we will follow the pilot study's basic design and procedure. But a limitation of the pilot study is that it does not allow us to answer all our research questions. In this section, we will discuss how to adjust our design to address them.

4.5.1 Joining Task

Basically, we follow the Joining Task (JT) design used in the pilot experiment. We plan to focus on the same three dimensions through the queuing setting, queue length, service time, and elicitation question timing. We take additional levels of the queue characteristics and more rounds into consideration in order to gather more data points and examine people's relative cost of travel. As shown in Table 4.5, each subject will play 11 rounds (one as a reset round) in random order, controlling for the total waiting time (120 seconds). Note that we set the travel time equal to the service time for a customer in every condition. Therefore, for each round, a participant only needs to (1) make a joining decision, (2) answer an elicitation question, and (3) state her affective state (see detail in next section). Unlike the pilot study,

Table 4.5: Summary of Study 1 Experimental Conditions

Condition	Queue Length (clients)	Service Time (sec./client)	Travel Time (sec.)	Elicitation Question Timing	Total Waiting Time (sec.)
1	11	10	10	Before	120
2	12	10	10	After	120
3	7	15	15	Before	120
4	8	15	15	After	120
5	5	20	20	Before	120
6	6	20	20	After	120
7	3	30	30	Before	120
8	4	30	30	After	120
9	1	60	60	Before	120
10	2	60	60	After	120

they do not need to complete waiting at the store in all rounds. They will only be randomly assigned one round to complete the wait for the store's rewards. Their payment for the JT depends on the wait completion for the assigned round.

4.5.2 Affective State Measurement

In Study 1, we plan to measure participants' real-time affective states before and after traveling to a queue and to investigate the relationship between affective states and individuals' valuation. The affective response is first studied in observable queues by Carmon and Kahneman (1995). They allow subjects to dynamically choose their real-time affect on "Affect meter" during the entire waiting period. Unlike their study, we mainly focus on two points in the remote queuing system, one at home and the other at the store. We thus consider a pop-up window for participants' affective states with the question, "Please indicate how you are feeling right now." (7-point Likert scale between extremely unpleasant and extremely pleasant). This design allows us to measure individuals' affective states at the designated times. In addition, the questions are asked after participants' joining decisions, which enables us to focus on the cases in which participants prefer to join. Note that a participant will be requested to report her affective state after she selects her *elicitation question*. That is, she only needs to declare her affective state once for each round. The within-subject approach enables us to understand how participants' utilities are influenced by their affective states before and after travel.

Table 4.6: Queuing Information Levels of Study 1

Queuing Information Level	Information Content
Basic	Total Waiting Time
Sufficient	Queuing Characteristics
Complete	Queuing Characteristics & Interface

4.5.3 Queuing Information Level

In addition, we plan to investigate the effect of queuing information-sharing levels on individuals' gaps in affective state before and after traveling to a queue. To do so, we plan to introduce another treatment for queuing information sharing for our last hypothesis. We consider three levels of queuing information in Table 4.6. At the basic level, participants only know the waiting time (i.e., average and distribution of the total waiting time). At the sufficient level, they know the queuing characteristics (queue length and service time) of the wait. At the complete level, besides the queuing characteristics, they can also observe how the wait appears to them, i.e., the queuing interface. This design allows us to understand how the information-sharing level impacts an individual's affective state before and after traveling to a queue. We can also check whether the information levels moderate individuals' utility changes because of the travel. Therefore, taking into account the interaction of the total of 10 conditions and three information-sharing levels, we propose to recruit 300 individuals for Study 1, ensuring 100 observations on average for each condition.

4.6 Conclusions

In this study, we focus on the impact of the travel to a queue on an individual's joining behavior. Past literature typically assumes that joining a queue does not take any time. We consider a more practical queue that customers must travel to. By controlling the total waiting time, our pilot study finds a discrepancy in individuals' utility valuation before and after traveling. Compared to before traveling to a queue, participants' utilities are lower after traveling when queues are fast and long; but when queues are slow and short, we find partial support for their utilities being higher after than before traveling. The finding does not follow the rational assumption that people's utility depend on the total waiting time. This is an interesting question since it is an everyday dilemma and impacts customers' queuing and consuming behaviors in a service system. It is also important for queuing management, such as reducing the valuation discrepancy and increasing consumer valuation after traveling. Our study aims to determine whether the mechanism (i.e., "cold-to-hot" empathy gap) drives individuals' behavior and to answer the practical question by conducting a human-subject experiment. Finally, we believe that a higher level of queuing information sharing reduces an individual's gap in affective state before and after traveling and creates value for the potential customers.

5.0 Conclusions

This thesis investigates new ways to create value in a value chain at two stages. Particularly, I investigate how to use Blockchain Technology to build a deep-tier supply chain finance system. Using economic models, we find that the new technology implementation needs to be carefully evaluated, and we need to consider how it affects all the involved members in a supply chain. Though supply chain members may have conflicting objectives, we must find proper ways to benefit every member as a planner. The results show that when implementing BT-SCF, the focal company should pay attention to the price elasticity of the final product. When the elasticity is above a threshold, BT-SCF implementation can benefit everyone. Otherwise, some members will be against implementing the new system. The main contribution of Chapter 2 is to propose a new framework for deep-tier supply chain finance with Blockchain Technology and provide suggestions to increase profitability of every supply chain member. That is, we figure out how to improve the competitiveness of the entire supply chain.

In Chapter 3, we understand how a customer's utility is impacted by wait experienced and prospective. Through experiments, we find that human behavior does not always follow rational assumptions. It is related to queuing characteristics as well as individual characteristics. Results show that participants with different personal traits behave in opposite directions on the impact of experienced wait. This finding sheds light on queuing management to satisfy customers during the wait. More attention should be given to the customers who have a negative attitude. Moreover, a service provider is able to take advantage of this feature and provide extra service within that customer pool. For the prospective wait, the finding that participants focus on queue length and service time to evaluate the remaining wait helps service providers better manage customers' expectations by reducing queue length or service time. Chapter 4 extends the queuing system to remote customers. Results show a difference in individuals' utility before and after traveling to a queue. These findings do not follow the assumption of rationality. We are planning to figure out the behavioral theory that drives customers' behavior. Referring to the "cold-to-hot" empathy gap, we believe that the difference before and after traveling is due to self-control issues. In addition, queuing information is thought to mitigate this gap.

This thesis contributes to the growing literature in supply chain finance & Blockchain Technology, and behavioral queuing. We address the questions relating to new technology implementation and customer behavior in a queuing system. Theoretical modeling helps us to investigate the optimal strategy. Behavioral methodologies enable us to understand the actual response of customers better. Combining these methods allows us to learn a complete picture of the problem and provides more practical solutions. In the future, I will employ these methods to continue my research in the operations management field, specifically behavioral queuing and Blockchain Technology in supply chain management. In addition, considering both perspectives of new technologies and human behavior can help design a better system. We believe that incorporating these aspects constitutes future research with great potential.

Appendix A Chapter 2

A.1 Proofs

A.1.1 Proof of Lemma 1

Rearranging terms in Eq. 2.5 yields

$$r_M T_M = 1 - \frac{p \int_0^{\theta_M} x dF_p(x) + p\theta_M \bar{F}_p(\theta_M)}{B_M} \tag{A.1}$$

Since $F_p(\cdot)$ follows IGFR and substituting $B_M = p\theta_M$, we get

$$r_M T_M = 1 - \frac{\int_0^{\theta_M} \bar{F}_p(x)dx)}{\theta_M} \tag{A.2}$$

If $r_S T_S \leq \bar{r}_M T_M$, w_S yields

$$w_s(r_S T_S) = \frac{c_S(1+\beta_S)}{1 - r_S T_S} \leq w_s(\bar{r}_M T_M) = \frac{c_S(1+\beta_S)}{(1 - \bar{r}_M T_M)} \tag{A.3}$$

Hence, the supplier will have a lower profit with the early payment rate under the supply chain finance endorsed by the retailer.

A.1.2 Proof of Lemma 2

Rearranging terms in Eq. 2.3, and substitute $r_M T_M$ in Lemma 1,

$$\begin{aligned}\pi_M = ((1+\alpha_M T_M)(1+\beta_R)w_M - \frac{\alpha_M T_M}{\theta_M}(w_M - w_S)q)w_M \int_0^{\theta_M} \bar{F}_p(x)dx + \\ (w_M q - p\theta_M) - c_M q - w_S q + \alpha_M(T_S - T_M - L_R + L_M)w_S q\end{aligned} \tag{A.4}$$

Substituting $B_M = p\theta_M$,

$$\frac{d^2\pi_M}{d\theta_M^2} = \frac{1}{\theta_M^3}(-2q(\int_0^{\theta_M}(1-F(x))dx)T_M(w_M-w_S)\alpha_M - \theta_M(p\theta_M^2 F^{'}(\theta_M) + T_M\alpha_M(p\theta_M^2 F^{'}(\theta_M) + qw_M(-2+2F(\theta_M)-\theta_M F^{'}(\theta_M)) + qw_S(2-2F(\theta_M)+\theta_M F^{'}(\theta_M))))) \tag{A.5}$$

Hence π_M is quasi-concave in θ_M, there exists a unique optimal solution, θ_M^*, to maximize π_M. Since $B_M \in [(w_M - w_S)q, w_M q], \theta_M \in [\frac{(w_M-w_S)q}{p}, \frac{w_M q}{p}]$.

