Strategic Blockchain Adoption in Supply Chain Operations

by

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Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contributions

Chapters 2, 3, and 4 of this thesis are co-authored by myself and my supervisors, Prof. Samir Elhedhli, and Prof. Joe Naoum-Sawaya. Chapters 2 and 3 are submitted papers.

Abstract

Supply chains have often benefited from breakthroughs in information technology. Most recently, blockchain is promising to revolutionize the way supply chains are designed and operated. In this thesis, we explore blockchain adoptions in three supply chain settings. First, we optimize blockchain deployment at the supply chain network design stage and propose a mixed-integer quadratic programming model for it. Based on a case study from the fresh flowers supply chain, we find that significant cost savings could be achieved from the strategic deployment of blockchain throughout the supply chain as opposed to full blockchain adoption, which translates to lower market prices to consumers, increased demand, better product quality products, and higher profits. In the second, we investigate the potential of blockchain adoption to deter counterfeiters. We present a game-theoretic model that uses blockchain technology to increase the capability of detecting deceptive counterfeits. We find that blockchain is not always financially viable for manufacturers to discourage counterfeiting and it becomes less attractive for premium and luxury products. Our framework also demonstrates that manufacturers can strategically balance product quality and blockchain investment to combat counterfeiting. Last, we explore the potential of blockchain to accurately track carbon emissions. We study a competitive supplier selection problem with one manufacturer and two suppliers and investigate the use of financial incentives to encourage suppliers to adopt greener technologies. The game-theoretic framework is modelled as a bi-level optimization problem. We find that financial incentives are effective in fostering greener components from the suppliers and that blockchain offers suppliers the flexibility to explore emission reductions either by better reporting or technological upgrades.

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Dedication

I dedicate this thesis to my sons, Antonio and Samuel. Your love gave me the energy to keep running in the marathon that a Ph.D. degree is. I hope this thesis, which is the result of hard work and persistence, inspires you to always be curious and creative.

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Chapter 1

Introduction

To survive the ever-increasing competition, companies are continuously taking measures to reduce costs, increase efficiency, and positively differentiate their products. These measures include the outsourcing of non-core activities, the globalization of suppliers, and mergers and acquisitions (Isik, 2010). As supply chains are becoming global, complexity is increasing due to suppliers being located in different geographical regions and that are operating under different local regulations and standards (Wu and Pullman, 2015). In parallel, firms are increasingly being held responsible for the environmental, social, and economic impacts of their activities, as well as their partners' operations (van Donk et al., 2010; Hartmann and Moeller, 2014). On top of that, societies are becoming more connected and customers are seeking more transparency before buying a product. There is a growing segment of customers that want supply chain transparency and that are willing to pay for the information, particularly in the food and luxury markets (Choi, 2019; Sunny et al., 2020; Balzarova, 2020). Achieving supply chain transparency is a challenge for companies, as many have little or no visibility over their second or third-tier suppliers (Abeyratne and Monfared, 2016). Blockchain technology (BCT) offers information transparency and security that can support this endeavour through integrated and immutable records.

Decentralized ledgers, such as blockchain, are a promising alternative for better information systems. Blockchain development was tied to the creation of cryptocurrencies such as Bitcoin (Nakamoto et al., 2008), and can be defined as a list of records organized in a decentralized chain architecture, where each block contains information about the corresponding transaction and a link to previous blocks. Blockchain architecture turns posterior data modification infeasible and has the potential to revolutionize many traditional systems with traceable, reliable, transparent, and above all safe information (Abeyratne and Monfared, 2016). The implementation of blockchain can be through a service provider or developed internally. The potential of blockchain has attracted renowned companies (e.g., IBM, Microsoft) and created new providers (e.g., Ethereum, Hyperledger, Ripple). More importantly, blockchain technology can transform every step of a supply chain, improving procurement processes, generating transparency and provenance, integrating suppliers and manufacturers, and supporting informed decisions from customers (Dutta et al., 2020; Babich and Hilary, 2020a; Goyat et al., 2019). The World Economic Forum (WEF) lists BCT as one of the six megatrends that will shape our future society and estimates that by 2027 information regarding 10% of global Gross Domestic Product will be stored on blockchain (WEF, 2015). To take full advantage of blockchain features, the adoption decision must be considered at a strategic level together with other crucial decisions in supply chain design and operations management. Quantitative models in supply chain operations that consider blockchain implementation are still scarce (Dutta et al., 2020), and this thesis contributes to enriching the relevant literature by proposing frameworks and insights to support managers and practitioners. More specifically, this thesis explores the strategic deployment of blockchain for supply chain network design, to deter counterfeiting, and for supplier competition under carbon emission restrictions.

In Chapter 2, we study the application of blockchain in the supply chain network design of perishable products. We propose a framework that optimizes the blockchain implementation along with other strategic and operational decisions, accounting for the overall impact on profitability. Our framework is based on a mixed-integer quadratic programming formulation that presents a new form of product differentiation based on the data collected and stored with blockchain. Blockchain adoption is modelled as binary variables that indicate which transportation routes use blockchain to store information. This design enables a strategic deployment of blockchain, which contributes to the resiliency of the supply chain against changes in consumer preferences and blockchain costs. We also showcase the opportunity to monetize the data through a newline of blockchain-enabled products that are sold with a price premium. To illustrate the benefits of the proposed framework we present a case study on the global supply chain of fresh-cut flowers. The proposed framework leads to significant cost savings compared to the full adoption of blockchain technology throughout the supply chain, which translates to lower market prices to consumers and increased demand. Furthermore, the proposed data-enabled product differentiation leads to higher profits and higher quality products.

Chapter 3 examines the strategic implications of blockchain technology as a deterrent against the sales of deceptive counterfeit products. We investigate the use of blockchain to eliminate the financial advantage of counterfeiters, to the point where it is no longer economically attractive for them to enter the market. We propose a mathematical formulation to model the competition between the genuine and counterfeit firms, deriving analytically the equilibrium states and the optimal blockchain implementation level. We later investigate the interplay between quality differentiation and blockchain technology. Our approach focuses on the balance between the cost and implementation level compared to the gain that can be obtained by turning the market less attractive to counterfeiters. Moreover, we show that manufacturers can strategically balance between product quality and investment in blockchain to combat counterfeiting. Furthermore, our results demonstrate that with the availability of blockchain, genuine manufacturers may become less interested in investing in improving product quality to differentiate their products from counterfeits but rather rely on blockchain to prevent the sales of counterfeits.

Chapter 4 investigates the use of blockchain to track carbon emissions in a multi-tiered supply chain. We explore a supplier competition setting with carbon emission restriction, where a manufacturer decides on the allocation of outsourced orders and can award bonuses to foster lower emissions from suppliers. Suppliers can decide on blockchain adoption and technological upgrades to reduce emissions. We propose a mixed-integer programming formulation to represent the supplier's and manufacturer's problems. The numerical results show that the manufacturer can choose among several equally profitable allocations and bonus arrangements and can incentivize the suppliers to use blockchain and adapt technologies that lower carbon emissions. The results also indicate the opportunity for governmental participation with subsidies to offset blockchain costs and foster greener products.

In Chapter 5, we conclude the thesis by presenting the main conclusions and highlighting potential future research directions.

Chapter 2

Blockchain-Enabled Supply Chains: An Application in Fresh-Cut Flowers

2.1 Introduction

Modern supply chains often involve multiple global players with different standards, quality, work ethics, and government regulations. It is common to source raw materials from one continent, manufacture in another, and serve markets all over the world. When information is stored in individual databases and is not shared between supply chain stakeholders, it does not benefit the entire supply chain. An integrated supply chain requires a continuous flow of both materials and information (Prajogo and Olhager, 2012).

The goal of supply chain management is to improve efficiency and cost-effectiveness in the flow of goods and services (Simchi-Levi et al., 2004). However, efficiency is bound by how the supply chain is designed. Traditional supply chain network design (SCND) models have decisions at three levels: strategic, operational, and tactical. The strategic configuration of the chain is a crucial step that determines the efficiency of the tactical operations, with long-term effects for firms and customers (Santoso et al., 2005). According to Simchi-Levi et al. (2004), SCND is the main tool to decrease costs in a supply chain. SCND models typically aim at minimizing costs while knowledge management is often ignored (Eskandarpour et al., 2015). Davenport (1994) defines knowledge management as the process of capturing, distributing, and using information. Competitive advantage can be achieved when companies effectively manage knowledge throughout the supply chain (Jaska et al., 2010).

Over the recent few years, many industrial sectors have been facing systematic changes with digital systems, such as internet of things and artificial intelligence. With more data available, connected devices, and computational power, traditional businesses are being reshaped to benefit from the advantages offered by these technological advancements. To achieve these benefits, information must be integrated and widely available in the supply chain, which is a challenge due to the many actors and individual data silos. In a multi-tiered network, companies are often less willing to share information, mainly due to culture, legal aspects, or power relations (Kembro et al., 2017). These challenges are alleviated through the integration of technology. In fact, information technology has been an essential enabler for the development of supply chains (Ben-Daya et al., 2019), starting with information systems, enterprise resource planning, global positioning system (GPS), and radio-frequency identification (RFID). More recently, distributed ledgers and blockchain technology (BCT) have become a prominent technology to advance supply chains.

The World Economic Forum (WEF) lists BCT as one of the six megatrends that will shape our future society (WEF, 2015). Blockchain development was tied to the creation of cryptocurrencies such as Bitcoin (Nakamoto et al., 2008) and can be defined as a list of records organized in a decentralized chain architecture, where each block contains information about the corresponding transaction and a link to previous blocks. The blocks are added in a linear order on a public ledger, and transactions are validated in a peer-to-peer structure. The blockchain design, based on a cryptographic hash to previous nodes, provides immutable data, with distributed storage and controlled user access (Abeyratne and Monfared, 2016). WEF estimates that, by 2027, information regarding 10% of global Gross Domestic Product will be stored on blockchain (WEF, 2015).

Although blockchain has its largest development in the financial sector, BCT adoption is increasing in other sectors, including operations and supply chain management. Babich and Hilary (2020a) argue that operations management can benefit from distributed ledger systems due to visibility, aggregation, validation, automation, and resilience. Information can be shared in real-time among all players in the chain, increasing transparency and product traceability. With reliable data, suppliers can plan and better estimate demand, and customers can make more informed buying decisions. Blockchain can reduce the challenges in information sharing, by strategically defining what data will be shared and the access level of each player. Furthermore, supply chain transparency and integrated information can be a tool to differentiate products and create value from information that traditionally was used solely to improve supply chain operations. Sectors like the pharmaceutical and food industries could benefit from blockchain-enabled product differentiation, provenance, and trustability (Petersen et al., 2018).