A.1.3 Proof of Lemma 3

Since π_M^B in Eq. 2.10 and π_M in Eq. 2.3, $\pi_M^B \geq \pi_M$ yields

$$q^B \geq \frac{1}{c_M - (1-r_M^B T_M)(w_M^B - w_S^B)}(q(c_M + w_S + (L_R - L_M + r_M T_M^2 - T_S)w_S\alpha_M - w_M(1-\alpha_M T_M + \alpha r_M T_M^2)) + p\theta_M(r_M - \alpha_M + r_M\alpha_M T_M)T_M) \tag{A.6}$$

Thus,

$$\underline{q}_M^B = \frac{1}{c_M - (1-r_M^B T_M)(w_M^B - w_S^B)}(q(c_M + w_S + (L_R - L_M + r_M T_M^2 - T_S)w_S\alpha_M - w_M(1-\alpha_M T_M + \alpha r_M T_M^2)) + p\theta_M(r_M - \alpha_M + r_M\alpha_M T_M)T_M) \tag{A.7}$$

A.1.4 Proof of Lemma 4

Since $r_M^B = r_S^B$ by assumption and Eq. 2.12, r_S^B yields

$$r_S^B = \frac{1+\beta_M}{q^B(T_M(1+\beta_M) - L_M + L_R)}(q^B - (\int_0^{\theta^B}(1 - F_{p^B}(x))dx)(1+\beta_R)) \tag{A.8}$$

Since w_S in Eq. 2.1 and w_S^B in Eq. 2.8, the supplier will be beneficial to join BT-SCF when $r_S^B \leq \frac{r_S T_S}{T_M + L_R - L_M}$. Hence, q^B yields

$$q^B \geq \frac{\left(\int_0^{\theta^B} \left(1 - F_{p^B}(x)\right) dx\right) (T_M - L_M + L_R)(1+\beta_M)(1+\beta_R)}{T_M(1+r_S T_S)(1+\beta_M) - L_M(1+r_S T_S+\beta_M) + L_R(1+r_S T_S+\beta_M)} \tag{A.9}$$

Thus,

$$\underline{q}_S^B = \frac{\left(\int_0^{\theta^B} \left(1 - F_{p^B}(x)\right) dx\right) (T_M - L_M + L_R)(1+\beta_M)(1+\beta_R)}{T_M(1+r_S T_S)(1+\beta_M) - (L_M - L_R)(1+r_S T_S+\beta_M)} \tag{A.10}$$

A.1.5 Proof of Proposition 1

Since the demand distribution, $F_p(\cdot)$, is IGFR, and substitute Eq. 2.6, π_R in Eq. 2.7 yields

$$\frac{d\pi_R}{dq} = w_M\left(-1 + (1 - F_p(q))(1+\beta_R)\right) = 0 \tag{A.11}$$

Hence, the optimal order quantity in T-SCF, q^*, yields

$$q^* = F_p^{-1}\left(\frac{\beta_R}{1+\beta_R}\right) \tag{A.12}$$

Similarly, the optimal order quantity in BT-SCF, q^{B*}, yields

$$q^{B*} = F_{p^B}^{-1}\left(\frac{\beta_R}{1+\beta_R}\right). \tag{A.13}$$

A.1.6 Proof of Proposition 3

Since Eqs. 2.1, 2.3, 2.7, 2.8, 2.10, 2.14, the SC profit change of the SC $\Delta\pi_R + \Delta\pi_M + \Delta\pi_S$ yields

$$
\begin{aligned}
\Delta\pi_R + \Delta\pi_M + \Delta\pi_S = p^B \int_0^{q^B} \bar{F}_{p^B}(x)\,dx - p\int_0^q \bar{F}_p(x)\,dx + q^B((1 - r_M^B T_M)(w_M^B - w_S^B) - c_M \\
+(1 - r_S^B(L^R - L_M + T_M))w_S^B - (c_S + c_M + w_M^B))+ \\
q\left(c_M + c_S + r_S T_S w_S - \alpha_M\left(T_S - T_M - L_R + L_M\right)w_S + \alpha_M T_M\left(1 - r_M T_M\right)\left(w_M - w_S\right)\right)) \\
+\left(r_M T_M - \alpha_M T_M\left(1 - r_M T_M\right)\right)\theta_M p
\end{aligned}
\tag{A.14}
$$

A.1.7 Proof of Proposition 4

Since in T-SCF $w_i = \frac{w_{i+1}(1+\beta_i)}{1-r_iT_i}$, where $i \in [1, 2, 3, \ldots, n]$, the wholesale price reduction of tier i due to lower financial cost in BT-SCF yields

$$
\Delta w_i = -\frac{w_{i+1}\left(1+\beta_i\right)}{\left(1-r_iT_i\right)\left(1-r_i^B\left(T_1+L_0-L_{i-1}\right)\right)}\left(r_iT_i - r_i^B\left(T_1+L_0-L_{i-1}\right)\right) \tag{A.15}
$$

When $r_i^B\left(T_1+L_0-L_{i-1}\right) < r_iT_i$, $\Delta w_i > 0$. The wholesale price of tier i supplier is lower in BT-SCF. Accordingly, the final sales price reduction because of the change of tier i member's wholesale price yields

$$
\begin{aligned}
\Delta p = -\left(1+\beta_1\right)\left(1+\beta_0\right)\frac{\left(1+\beta_2\right)}{1-r_2^B\left(T_1+L_0-L_1\right)}\cdots\frac{\left(1+\beta_i\right)}{1-r_i^B\left(T_{i-1}+L_0-L_{i-1}\right)}\frac{w_{i+1}}{1-r_iT_i} \\
\left(r_iT_i - r_i^B\left(T_1+L_0-L_{i-1}\right)\right)
\end{aligned}
\tag{A.16}
$$

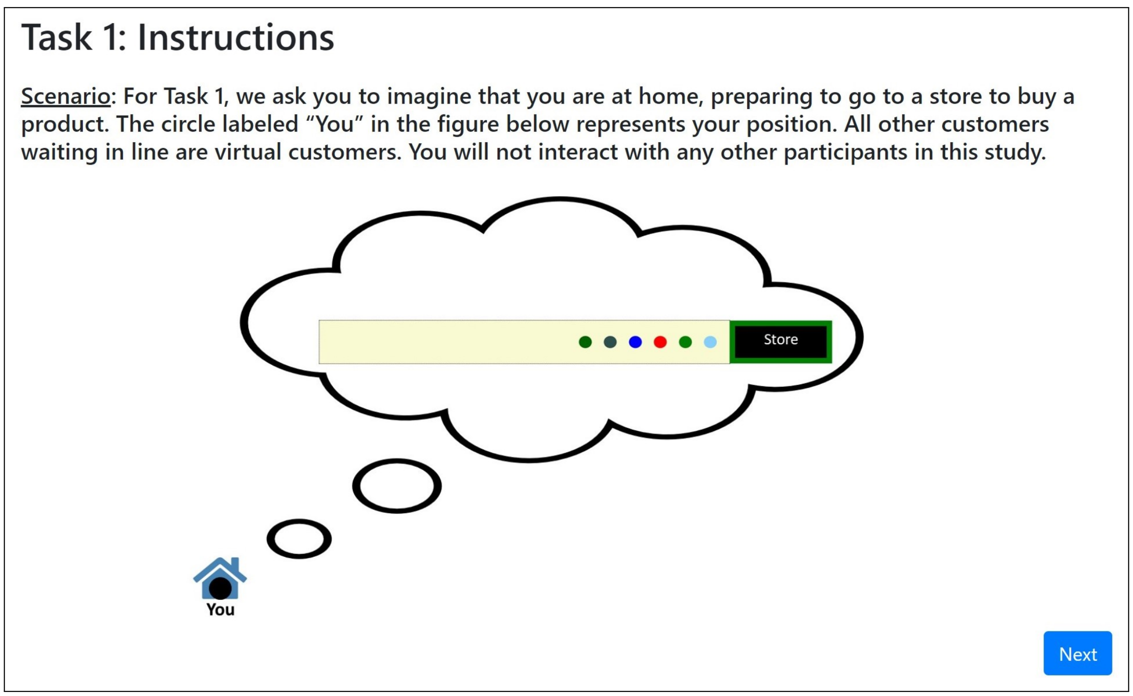
Since $\frac{1}{1-r_i^B(T_1+L_0-L_{i-1})} \geq 1$, hence $\Delta p > 0$.

Appendix B Chapter 3

B.1 Experimental Protocol

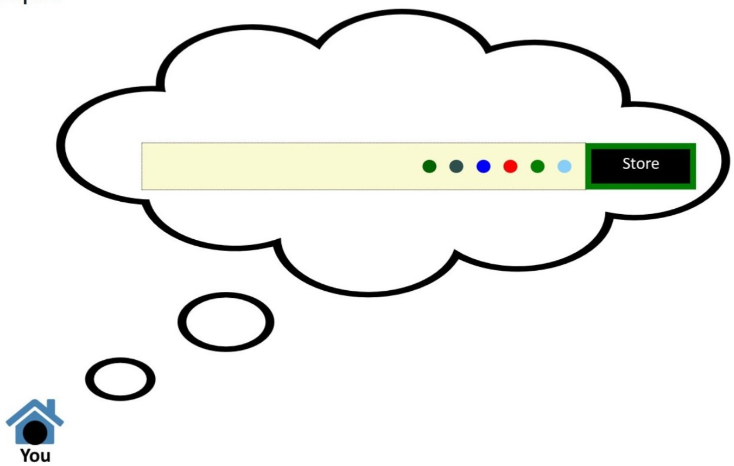
B.1.1 Queuing Task: Instruction

Here we present the main instructions for the Queuing Task. Each figure below represents a separate screen of the participants' interface.



Task 1: Instructions - store information

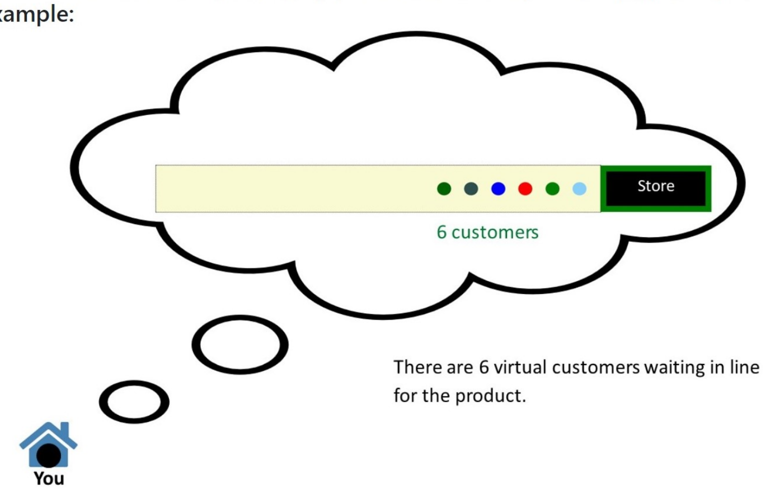
You will see the following information about the store: (1) how many people are waiting in line; (2) how long it takes to serve each customer; and (3) the value of the product (in points) that you can get at the store. For example:



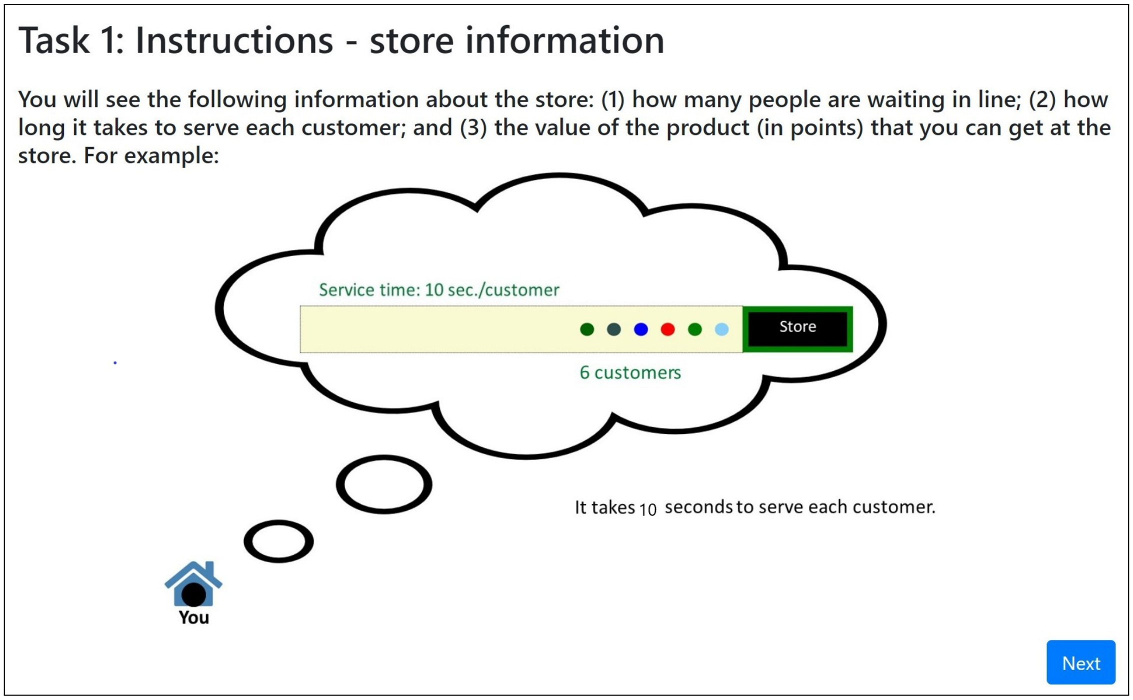
Next

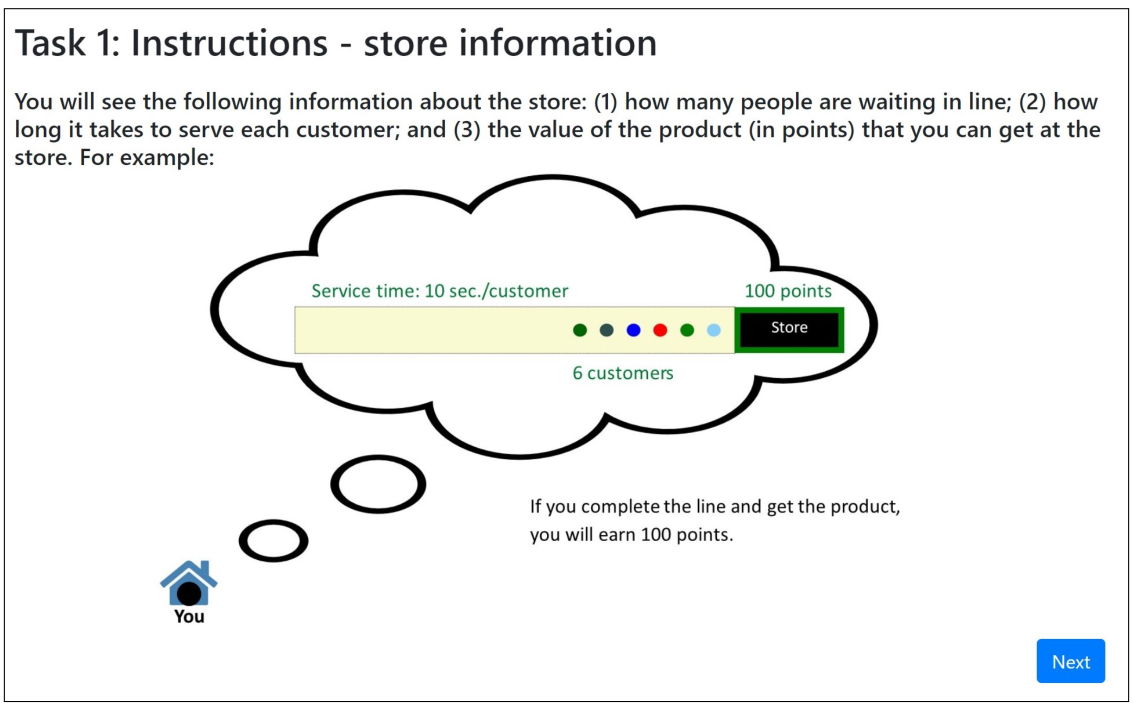
Task 1: Instructions - store information

You will see the following information about the store: (1) how many people are waiting in line; (2) how long it takes to serve each customer; and (3) the value of the product (in points) that you can get at the store. For example:



Next


Task 1: Instructions - store information
You will see the following information about the store: (1) how many people are waiting in line; (2) how long it takes to serve each customer; and (3) the value of the product (in points) that you can get at the store. For example:
Service time: 10 sec./customer
Store
6 customers
It takes 10 seconds to serve each customer.
You
Next


Task 1: Instructions - store information
You will see the following information about the store: (1) how many people are waiting in line; (2) how long it takes to serve each customer; and (3) the value of the product (in points) that you can get at the store. For example:
Service time: 10 sec./customer
100 points
Store
6 customers
If you complete the line and get the product, you will earn 100 points.
You
Next

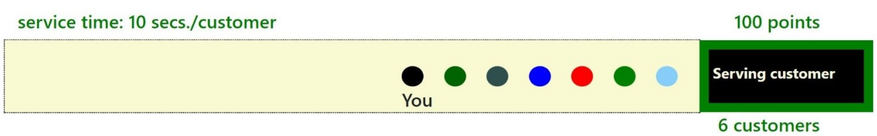
Task 1: Instructions - store information

Then, you will be asked to click a button to go to the store, as in the image below. After clicking the button, you will leave home and walk across the screen to join the line at the store. The store will be in the next screen.

Next

Task 1: Instructions - arrive at the store

Once you arrive at the store, you will join the end of the line and start to wait for the product.

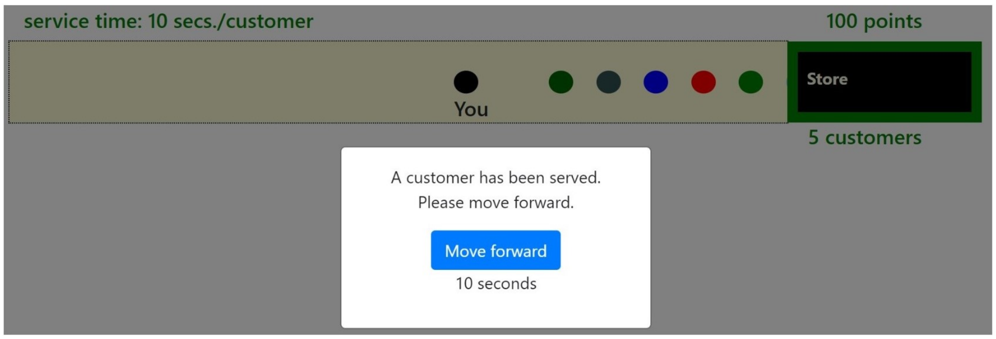


Next

Task 1: Instructions - how you wait in line

In order to get the store's product, you have to pay close attention and click the "Move forward" button every time a customer is served. Whenever the line moves, the "Move Forward" button will appear on your screen, as in the image below.

IMPORTANT: if you do ***NOT*** click the "Move Forward" button within 10 seconds, then you will ***NOT*** be able to complete Task 1 and will earn ***0 points*** in Task 1.



Next

Task 1: Instructions - end of the line

If you pay attention and click the button on time, then you WILL be able to get the product and earn points at the store if you complete the line. You will then see a message like in the image below.

Next

Task 1: Instructions - Alternative Product Offer

Please continue to read these instructions carefully.

After you join the line, you will also receive an **Alternative Product Offer**. The Alternative Product may be offered **anytime** between when you arrive at the store and before you complete the line.

Next

Task 1: Instructions - Alternative Product Offer

When you receive an Alternative Product Offer, you will be asked to state the minimum value (in points) for which you would prefer to **leave** the store and get this Alternative Product. We will refer to it as your **minimum acceptable value** for the Alternative Product. The Alternative Product does **NOT** require any waiting on your part.

Then, the computer will randomly select the value of the Alternative Product, from 1 to 100 , with each value equally likely. We will refer to this value as X. **Based on your minimum acceptable value and the value of X**, one of the following two things will happen:

- *If X is greater than your minimum acceptable value*, then you will get the Alternative Product and will leave the store with X points. In this case, you will not get the store's product.
- *If X is less than or equal to your minimum acceptable value*, then you will continue to wait in line for the store's product. Once you complete the line, you will earn the value of the store's product.

Next

Task 1: Instructions - Alternative Product Offer

In the next screens, you will see an example for how the Alternative Product value is determined. Please pay attention. You will be asked to complete a short comprehension quiz about it.

Next: Example of an Alternative Product Offer

Task 1: Instructions - Alternative Product Offer Example

Imagine that you arrived at the store and are waiting to receive the store's product, valued at 100 points. The pop-up box below appears, offering you an alternative product that you could receive **without waiting**.

You are now offered an Alternative Product.
What is the minimum acceptable value of this Alternative Product (in points) such that you prefer it over waiting in line for the store's product?

Please choose a whole number between 0 and 100.
20
The computer will then randomly select X, the value of the Alternative Product, from 1 to 100.