The supply chain behind the availability of fresh produce from all over the globe and in any season of the year is impressive. Intricate coordination of producers, distributors, retailers, and grocery stores is vital to provide fresh produce at affordable prices when needed. Perishable products are very important in retail, as they account for more than 40% of the grocery chains' revenues (Buck and Minvielle, 2013). According to a survey from McKinsey, quality and freshness rank over price in customer preference on produce (Läubli and Ottink, 2018). Therefore, for a successful operation, factors such as freshness, lead time, quality, in addition to cost, need to be considered when designing the supply network. The ability to trace and track conditions and product age is critical to ensure that the products arrive with the desired quality at the right time. However, there are many challenges to product tracking due to the global scale of supply chains and the involvement of multiple players (Marucheck et al., 2011).

In this chapter, we propose a framework to integrate blockchain technology as a strategic decision at the supply chain network design level. The proposed framework optimizes the implementation of BCT throughout the supply chain taking into account the cost of deployment and the overall impact on profitability. As such, we argue that the strategic deployment of BCT renders the supply chain performance more robust to changes in consumer preference and, very importantly, to blockchain costs, which have so far been volatile. Traditionally supply chain data is shared among players to improve performance and reduce cost. Alternatively, the present work proposes an approach to create value to consumers from the supply chain data and offers an opportunity to monetize the data. As such, a new line of data-enabled products is sold at a premium to a growing segment of consumers that are mindful of reliable product sourcing information and are willing to pay for it. We consider this to be a price premium since the model differentiates products based on the data, charging more for the new category of certified-fresh products in comparison to regular products.

To showcase the benefits of the proposed framework, a case study on the global supply chain of fresh-cut flowers is presented. The results illustrate the value of the strategic deployment of BCT throughout the supply chain network for the consumers as well as the supply chain stakeholders. Furthermore, the presented case study demonstrates the value of data-enabled product differentiation and the opportunity of monetizing supply chain data through BCT adoption.

The remainder of this chapter is organized as follows. A review of the current literature is presented in Section 2.2. The proposed framework and the problem formulation are discussed in Section 2.3. Section 2.4 presents the case study on the global supply chain of fresh-cut flowers. Section 2.5 concludes the chapter and highlights future research opportunities.

2.2 Literature review

Technology has played a significant role in product development, production processes, operations management, and supply chains (Cohen and Lee, 2020). Supply chain design particularly evolved with the adoption of technological advancements such as enterprise resource planning systems (Gezgin et al., 2017) and RFID tags, which transformed supply chains into more flexible, agile, open, and collaborative networks (Accenture, 2013). A new paradigm of production and distribution emerged with the adoption of industry 4.0 (Kagermann et al., 2013), the massive deployment of sensors, internet of things, flexible manufacturing, and intensive automation. Following this technological evolution, blockchain has the potential to reshape supply chains (Deloitte, 2017). The efficiency of a supply chain is sustained on the trust between the different stakeholders, which can be supported by the information reliability that is enabled by blockchain technology.

The research on information sharing in supply chains is well established particularly in the areas of inventory management and forecasting, (e.g., Lee et al., 1997; Gavirneni et al., 1999; Lee et al., 2000; Chen et al., 2000; Aviv, 2001; Kim and Chai, 2017; Srinivasan and Swink, 2018). The present work complements the research on information sharing and outlines a new paradigm based on monetizing the supply chain information by selling it to consumers in the form of data-enabled products that are supported by BCT.

The literature on blockchain in operations and supply chain management is very recent, focusing mostly on opportunities and trends and/or presents case studies. For instance, Abeyratne and Monfared (2016) discusses how blockchain increases transparency in a supply chain, mitigating environmental and social risks. Hackius and Petersen (2017) explores the potential for BCT in easing paperwork processing in marine freight, in identifying counterfeit products, in facilitating origin tracking by distributed ledger systems, and in the operation of the internet of things. Saberi et al. (2019) focuses on the research possibilities for blockchain adoption in sustainable supply chain management. The authors emphasize that there are potential barriers to BCT adoption, such as inter-organizational barriers, intra-organization barriers, system-related barriers, and external barriers. Cole et al. (2019) highlights that, despite the potential benefits of BCT, as presented by the literature, the adoption may not fit all companies, due to cost, energy consumption, and additional digital waste. Most recently, Babich and Hilary (2020a) discusses the present state of blockchain technology and its application to operations management and highlights the potential benefits improving visibility, aggregation, validation, automation, and resilience.

The literature on the modelling aspect of blockchain implementation is still limited. Chang et al. (2018) proposes a model that captures the level of BCT implementation and its impact on demand, prices, and inventories. The mathematical model considers the adoption degree of BCT as a decision variable, with an objective function that maximizes the total expected discounted profit. Results show that the implementation of BCT impacts the ordering quantity and leads to lower price and inventory levels. A game-theoretic model focusing on blockchain-enabled supply chains for diamonds has been presented in Choi (2019). The trade-off between traditional jewelry retail and the blockchain-enabled channel is evaluated and the results show that blockchain under certain conditions can be beneficial to both the manufacturer and the consumer. In Choi and Luo (2019), the impact of improving data quality through blockchain on social welfare is evaluated and the results show that blockchain can improve social welfare but may reduce supply chain profitability. Fan et al. (2020) proposes a three-echelon supply chain game-theoretic model that incorporates blockchain. The consumer's utility function includes a value for traceability awareness when blockchain is present. Results show traceability awareness is key for blockchain adoption while the manufacturer is responsible for the largest share of the cost. Liu and Guo (2021) proposes a model to evaluate the impact of blockchain on the supply chain of fresh products. The model considers blockchain effect on the quality, safety, and reliability of the information disclosed by the manufacturer. The paper demonstrates that if freshness and information on reliability improve, with blockchain use, the overall profit of the supply chain also increases. He et al. (2021) proposes a three stage game-theoretic for price optimization with blockchain consideration. The paper considers the supply of fresh products with customers that are concerned about freshness and safety. The results show that the pricing strategy depends on how customers value freshness over safety. When freshness dominates, prices are higher and the blockchain cost is sustained by the suppliers. Manupati et al. (2020) proposes a blockchain-enabled supply chain network design model under carbon taxation policy. The authors present a non-linear mixed-integer formulation that uses blockchain to account for emissions based on smart contracts.

This work proposes an optimization model for blockchain-enabled network design for fresh produce. To our knowledge, such a framework has not been discussed previously in the literature and thus our model complements existing work on blockchain-enabled supply chains particularly Chang et al. (2018), Manupati et al. (2020), Fan et al. (2020), Liu and Guo (2021), and He et al. (2021). We note that there is also a vast literature on the incorporation of perishability in supply chain network design by accounting for quality degradation such as Blackburn and Scudder (2009); Cai et al. (2010); Rong et al. (2011); de Keizer et al. (2017) though none of these considers blockchain.

2.3 Proposed framework and problem formulation

The optimization of production-distribution networks has been extensively studied in the supply chain design literature (Sarmiento and Nagi, 1999). The common approach is to consider a three-echelon production-distribution network where the locations of facilities at each of the echelons are optimized jointly with the transportation links to ensure the flow of products from production sites to customer zones. Optimization models, as well as solution approaches for the production distribution supply chain network design problem, were presented in Elhedhli and Goffin (2005) and Amiri (2006). Several extensions have also been proposed to account for inventory (Vidyarthi et al., 2007), reverse logistics (Alumur et al., 2012), multi-period (Pan and Nagi, 2013), and disruption risk (Sadghiani et al., 2015). This work extends the production distribution supply chain network design literature by proposing a model that accounts for blockchain. Similar to the models that have been presented in the literature, we consider a three-echelon production-distribution network and propose a model to jointly optimize the design of the network along with the deployment of blockchain to track product flow through the network.

We assume that fresh produce is harvested at production sites, consolidated at distribution centres, and then transported and sold at customer zones. We assume that all production sites can satisfy the allocated demand. Multiple transportation modes are assumed to exist between the different sites. Products age as they are transported between the different supply chain echelons. Transportation modes differ by their cost and transportation time, which impacts the product age (i.e., freshness level). We assume that freshness levels are discrete and limited to a few categories, two in our model. Blockchain can be adopted at certain transportation links along the supply chain to maintain a record of the product age. The demand at each customer zone is a function of the price and freshness level of the product. The model presented next captures the impact of blockchain technology implementation on the design of the network. Particularly, we assume that BCT adoption is a binary decision to represent if travel time information on a particular link, i.e., the ageing of the product, is tracked using blockchain. Blockchain usage incurs cost that is minimized along with the supply chain cost. We assume only variable costs for blockchain usage. Most manufacturers do not have the infrastructure or resources to implement their own blockchain platform and often rely on blockchain providers operating with a model that charges only for variable costs (Pun et al., 2021). With the consideration of implementation or fixed costs, a minimum production quantity would be necessary to justify the adoption of blockchain. Figure 2.1 depicts the blockchain-enabled supply chain that is considered in this framework. Products flow from one echelon to the next using a physical network and information is added to the blockchain at the transportation links.

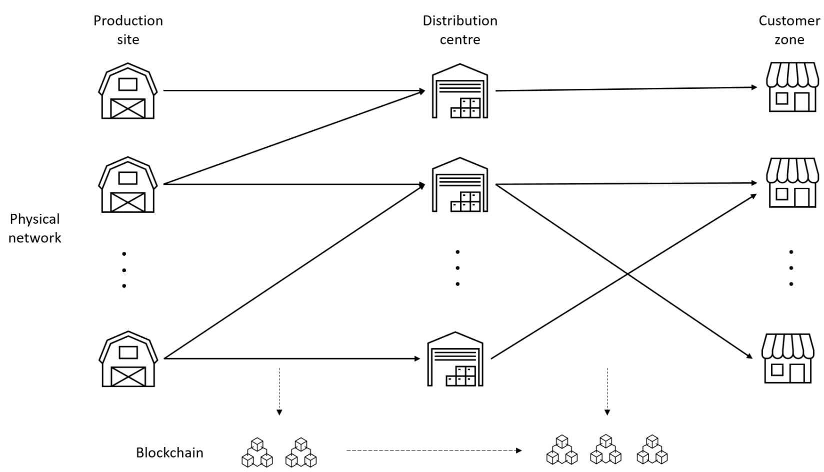


Figure 2.1: Blockchain-enabled supply chain

To formulate the problem, the following sets, indices, parameters, and decision variables are defined.