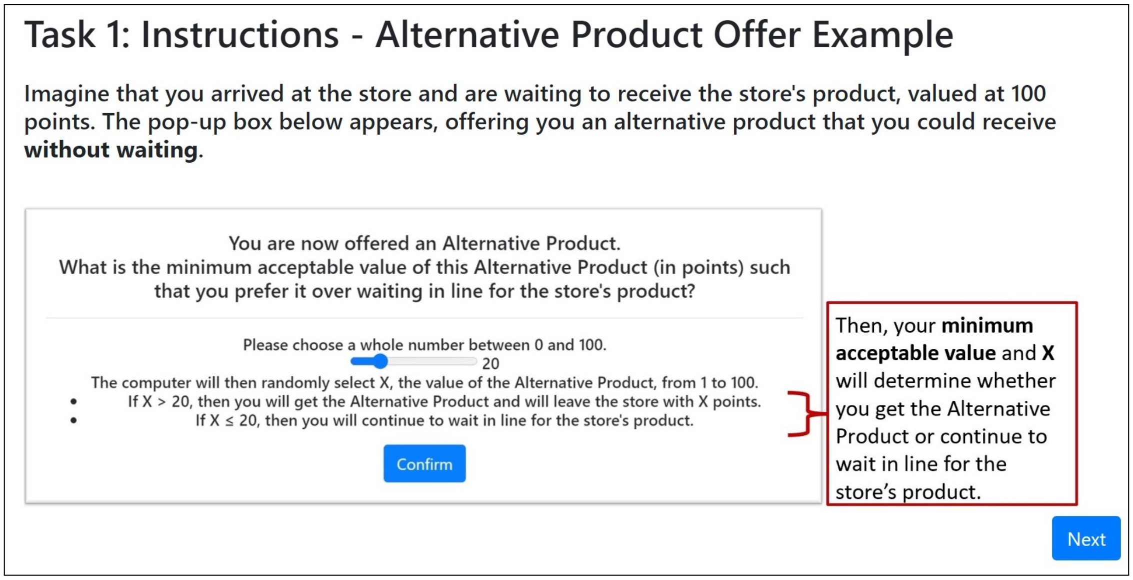
- If X > 20, then you will get the Alternative Product and will leave the store with X points.
- If X ≤ 20, then you will continue to wait in line for the store's product.

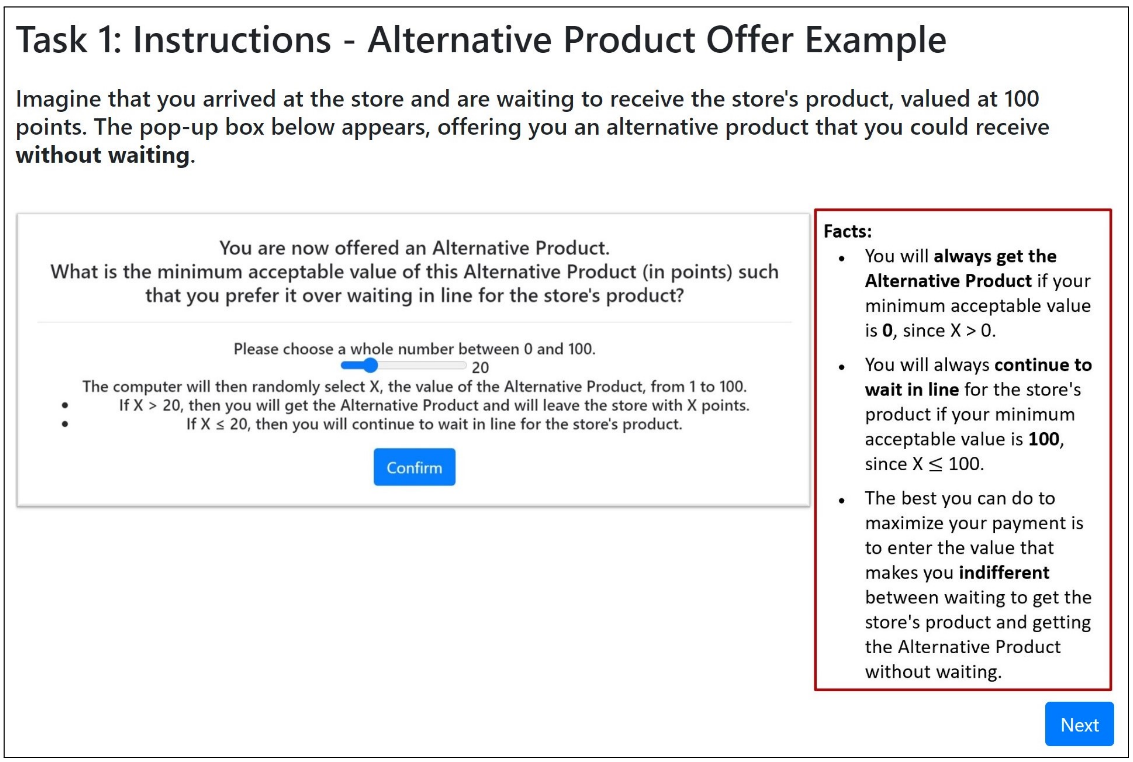
Confirm

First, you must **select** the **minimum acceptable value** (0-100) for the Alternative Product Offer. In this example, it is equal to 20.

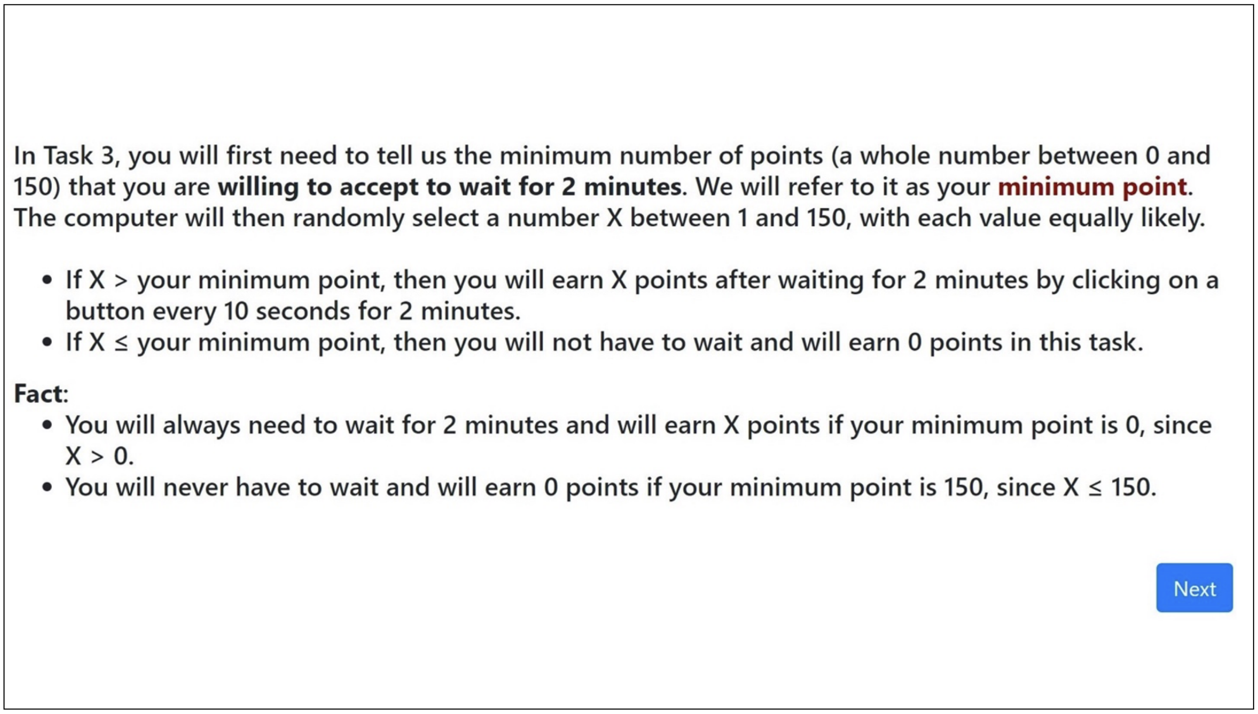
Note: You will be able to try different numbers before clicking confirm.

Next


Task 1: Instructions - Alternative Product Offer Example
Imagine that you arrived at the store and are waiting to receive the store's product, valued at 100 points. The pop-up box below appears, offering you an alternative product that you could receive without waiting.
You are now offered an Alternative Product.
What is the minimum acceptable value of this Alternative Product (in points) such that you prefer it over waiting in line for the store's product?
Please choose a whole number between 0 and 100.
20
The computer will then randomly select X, the value of the Alternative Product, from 1 to 100.
If X > 20, then you will get the Alternative Product and will leave the store with X points.
If X ≤ 20, then you will continue to wait in line for the store's product.
Confirm
Then, your minimum acceptable value and X will determine whether you get the Alternative Product or continue to wait in line for the store's product.
Next


Task 1: Instructions - Alternative Product Offer Example
Imagine that you arrived at the store and are waiting to receive the store's product, valued at 100 points. The pop-up box below appears, offering you an alternative product that you could receive without waiting.
You are now offered an Alternative Product.
What is the minimum acceptable value of this Alternative Product (in points) such that you prefer it over waiting in line for the store's product?
Please choose a whole number between 0 and 100.
20
The computer will then randomly select X, the value of the Alternative Product, from 1 to 100.
If X > 20, then you will get the Alternative Product and will leave the store with X points.
If X ≤ 20, then you will continue to wait in line for the store's product.
Confirm
Facts:
You will always get the Alternative Product if your minimum acceptable value is 0, since X > 0.
You will always continue to wait in line for the store's product if your minimum acceptable value is 100, since X ≤ 100.
The best you can do to maximize your payment is to enter the value that makes you indifferent between waiting to get the store's product and getting the Alternative Product without waiting.
Next