Sets:

I : set of production sites.

J : set of distribution centres.

K : set of customer zones.

L : set of transportation modes.

F : set of freshness levels.

A : set of transportation links.

Indices:

i, j : index for facilities; $i, j \in I \cup J \cup K$.

f : index for freshness level; $f \in F$.

l : index for transportation mode; $l \in L$.

Parameters and functions:

Γ : blockchain usage unit cost.

c_i : per unit production cost at site i; $i \in I$.

g_i : fixed cost for operating location i; $i \in I \cup J \cup K$.

τ_{ij}^l : per unit transportation cost between facilities i and j using mode l; $(i, j) \in A, l \in L$.

t_{ij}^l : transportation time between facilities i and j using mode l; $(i, j) \in A, l \in L$.

Note that t_{ij}^l also includes processing and storage time at location j.

$\bar{t}_{ij}$: maximum transportation time between facilities i and j (i.e., $\max_l\{t_{ij}^l\}$); $(i, j) \in A$.

$\bar{\Delta}^f$: maximum allowable product age for freshness level f; $f \in F$.

$\underline{\Delta}_i$: storage and processing time before shipping at production site i; $i \in I$.

$D_i^f(p_i^f)$: demand at customer zone i for products of freshness level f; $i \in K, f \in F$.

Decision variables:

x_{ij}^{lf} : quantity of products with freshness level f shipped between facilities i and j using transportation mode l; $(i,j) \in A, l \in L, f \in F$.

q_i : quantity produced at production site i; $i \in N$.

p_j^f : price at customer zone j for products of freshness level f; $j \in C, f \in F$.

Δ_j^f : age of products of freshness level f sold at customer zone j; $j \in C, f \in F$.

$$r_{ij}^l : \begin{cases} 1 & \text{if the travel time information of link } (i,j) \text{ using mode } l \text{ is stored on the blockchain;} \\ & (i,j) \in A, l \in L, \\ 0 & \text{otherwise.} \end{cases}$$

$$y_{ij}^{lf} : \begin{cases} 1 & \text{if mode } l \text{ is used to transport products of freshness level } f \text{ on link } (i,j); \\ & (i,j) \in A, l \in L, f \in F, \\ 0 & \text{otherwise.} \end{cases}$$

$$z_i : \begin{cases} 1 & \text{if location } i \text{ is used;} \quad i \in I \cup J \cup K, \\ 0 & \text{otherwise.} \end{cases}$$

Blockchain-enabled supply chain network design problem is formulated as

$$[BCT - SCND]: \quad \max \sum_{i \in K} \sum_{f \in F} D_i^f(p_i^f) p_i^f - \sum_{i \in I} c_i q_i - \sum_{(i,j) \in A} \sum_{l \in L} \sum_{f \in F} \tau_{ij}^l x_{ij}^{lf}$$
$$- \sum_{i \in I \cup J \cup K} g_i z_i - \sum_{(i,j) \in A} \sum_{l \in L} \sum_{f \in F} \Gamma r_{ij}^l x_{ij}^{lf} \tag{2.1}$$
$$\text{s.t.} \sum_{j \in D, (i,j) \in A} \sum_{l \in L} \sum_{f \in F} x_{ij}^{lf} \leq q_i \qquad \forall i \in I; \tag{2.2}$$

$$\sum_{i \in D,(i,j) \in A} \sum_{l \in L} x_{ij}^{lf} = D_j^f(p_j^f) \qquad \forall j \in C, f \in F; \tag{2.3}$$

$$\sum_{i \in N,(i,j) \in A} \sum_{l \in L} x_{ij}^{lf} = \sum_{i \in C,(i,j) \in A} \sum_{l \in L} x_{ji}^{lf} \qquad \forall j \in J, f \in F; \tag{2.4}$$

$$q_j \le M z_j \qquad \forall j \in N; \tag{2.5}$$

$$\sum_{i \in I,(i,j) \in A} \sum_{l \in L} \sum_{f \in F} x_{ij}^{lf} \le M z_j \qquad \forall j \in J; \tag{2.6}$$

$$\sum_{i \in J,(i,j) \in A} \sum_{l \in L} \sum_{f \in F} x_{ij}^{lf} \le M z_j \qquad \forall j \in K; \tag{2.7}$$

$$\Delta_j^f \ge \Delta_i^f + t_{ij}^l r_{ij}^l + \bar{t}_{ij}(1 - r_{ij}^l) - M(1 - y_{ij}^{lf})$$

$$\forall (i,j) \in A, l \in L, f \in F; \tag{2.8}$$

$$\Delta_i^f \le \bar{\Delta}^f \qquad \forall i \in K, f \in F; \tag{2.9}$$

$$\Delta_i^f \ge \underline{\Delta}_i \qquad \forall i \in I, f \in F; \tag{2.10}$$

$$x_{ij}^{lf} \le M y_{ij}^{lf} \qquad \forall (i,j) \in A, l \in L, f \in F; \tag{2.11}$$

$$r_{ij}^l \le \sum_{f \in F} y_{ij}^{lf} \qquad \forall (i,j) \in A, l \in L; \tag{2.12}$$

$$r_{ij}^l, y_{ij}^{lf}, z_j \in \{0,1\} \qquad \forall (i,j) \in A, l \in L, f \in F; \tag{2.13}$$

$$q_i, p_j^f, x_{ij}^{lf}, \Delta_j^f \ge 0 \qquad \forall (i,j) \in A, l \in L, f \in F. \tag{2.14}$$