B.1.2 Value of Time Task: Instruction

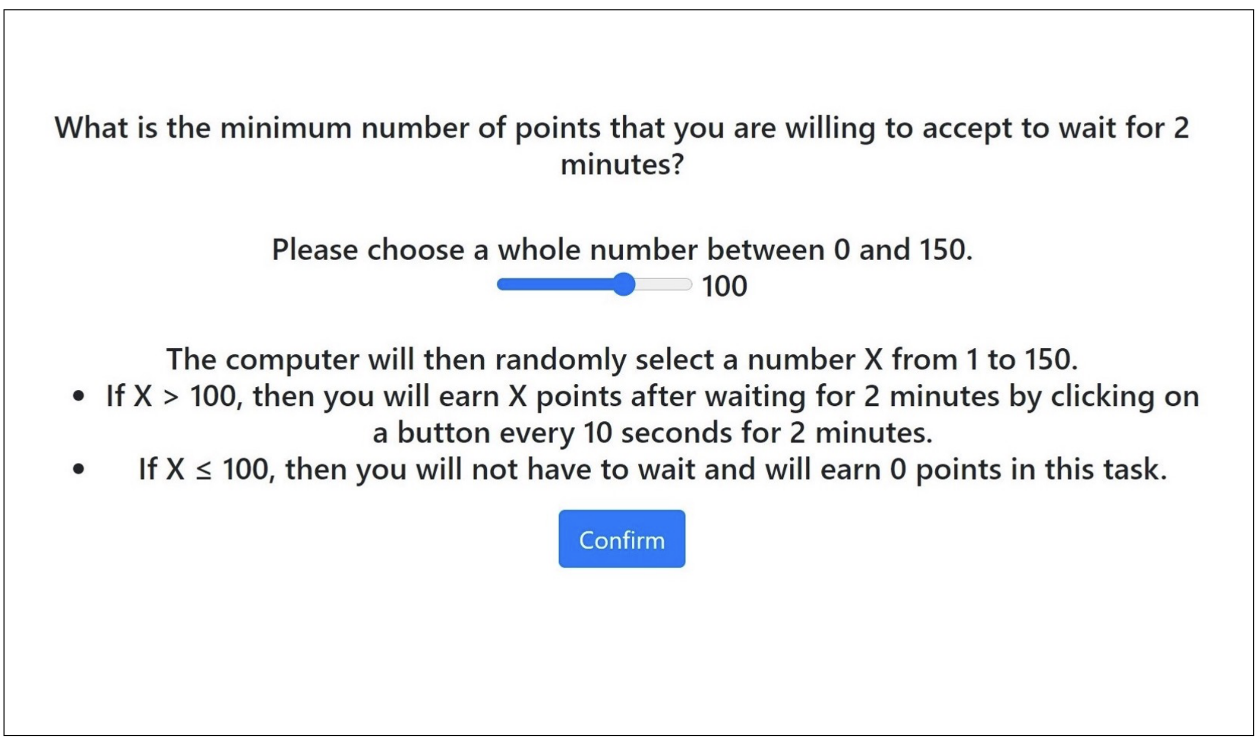


In Task 3, you will first need to tell us the minimum number of points (a whole number between 0 and 150) that you are **willing to accept to wait for 2 minutes**. We will refer to it as your **minimum point**. The computer will then randomly select a number X between 1 and 150, with each value equally likely.

- If X > your minimum point, then you will earn X points after waiting for 2 minutes by clicking on a button every 10 seconds for 2 minutes.
- If X ≤ your minimum point, then you will not have to wait and will earn 0 points in this task.

Fact:
- You will always need to wait for 2 minutes and will earn X points if your minimum point is 0, since X > 0.
- You will never have to wait and will earn 0 points if your minimum point is 150, since X ≤ 150.

Next



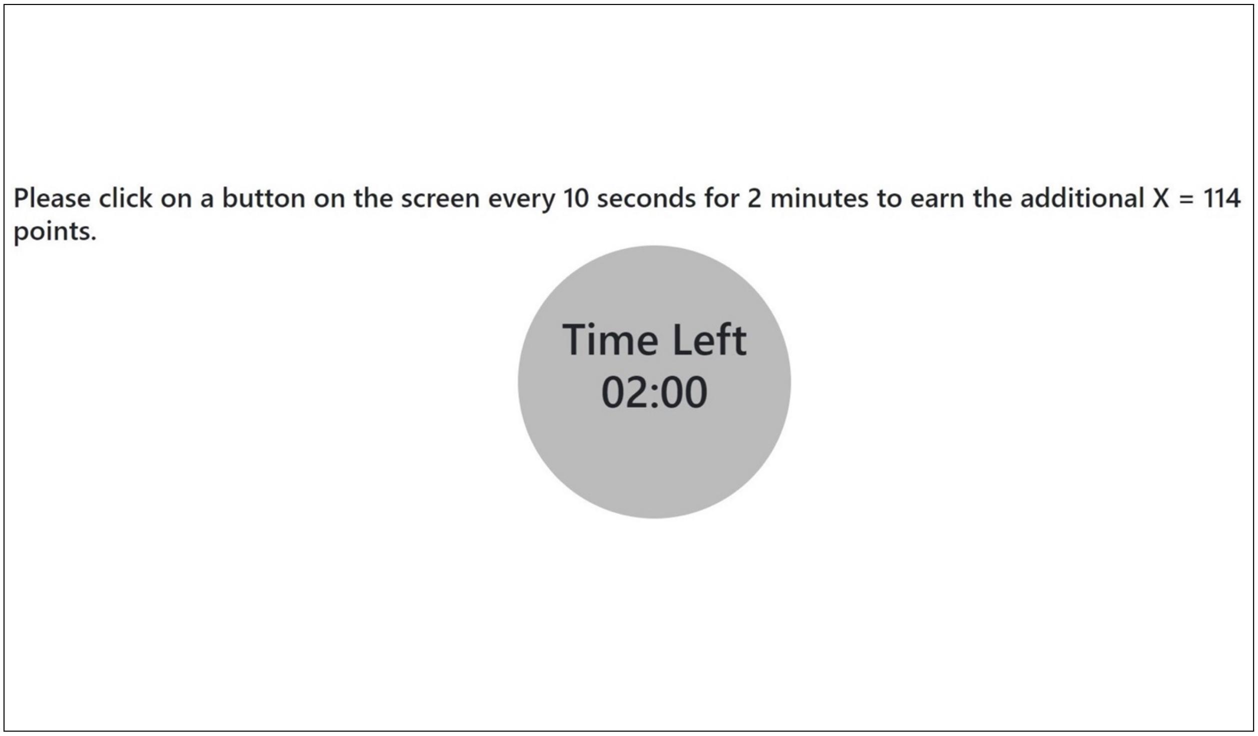
What is the minimum number of points that you are willing to accept to wait for 2 minutes?

Please choose a whole number between 0 and 150.
100

The computer will then randomly select a number X from 1 to 150.
- If X > 100, then you will earn X points after waiting for 2 minutes by clicking on a button every 10 seconds for 2 minutes.
- If X ≤ 100, then you will not have to wait and will earn 0 points in this task.

Confirm

Wait to Earn Experimental Tokens: Example



B.1.3 Exit Survey

Exit Survey: Task 1

1. In a few words, how did you determine your minimum acceptable values for the Alternative Products (that is, when you saw the pop-up screen at the bottom of the screen)?

You are now offered an Alternative Product.
What is the minimum acceptable value of this Alternative Product (in points) such that you prefer it over waiting in line for the store's product?

Please choose a whole number between 0 and 100.
0
The computer will then randomly select X, the value of the Alternative Product, from 1 to 100.

- Since X > 0, then you will earn get the Alternative Product and will leave the store with X points.
-

Confirm

Next

Exit Survey: Task 1

2. Please indicate how much you agree or disagree with each of the following statements. "In order to determine my **minimum acceptable values** for the Alternative Product..."

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I considered the number of places that I had already moved in line.	○	○	○	○	○
I considered the number of customers waiting ahead of me.	○	○	○	○	○
I estimated the total time that I had already spent waiting in line.	○	○	○	○	○
I considered how long it took to serve each customer.	○	○	○	○	○
I considered the value of the product that I could get at the store.	○	○	○	○	○
I estimated the total time that it would take me to complete the line.	○	○	○	○	○

Next

Exit Survey: Task 1

3. Please indicate how much you agree or disagree with each of the following statements. “When I estimated the total **time that it would take me to complete the line**...”

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I considered the number of virtual customers waiting ahead of me.	○	○	○	○	○
I considered how long it took to serve each customer.	○	○	○	○	○

Next

Exit Survey: Task 1

4. Please indicate how much you agree or disagree with each of the following statements. “When I estimated the total **time that I had already spent in line**...”

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I considered the number of places that I had already moved in line.	○	○	○	○	○
I considered how long it took to serve each customer.	○	○	○	○	○

Next

Exit Survey: Task 1

5. Please indicate how much you agree or disagree with each of the following statements regarding your decisions in Task 1:

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I did not understand the instructions for Task 1, the task with the stores.	○	○	○	○	○
I tried to maximize my payoff.	○	○	○	○	○
I tried to reduce the time spent in the study.	○	○	○	○	○

Next

Exit Survey: Task 1

7. Please indicate how much you agree or disagree with each of the following statements regarding your decisions on the stores in Task 1.

☐ When making my decisions, I thought of my decisions I had made in previous stores from Task 1.

☐ When making my decisions, I thought of my own experience waiting in line in the real world.

☐ When making my decisions, I thought of my own recent experiences waiting line (after stay-at-home orders due to Covid-19).

Next

Exit Survey: About You

1. Which best describes your gender identity.

○ Male

○ Female

○ Prefer not to disclose

○ Other (please specify) __________

Next

2. Please specify your age:

3. Please specify your race / ethnic origin. Please select all that apply

- [ ] White
- [ ] Asian
- [ ] Hispanic / Latin American
- [ ] African American
- [ ] Prefer not to disclose
- [ ] Other (please specify)

Next

4. What is the highest level of education you have completed?

----

5. What is the range of your annual household income?

Next

6. Are you currently...? (Please select all that apply).

- ☐ Employed full-time
- ☐ Employed part-time
- ☐ Self-employed
- ☐ Not employed
- ☐ A graduate student
- ☐ A college student
- ☐ Retired

Next

7. What is/was your major in college? (answer only if applicable)

Next

8. How much do you normally earn (in US dollars) per hour, on average, on Prolific?

Next

9. In comparison to others, are you a person who is generally willing to give up something today in order to benefit from that in the future or are you not willing to do so?