The objective function (2.1) maximizes the net profit. The first component is the total revenue, where the realized demand $D_i^f(p_i^f)$ at each customer zone i is multiplied by the product price at location i. The realized demand function $D_i^f(p_j^f)$ for each customer zone i and freshness level f is dependent on price p_i^f. The remaining costs are the transportation cost, the fixed cost for establishing the operations at each facility, and the blockchain usage cost, respectively. Constraints (2.2) set the production for each plant. Constraints (2.3) ensure that the demand for each customer zone is satisfied. Conservation of flow at the distribution locations is defined in (2.4). Constraints (2.5) - (2.7) indicate that if there is product flow then the concerned facilities must be opened. Constraints (2.8) define the age of the products as the total transportation time for the links where BCT is used. When BCT is not used, the shipping time cannot be certified, and the age is assumed to be the worst transportation time $\bar{t}_{ij}$. Constraints (2.9) set the maximum age for each freshness level. Constraints (2.10) set the initial product age starting from the production sites. Constraints (2.11) indicate the active links. Constraints (2.12) ensure that blockchain is not considered on inactive transportation links. The variable types are defined in (2.13) - (2.14). M is a very large number.

The proposed formulation has two non-linear terms in the objective function, the revenue and the blockchain storage cost. For the revenue, as to be discussed in section 2.4, we assume that the demand is a linear function of price. The resulting quadratic revenue function is solvable using commercial optimization solvers. The other non-linear term is the blockchain storage cost in which a binary variable (blockchain usage) is multiplied by a continuous variable (product flow). To linearize this term, an auxiliary variable, w_{ij}^{lf}, is introduced and additional constraints are added. The resulting model is

$$
\begin{aligned}
[BCT - SCND]: \quad & \max \sum_{i \in K} \sum_{f \in F} D_i^f(p_i^f) p_i^f - \sum_{i \in I} c_i q_i - \sum_{i,j \in A} \sum_{l \in L} \sum_{f \in F} \tau_{ij}^l x_{ij}^{lf} \\
& \quad - \sum_{i \in I \cup J \cup K} g_i z_i - \sum_{i,j \in A} \sum_{l \in L} \sum_{f \in F} \Gamma w_{ij}^{lf} \qquad (2.15) \\
& \text{s.t.}(2.2) - (2.14); \\
& \quad w_{ij}^{lf} \leq M r_{ij}^l \qquad \forall (i,j) \in A, l \in L, f \in F; \qquad (2.16) \\
& \quad w_{ij}^{lf} \leq x_{ij}^{lf} \qquad \forall (i,j) \in A, l \in L, f \in F; \qquad (2.17) \\
& \quad w_{ij}^{lf} \geq x_{ij}^{lf} - M(1 - r_{ij}^l) \qquad \forall (i,j) \in A, l \in L, f \in F; \qquad (2.18) \\
& \quad w_{ij}^{lf} \geq 0 \qquad \forall (i,j) \in A, l \in L, f \in F. \qquad (2.19)
\end{aligned}
$$

In the objective function (2.15), the term $r_{ij}^{l} x_{ij}^{lf}$ from (2.1) is replaced by the new variable w_{ij}^{lf}. The new constraints (2.16) - (2.18) are a set of logical constraints that define w_{ij}^{lf} to be equal to zero when blockchain is not used ($r_{ij}^{l} = 0$), and w_{ij}^{lf} to be equal to x_{ij}^{lf} if blockchain is used ($r_{ij}^{l} = 1$).

The proposed formulation optimizes the deployment of BCT as part of the design stage of the supply chain network. As discussed in the case study that is presented in the following section, optimizing the placement of BCT lowers the costs of the supply chain compared to the full deployment of BCT. Evidently, the lower cost translates to lower product prices for consumers. Furthermore, product differentiation is achieved based on the product freshness that is based on the information stored on the blockchain. As presented in the analysis of the case study, higher quality products that are certified by the blockchain are sold at a premium compared to other products that are not certified by data. The proposed approach thus differentiates product pricing based on the accompanying information, which is a way to monetize the supply chain data through the use of blockchain. BCT is a unique technology that enables such a framework due to the main characteristics of reliability and, most importantly, trust.

The following section presents the case study on the global supply chain of fresh-cut flowers. $[BCT - SCND]$ is adapted to this case and insights are presented.

2.4 Case study - fresh-cut flowers

The cut-flower business is an important and global market. In 2017, \$8.5B worth of flowers were sold globally, and the main producing countries are the Netherlands with 43% of the global supply, followed by Latin American countries Colombia with 15%, and Ecuador with 10%. Kenya is the fourth top producer with 8% and the largest in Africa. As for the import of flowers, the United States is the top destination with a total of 20%, followed by Germany with 14%, then UK and Netherlands with 11% each, according to data from OEC (2017).