Strongly willing	Somewhat willing	Neither willing nor unwilling	Somewhat unwilling	Strongly unwilling
○	○	○	○	○

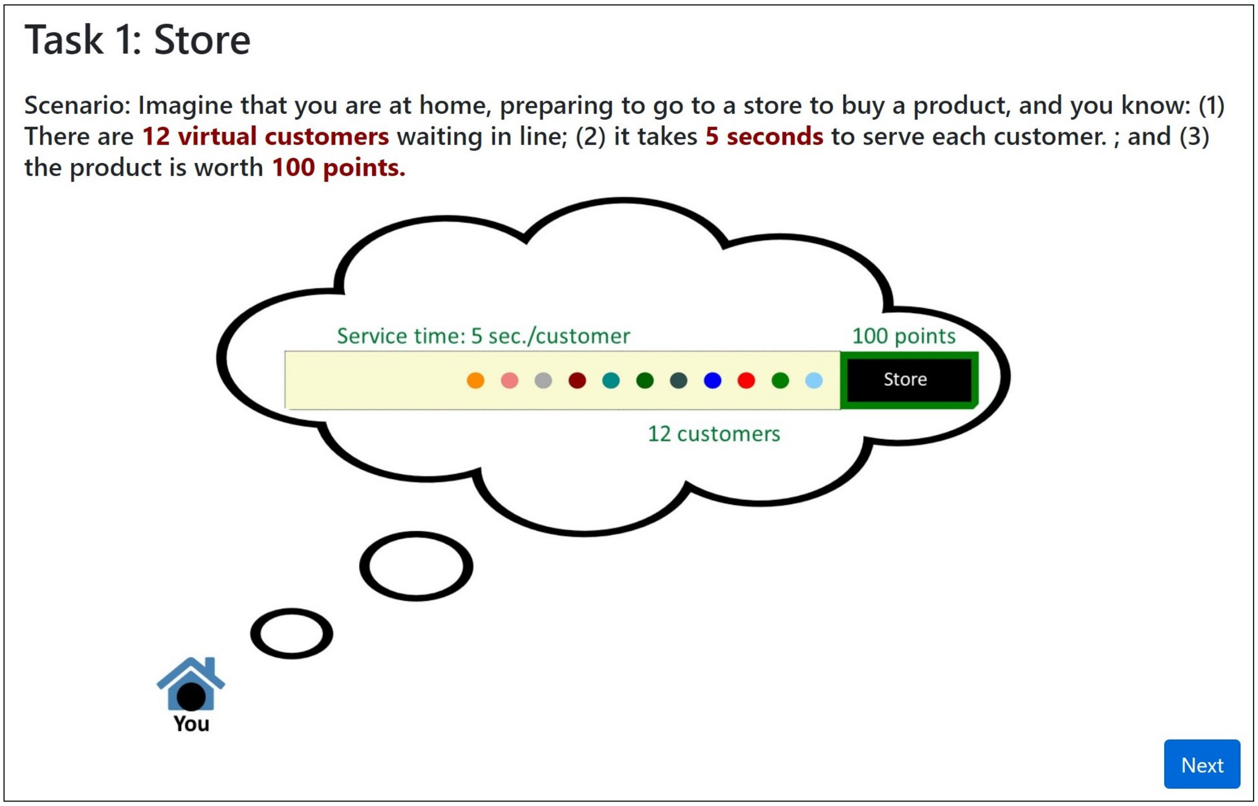
10. Do you get upset when you have to wait for anything?

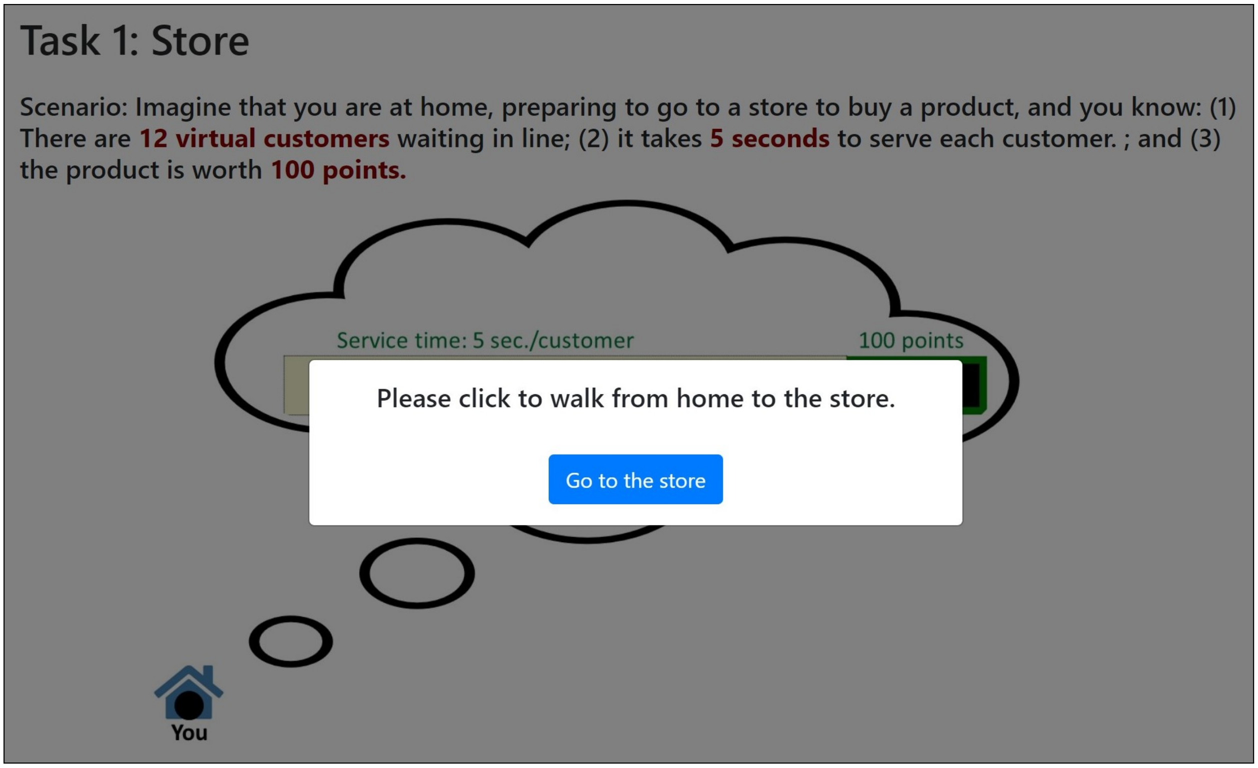
- ○ Yes
- ○ No

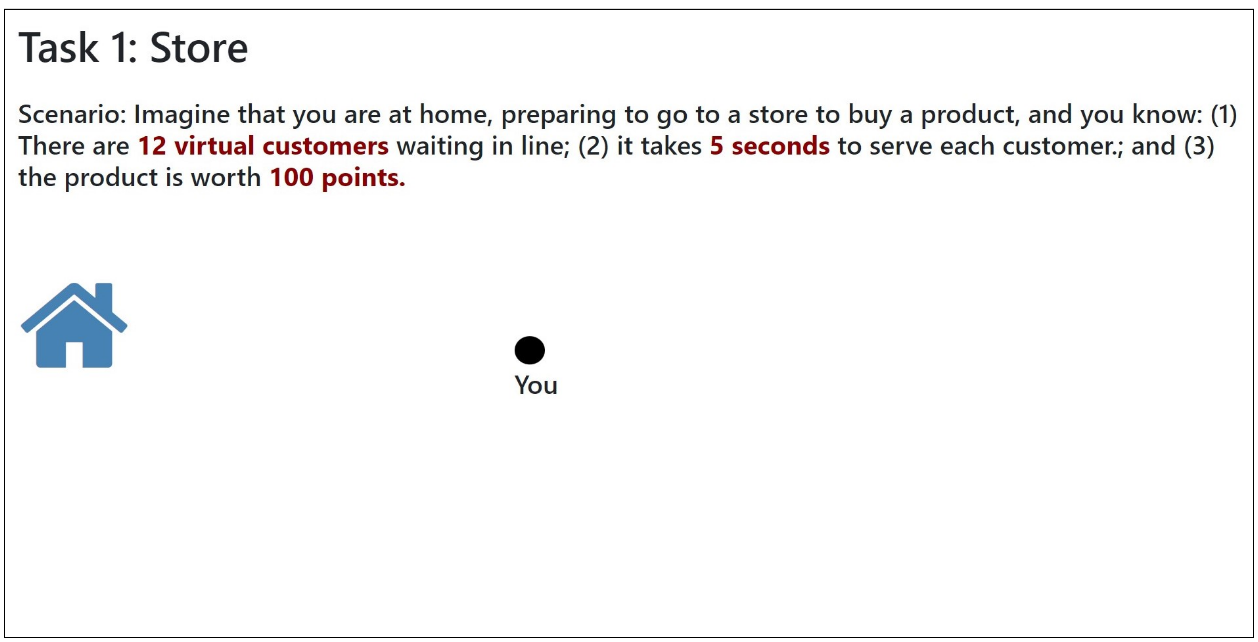
Next

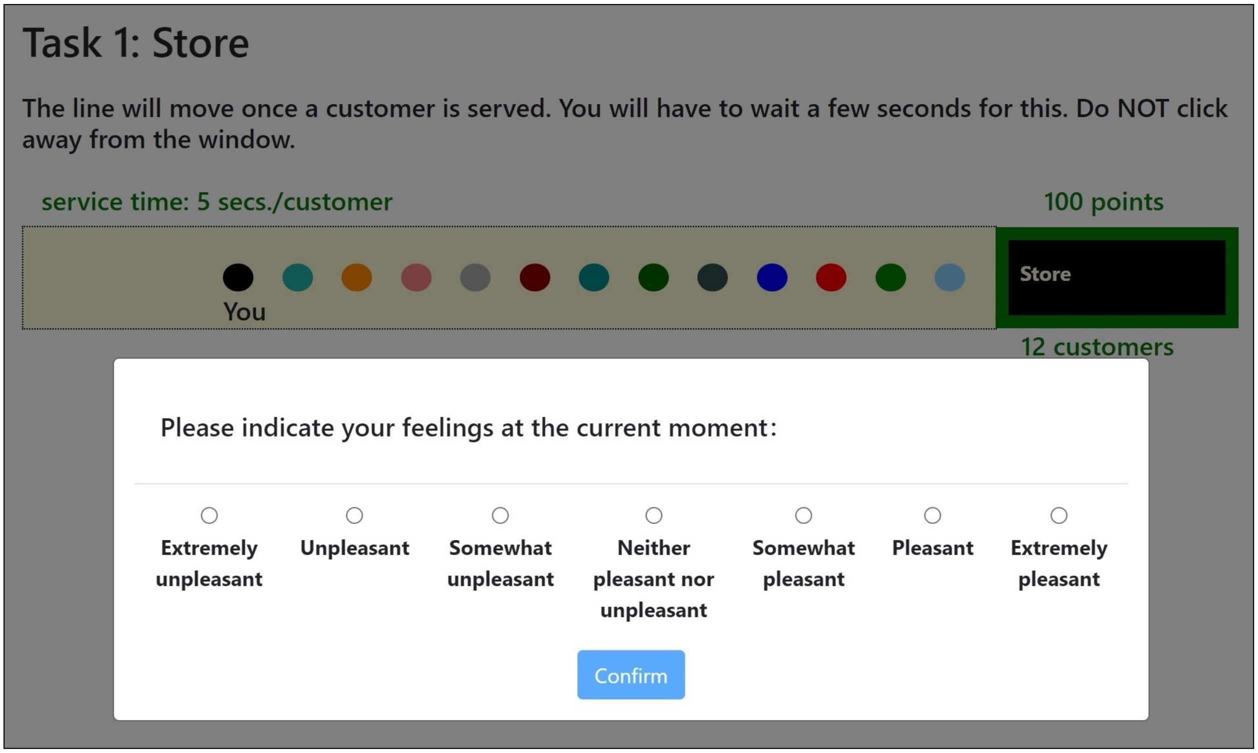
Appendix C Chapter 4

C.1 Joining Task




Task 1: Store
Scenario: Imagine that you are at home, preparing to go to a store to buy a product, and you know: (1) There are 12 virtual customers waiting in line; (2) it takes 5 seconds to serve each customer. ; and (3) the product is worth 100 points.
Service time: 5 sec./customer
100 points
Please click to walk from home to the store.
Go to the store
You


Task 1: Store
Scenario: Imagine that you are at home, preparing to go to a store to buy a product, and you know: (1) There are 12 virtual customers waiting in line; (2) it takes 5 seconds to serve each customer.; and (3) the product is worth 100 points.
You


Task 1: Store
The line will move once a customer is served. You will have to wait a few seconds for this. Do NOT click away from the window.
service time: 5 secs./customer
100 points
You
Store
12 customers
Please indicate your feelings at the current moment:
Extremely unpleasant
Unpleasant
Somewhat unpleasant
Neither pleasant nor unpleasant
Somewhat pleasant
Pleasant
Extremely pleasant
Confirm

Bibliography

Afeche, P. and Sarhangian, V. (2015). Rational Abandonment from Priority Queues: Equilibrium Strategy and Pricing Implications. *Columbia Business School Research Paper*, pages 1–48.

Akşin, Z., Ata, B., Emadi, S. M., and Su, C.-L. (2013). Structural estimation of callers' delay sensitivity in call centers. *Management Science*, 59(12):2727–2746.

Akşin, Z., Gencer, B., and Gunes, E. (2020). How observed queue length and service times drive queue behavior in the lab. Working paper, Koç University, Istanbul.

Allen, R. G. and Lerner, A. (1934). The concept of arc elasticity of demand. *Review of Economic Studies*, 1(3):226–229.

Allon, G. and Kremer, M. (2018). Behavioral foundations of queueing systems. *The Handbook of Behavioral Operations*, 9325:325–366.

Amberg, N., Jacobson, T., and Schedvin, E. V. (2020). Trade Credit and Product Pricing: The Role of Implicit Interest Rates. *Journal of the European Economic Association*, 00(0):1–32.

Babich, V. and Hilary, G. (2019). Distributed Ledgers and Operations : What Operations Management Researchers Should Know about Blockchain Technology. *Manufacturing and Service Operations Management*.

Banciu, M. and Mirchandani, P. (2013). Technical note - New results concerning probability distributions with increasing generalized failure rates. *Operations Research*, 61(4):925–931.

Batt, R. J. and Terwiesch, C. (2015). Waiting patiently: An Empirical Study of Queue Abandonment in an Emergency Department. *Management Science*, 61(1):39–59.

Becker, G. M., DeGroot, M. H., and Marschak, J. (1964). Measuring Utility by A Single-Response Sequential Method. *Behavioral Science*, 9(3):226–232.

Bolandifar, E., DeHoratius, N., Olsen, T., and Wiler, J. (2019). An empirical study of the behavior of patients who leave the emergency department without being seen. *Journal of Operations Management*, 65(5):430–446.

Buell, R. W. (2021). Last-place aversion in queues. *Management Science*, 67(3):1430–1452.

Carmon, Z. and Kahneman, D. (1995). The experienced utility of queuing: Experience profiles and retrospective evaluations of simulated queues. Working paper, Duke University, Durham, NC.

Chen, D. L., Schonger, M., and Wickens, C. (2016). oTree-An open-source platform for laboratory, online, and field experiments. *Journal of Behavioral and Experimental Finance*, 9:88–97.

Chen, J., Cai, T., He, W., Chen, L., Zhao, G., Zou, W., and Guo, L. (2020). A blockchain-driven supply chain finance application for auto retail industry. *Entropy*, 22(1):95.

Chen, Y., Xu, M., and Zhang, Z. G. (2009). A risk-averse newsvendor model under the CVaR criterion. *Operations Research*, 57(4):1040–1044.

Chod, J. (2016). Inventory, Risk Shifting, and Trade Credit. *Management Science*, (January 2019).

Conte, A., Scarsini, M., and Sürücü, O. (2016). The impact of time limitation: Insights from a queueing experiment. *Judgment and Decision Making*, 11(3):260–274.

Cui, S., Veeraraghavan, S. K., Wang, J., and Zhang, Y. (2018). In-queue observation and abandonment. Working paper, Georgetown University, Washington, DC.

Dada, M. and Hu, Q. (2008). Financing newsvendor inventory. *Operations Research Letters*, 36(5):569–573.

Dalal, D. K. and Zickar, M. J. (2012). Some Common Myths About Centering Predictor Variables in Moderated Multiple Regression and Polynomial Regression. *Organizational Research Methods*, 15(3):339–362.

Dong, L., Qiu, Y., Xu, F., and Louis, S. (2021). Blockchain-Enabled Deep-Tier Supply Chain Finance. *SSRN Electronic Journal*.

Donohue, K., Katok, E., Leider, S., and Eds (2018). *The Handbook of Behavioral Operations*.

Durrande-Moreau, A. and Usunier, J. C. (1999). Time Styles and the Waiting Experience: An Exploratory Study. *Journal of Service Research*, 2(2):173–186.

Eckel, C. C. and Grossman, P. J. (2002). Sex differences and statistical stereotyping in attitudes toward financial risk. *Evolution and human behavior*, 23(4):281–295.

Elliott, C. (2019). Catch you later: The quiet rise of call back systems. `https://www.forbes.com/sites/christopherelliott/2019/11/22/call-back-systems-rise`. Accessed: 2022-07-14.

Falk, A., Becker, A., Dohmen, T. J., Huffman, D., and Sunde, U. (2016). The preference survey module: A validated instrument for measuring risk, time, and social preferences. Working paper, University of Bonn, Bonn.

Futures, F. (2019). Half of SMEs are getting paid after 72 days. `https://www.fintechfutures.com/2019/05/half-of-smes-are-getting-paid-after-72-days/`. Accessed: 2022-07-14.

Gambetti, E. and Giusberti, F. (2012). The effect of anger and anxiety traits on investment decisions. *Journal of Economic Psychology*, 33(6):1059–1069.

Gaur, V. and Gaiha, A. (2020). Building a Transparent Supply Chain. *Harvard Business Review*.

Gneezy, U. and Potters, J. (1997). An experiment on risk taking and evaluation periods. *The Quarterly Journal of Economics*, 112(2):631–645.

Greene-Roesel, R., Castiglione, J., Guiriba, C., and Bradley, M. (2018). BART perks: Using incentives to manage transit demand. *Transportation Research Record*, 2672(8):557–565.

Gupta, N., Rigotti, L., and Wilson, A. (2021). The experimenters' dilemma: Inferential preferences over populations. arXiv preprint arXiv:2107.05064.

Hackius, N. and Petersen, M. (2017). Blockchain in Logistics and Supply Chain: Trick or Treat? *Digitalization in Supply Chain Management and Logistics*.

Halevy, Y. (2007). Ellsberg revisited: An experimental study. *Econometrica*, 75(2):503–536.

Hannigan, C. and Flicker, B. (2020). On people's queue joining behavior. Working Paper, The University of Chicago, Chicago.

Hassin, R. and Haviv, M. (1995). Equilibrium strategies for queues with impatient customers. *Operations Research Letters*, 17(1):41–45.

Hassin, R. and Roet-Green, R. (2020). On Queue-Length Information when Customers Travel to a Queue. *Manufacturing & Service Operations Management*, pages 1–16.

Hastig, G. M. and Sodhi, M. M. S. (2020). Blockchain for Supply Chain Traceability: Business Requirements and Critical Success Factors. *Production and Operations Management*, 29(4):935–954.

Haynes, S. G., Levine, S., Scotch, N., Feinleib, M., and Kannel, W. B. (1978). The relationship of psychosocial factors to coronary heart disease in the Framingham study: I. Methods and risk factors. *American Journal of Epidemiology*, 107(5):362–383.

Hernandez-Maskivker, G. and Ryan, G. (2016). Priority systems at theme parks from the perspective of managers and customers. *Technology Innovation Management Review*, 6(11).

Hu, K., Xu, X., and Qu, A. (2021). The psychology of virtual queue: When waiting feels less like waiting. *Available at SSRN 3933040*.

Hui, M. K. and Tse, D. K. (1996). What to tell consumers in waits of different lengths: An integrative model of service evaluation. *Journal of Marketing*, 60(2):81–90.

Iacobucci, D., Schneider, M. J., Popovich, D. L., and Bakamitsos, G. A. (2016). Mean centering helps alleviate "micro" but not "macro" multicollinearity. *Behavior Research Methods*, 48(4):1308–1317.

Jaccard, J., Wan, C. K., and Turrisi, R. (1990). The Detection and Interpretation of Interaction Effects Between Continuous Variables in Multiple Regression. *Multivariate Behavioral Research*, 25(4):467–478.

Janakiraman, N., Meyer, R. J., and Hoch, S. J. (2011). The psychology of decisions to abandon waits for service. *Journal of Marketing Research*, 48(6):970–984.

Jayachandran, P. (2017). The difference between public and private blockchain - Blockchain Unleashed: IBM Blockchain Blog. https://www.ibm.com/blogs/blockchain/2017/05/the-difference-between-public-and-private-blockchain/. Accessed: 2022-03-14.