The delicacy and perishability of fresh-cut flowers lead to significant supply chain challenges. To transport flowers from farms to customers across continents, a very balanced and complex supply chain is needed. The transport from farms to distribution centres is mainly done in refrigerated containers, either by plane or cargo ships. Once close to the customer zones, refrigerated trucks perform the last mile to retailers or grocery stores (Grower Direct, 2020). The coordination of several players and custom agencies is crucial in this time-sensitive supply chain. Blockchain technology adoption in the floral industry has attracted companies and producers, most notably IBM and Maersk (IBM, 2017).

For this case study, the Canadian imports of flowers are considered. A report from IBISWorld (2017) indicates that revenue from florists in Canada totalled $673 million, with 45% of the costs being the purchase cost. According to the Canadian International Merchandise Trade Database, in 2017, Canada imported 12.4 million dozen roses, for a total of $76.1 million, mainly from Colombia and Ecuador (Government of Canada, 2018). When accounting for all cut flowers, the imports totalled $79 million (OEC, 2017). The parameters for the case study are detailed next.

Production farms: The top 3 flower exporters to Canada, accounting for 89.4%, are considered. The locations are real farms from the largest flower producers in Colombia, Ecuador, and the Netherlands. The detailed parameters for production sites are presented in Table 2.1.

Table 2.1: Production site parameters

site (i)	f_i	c_i	$\underline{\Delta}_i$	location	coordinates
1	\$100,000	\$1.0	0.5 days	Netherlands (NLD)	52.26, 4.78
2	\$100,000	\$1.0	0.5 days	Colombia (COL)	6.04, -75.41
3	\$100,000	\$1.0	0.5 days	Ecuador (ECU)	-0.12, -78.28

Distribution centres: Four distribution centres are considered. They are situated in top ports and are close to the biggest population zones in Canada. The first is located in Halifax, the second in Quebec City, the third in Toronto, and the fourth in Vancouver. For Halifax and Quebec, the exact coordinates are the ports. For Toronto and Vancouver, they are the airports, Pearson and Vancouver International, respectively. Table 2.2 presents the parameters for the distribution centres.

Table 2.2: Distribution centre parameters

centre (i)	f_i	location	coordinates
1	\$500,000	Halifax (HFX)	44.64, -63.57
2	\$500,000	Quebec (QBC)	46.82, -71.21
3	\$500,000	Toronto (TOR)	43.68, -79.63
4	\$500,000	Vancouver (VAN)	49.19, -123.17

Customer zones: Ten customer zones are considered among the Canadian provinces and territories. For each zone, the most populous city in the province was selected as the customer zone. Figure 2.2 shows the locations of the production sites, distribution centres, and customer zones. The parameters for the customer zones are detailed in Table 2.3.

Figure 2.2: Fresh-cut flowers case study - location map

Table 2.3: Customer zone parameters

zone (j)	f_j	location	coordinates	κ_j
1	\$10,000	Ontario (ON)	43.65, -79.38	0.388
2	\$10,000	Quebec (QC)	45.50, -73.58	0.225
3	\$10,000	British Columbia (BC)	49.28, -123.12	0.135
4	\$10,000	Alberta (AB)	51.04, -114.08	0.116
5	\$10,000	Manitoba (MB)	49.90, -97.14	0.036
6	\$10,000	Saskatchewan (SK)	50.45, -104.62	0.031
7	\$10,000	Nova Scotia (NS)	44.65, -63.61	0.026
8	\$10,000	Newfoundland and Labrador (N.L.)	47.56, -52.71	0.014
9	\$10,000	Prince Ed. Island/ New Bruns. (P.E.I/NB)	45.27, -66.06	0.025
10	\$10,000	Northwest Territories (NT)	62.45, -114.37	0.003

Transportation modes: Two transportation modes are considered between the locations. Between production sites and distribution centres, the first mode is air transit and the second is ocean freight. Between distribution and customer zones the fastest mode is air transit and the slowest is trucking. Transportation times are based on the distance between source and destination. Distances are calculated from point to point, with flight durations and truck driving times calculated using Google Maps. Sea transit times are obtained using the website *sea-distances.org* for an average ship speed of 24 knots. Vega et al. (2008) analyzes the transportation of flowers between Ecuador and Miami. A detailed breakdown of activities and time starting from harvesting to the final delivery at the customer zone are listed in Table 2.4. Following Vega et al. (2008), a fixed set-up of 12.5 hours is considered for transportation between production and distribution and 10 hours between distribution and customer zones. The set-up times are accordingly added to the total transportation time between each pair of locations.