Kelly, J. and Williams, A. (2016). Forty Big Banks Test Blockchain-Based Bond Trading System. `https://www.reuters.com/article/banking-blockchain-bonds/forty-big-banks-test-blockchain-based-bond-trading-system-idUSL8N16A30H`. Accessed: 2022-03-14.

Klos, A., Weber, E. U., and Weber, M. (2005). Investment decisions and time horizon: Risk perception and risk behavior in repeated gambles. *Management Science*, 51(12):1777–1790.

Kouvelis, P. and Zhao, W. (2017). Who Should Finance the Supply Chain ? Impact of Credit Ratings on Supply Chain Decisions. *Manufacturing & Service Operations Management*, 20 (1)(December):19–35.

Krishnan, R. (2016). How blockchain makes "deep tier" supplier finance possible. `http://www.scfbriefing.com/how-blockchain-makes-deep-tier-supplier-finance-possible/`. ccessed: 2022-01-14.

Larson, R. C. (1987). OR forum—perspectives on queues: Social justice and the psychology of queueing. *Operations research*, 35(6):895–905.

Leclerc, F., Schmitt, B. H., and Dube, L. (1995). Waiting Time and Decision Making: Is Time like Money? *Journal of Consumer Research*, 22(1):110.

Loewenstein, G. (2005). Hot-cold empathy gaps and medical decision making. *Health Psychology*, 24(4 SUPPL.):49–56.

Loewenthal, K. and Lewis, C. A. (2018). *An introduction to psychological tests and scales*. Psychology press.

Lu, Y., Musalem, A., Olivares, M., and Schilkrut, A. (2013). Measuring the effect of queues on customer purchases. *Management Science*, 59(8):1743–1763.

Luo, W. and Shang, K. (2013). Managing inventory for entrepreneurial firms with trade credit and payment defaults. *Available at SSRN*.

Lynn (2020). Financing Products Are Aplenty, But Why Aren't Enough SMEs Getting Them? *Funding Societies Blog*.

Ma, C., Kong, X., Lan, Q., and Zhou, Z. (2019). The privacy protection mechanism of Hyperledger Fabric and its application in supply chain finance. *Cybersecurity*, 2(1).

MacKinnon, K. R., Mykhalovskiy, E., Worthington, C., Gómez-Ramírez, O., Gilbert, M., and Grace, D. (2021). Pay to skip the line: The political economy of digital testing services for hiv and other sexually transmitted infections. *Social Science & Medicine*, 268:113571.

Maister, D. H. (1984). *The psychology of waiting lines*. Harvard Business Publishing, Boston.

Maister, D. H. (2005). The psychology of waiting lines.

Mandelbaum, A. and Shimkin, N. (2000). A model for rational abandonments from invisible queues. *Queueing Systems*, 36(1-3):141–173.

Miller, T. and Wongsaroj, S. (2017). The Domino Effect: the impact of late payments. *Sage*.

Morabito, V. (2017). Business Innovation Through Blockchain. *Cham: Springer International Publishing*.

Nakamoto, S. (2008). Bitcoin: A Peer-to-Peer Electronic Cash System. *Decentralized Business Review*, page 21260.

Naor, P. (1969). The regulation of queue size by levying tolls. *Econometrica: journal of the Econometric Society*, 37(1):15–24.

Naughter, T. (2017). Smart Contracts Vs. Traditional Contracts. https://www.contractworks.com/blog/smart-contracts-vs.-traditional-contracts. Accessed: 2022-03-10.

Neff, W. S. (2017). *Work & human behavior*. Routledge.

Normann, R. and Ramirez, R. (1993). From value chain to value constellation: Designing interactive strategy. *Harvard Business Review*, 71(4):65–77.

Okada, E. M. and Hoch, S. J. (2004). Spending Time versus Spending Money. *Journal of Consumer Research*, 31(2):313–323.

Osuna, E. E. (1985). The psychological cost of waiting. *Journal of Mathematical Psychology*, 29(1):82–105.

Palan, S. and Schitter, C. (2018). Prolific.ac—a subject pool for online experiments. *Journal of Behavioral and Experimental Finance*, 17:22–27.

Pallotta, F. (2021). Disney parks' new 'genie' app helps you skip lines. but you'll have to pay. https://www.cnn.com/2021/08/18/media/disney-parks-genie-app/index.html. Accessed: 2022-07-14.

Paolacci, G., Chandler, J., and Ipeirotis, P. G. (2010). Running experiments on amazon mechanical turk. *Judgment and Decision making*, 5(5):411–419.

Pazgal, A. I. and Radas, S. (2008). Comparison of customer balking and reneging behavior to queueing theory predictions: An experimental study. *Computers and Operations Research*, 35(8):2537–2548.

Peer, E., Rothschild, D., Gordon, A., Evernden, Z., and Damer, E. (2021). Data quality of platforms and panels for online behavioral research. *Behavior Research Methods*, pages 1–20.

Plott, C. R. and Zeiler, K. (2005). The Willingness to Pay-Willingness to Accept Gap , the "Endowment Effect," Subject Misconceptions , and Experimental Procedures for Eliciting Valuations. *The American Economic Review*, 95(3):530–545.

ProlificTeam (2022). Prolific. https://researcher-help.prolific.co/hc/en-gb/articles/360009223533-What-is-your-pricing-.Accessed:2022-03-24. Accessed: 2022-03-24.

Prosser, D. (2019). How Big Businesses Systematically Pay Their Small Suppliers Late. https://www.forbes.com/sites/davidprosser/2019/11/08/how-big-businesses-systematically-pay-their-small-suppliers-late/#2e71a5024eb0. Accessed: 2022-03-14.

Read, D. and Loewenstein, G. (1999). Enduring Pain for Money: Decisions Based on the Perception and Memory of Pain. *Journal of Behavioral Decision Making*, 12:1–17.

Rodriguez, A. E., Ibrahim, R., and Zhan, D. (2021). On customer (dis)honesty in priority queues: The role of lying aversion. Working Paper, University College London, London.

Rosic, A. (2016). What is Ethereum? [The Most Updated Step-by-Step-Guide!]. https://blockgeeks.com/guides/ethereum/. Accessed: 2022-3-10.

Shimkin, N. and Mandelbaum, A. (2004). Rational Abandonment from Tele-Queues : Nonlinear Waiting Costs with Heterogeneous Preferences. *Queueing Systems*, 47:117–146.

Soman, D. (2001). The mental accounting of sunk time costs: Why time is not like money. *Journal of Behavioral Decision Making*, 14(3):169–185.

Spielman, F. (2017). Rebate offer helped CTA Red Line commuters avoid Wrigley crowds. https://chicago.suntimes.com/2017/11/14/18318028/rebate-offer-helped-cta-red-line-commuters-avoid-wrigley-crowds. Accessed: 2022-3-10.

Strom, S. (2015). Big Companies Pay Later, Squeezing Their Suppliers. https://www.nytimes.com/2015/04/07/business/big-companies-pay-later-squeezing-their-suppliers.html. Accessed: 2022-3-10.

Su, X. (2007). Intertemporal Pricing with Strategic Customer Behavior. *Management Science*, 53(5):726–741.

Sun, J., Wu, J., Xiao, F., Tian, Y., and Xu, X. (2020a). Managing Bottleneck Congestion with Incentives. *Transportation Research Part B: Methodological*, 134:143–166.

Sun, K., Liu, Y., and Yang, L. (2020b). Order ahead for pickup: Promise or peril? *Available at SSRN 3673617*.

Swan, M. (2015). *Blockchain: Blueprint for a new economy.* " O'Reilly Media, Inc.".

Szabo, N. (1997). Formalizing and securing relationships on public networks. https://journals.uic.edu/ojs/index.php/fm/article/view/548/469. Accessed: 2022-07-14.

Tian, F. (2016). An agri-food supply chain traceability system for China based on RFID & blockchain technology. *2016 13th International Conference on Service Systems and Service Management, ICSSSM 2016*, pages 16–21.

Tong, J., DeCroix, G., and Song, J.-S. (2019). Modeling Payment Timing in Multiechelon Inventory Systems with Applications to Supply Chain Coordination. *Manufacturing & Service Operations Management*, (October).

Ülkü, S., Hydock, C., and Cui, S. (2020). Making the Wait Worthwhile: Experiments on the Effect of Queueing on Consumption. *Management Science*, 66(3):1149–1171.

Vliet, V. D. K., Reindorp, M. J., and Fransoo, J. C. (2015). The price of reverse factoring: Financing rates vs. payment delays. *European Journal of Operational Research*, 242(3):842–853.

Wang, K., Li, N., and Jiang, Z. (2010). Queueing system with impatient customers: A review. *Proceedings of 2010 IEEE International Conference on Service Operations and Logistics, and Informatics*, pages 82–87.

Wang, Y. (2016). What are the biggest obstacles to growth of SMEs in developing countries? – An empirical evidence from an enterprise survey. *Borsa Istanbul Review*, 16(3):167–176.

Webb, E. M., Yu, Q., and Bretthauer, K. M. (2017). Linking Delay Announcements, Abandonment, and Staffing: A Behavioral Perspective. *Kelley School of Business Research Paper*, 14(40).

Weinberg, B. (2019). Blockchain and KYC: Know Your Customer Better — OpenLedger Insights. `https://openledger.info/insights/blockchain-kyc/`. Accessed: 2022-03-14.

Wollenhaupt, G. (2021). Supply Chain: Deep-Tier Finance Gives SMEs A Boost. `https://www.gfmag.com/supply-chain-deep-tier-finance-gives-smes-boost/`. Accessed: 2022-02-14.

Wooldridge, J. (2002). *Econometric analysis of cross section and panel data*. MIT press.

Yaga, D., Mell, P., Roby, N., and Scarfone, K. (2018). Blockchain Technology Overview. *National Institute of Standards and Technology*, (October):1–68.

Yahsi, D. B. (2017). What is "Deep-Financing" and how does it improve your Supply Chain Competitiveness? Accessed: 2022-3-10.

Yang, S. A. and Birge, J. R. (2018). Trade credit, risk sharing, and inventory financing portfolios. *Management Science*, 64(8):3667–3689.

Yu, Q. (2020). When providing wait times, it pays to underpromise and overdeliver. *Harvard Business Review*.

Zhou, R. and Soman, D. (2003). Looking back: Exploring the psychology of queuing and the effect of the number of people behind. *Journal of Consumer Research*, 29(4):517–530.