Table 2.4: Activities from harvest to delivery and their durations, as presented by Vega et al. (2008)

Process	Duration (hours)
Post-harvest on farm, Ecuador	4-8
Storage on farm	12-72
Transportation to cargo agencies	1-6
Storage at cargo agency	4
Palletizing, Quito	6
Customs clearance, Quito	0.5
Loading to aircraft, Quito	1-2
Flight UIO-MIA nonstop	4
Customs clearance, Miami	4-12
Depalletizing, Miami	2-4

Costs: Bradsher (2006) indicates that farmers in China sell a single flower in the local market from \$0.04 to \$0.16 (\$0.48 to \$1.92 per dozen). We assume a production cost of \$1/dozen for this case study, which is consistent with Bradsher (2006). Transportation costs are considered to be proportional to the time/distance between locations and relative to each mode. Bradsher (2006) also defines air freight costs at around \$0.30 per stem (\$3.6/dozen in 2006 dollars and \$4.5 in 2019) from China to the US. To estimate the transportation costs, we assume a courier-type contract where the cost is proportional to the quantity transported and distance. For air transportation, an average cost of \$1.5 per pound of flowers (2 pounds per dozen) is assumed, which is equivalent to the cost presented by Bradsher (2006). For ocean freight, an average cost of \$0.4 per pound is considered, which makes air transportation on average 4 times more expensive than maritime. Truck transportation costs are estimated to be on average \$0.5 per pound, which makes air transit 3 times more expensive than trucks. The detailed transportation costs and times are presented in Tables 2.5 and 2.6.

For each facility, a fixed contract set-up cost is considered. The assumption is that these costs cover the allocation of the workforce and other administrative resources to enable the intended activities. The fixed cost for production sites is assumed to be \$100,000, \$500,000 for the distribution centres, and \$10,000 for each customer zone. Equivalent fixed costs were not available in the present literature, so they were estimated to best represent the case study set-up. The blockchain storage cost is based on Ernst & Young (2019) which estimated the unit cost per transaction to be \$0.858.

Table 2.5: Transportation times and cost between production and distribution locations

time t_{ij}^l (days) / cost τ_{ij}^l (\$)

Tran. mode (l)			Dist. centre (j) HFX	QBC	TOR	VAN
1	Prod. site (i)	NLD	1/2.5	1.1/2.7	1.2/2.9	1.3/3.3
		COL	1.4/3.5	1.3/3.3	1.1/2.7	1.3/3.3
		ECU	1.4/3.5	1.3/3.3	1/2.6	1.3/3.3
2		NLD	5.5/0.6	6/0.6	6.5/0.7	16.5/1.7

COL	4.5/0.5	5.5/0.6	6.5/0.7	8/0.8
ECU	6/0.6	7.5/0.8	8/0.8	8/0.8

Table 2.6: Transportation times and cost between the distribution centres and customer zones

time t^l_{ij} (days) / cost τ^l_{ij} (\$)

Tran. mode (l)	Dist. centre (i)		Customer zone (j)									
			ON	QC	BC	AB	MB	SK	NS	N.L.	P.E.I/NB	NT
1		HFX	0.6/1.6	0.5/1.4	1.1/2.7	0.9/2.2	0.9/2.2	1/2.5	-/-*	0.6/1.5	0.5/1.3	1.3/3.1
		QBC	0.5/1.4	0.5/1.3	1/2.6	1/2.5	0.8/2.1	1/2.5	0.7/1.7	0.8/2.1	0.7/1.7	1.2/3
		TOR	-/-*	0.5/1.3	0.8/2.1	0.8/1.9	0.6/1.6	0.7/1.8	0.6/1.5	0.7/1.7	0.6/1.5	1/2.5
		VAN	0.8/1.9	0.8/2	-/-*	0.5/1.4	0.6/1.6	0.6/1.5	1/2.5	1.1/2.8	1/2.5	0.6/1.6
2		HFX	2/0.7	1.5/0.5	5.2/1.7	4.4/1.5	3.4/1.1	3.9/1.3	0.5/0.2	2.3/0.8	0.8/0.3	5.8/1.9
		QBC	1.1/0.4	0.7/0.2	4.6/1.5	3.8/1.3	2.7/0.9	3.1/1.0	1.3/0.4	2.9/1	1/0.3	5.1/1.7
		TOR	0.5/0.2	0.9/0.3	3.8/1.3	3.3/1.1	2.2/0.7	2.6/0.9	1.9/0.6	3.5/1.2	1.7/0.5	4.6/1.5
		VAN	3.9/1.3	4.2/1.4	0.5/0.2	1.3/0.3	2.4/0.8	1.9/0.6	5.2/1.7	6.8/2.3	4.9/1.6	2.6/0.9

* No air transportation available since distribution centre and customer zone are located in the same city

Freshness levels: According to Vega et al. (2008), a rose should last from one week to two weeks after being cut. Thus, two freshness levels were considered, one for products that are at most three days old (certified fresh) and the other for the non-certified products which can be up to 9 days old. Equation (2.9) in [BCT-SCND] guarantees that no flower can be sold if its age is higher than 9 days, to ensure some remaining days of vase life.

Demand functions: We assume a linear demand function for each freshness level at each customer zone, of the form of $D_i^f = \bar{D}_i^f - m_i^f \times p_i^f$, where m_i^f is the slope and $\bar{D}_i^f$ the intercept. The assumption is that a small number of freshness levels (2 in this case) is sufficient to represent the market. Each freshness level is thus a product category with a clear differentiation based on the product quality, i.e., product age. The demand for each customer zone is assumed to be proportional to its relative population in Canada, by a factor (κ_j), as shown in Table 2.3. For each customer zone, the total population was obtained from Statistics Canada.

To determine the coefficients of the demand functions, the following assumptions were made. The sum of both intercepts was arbitrarily defined at 40 million dozen flowers. The demand for certified fresh products is assumed to be higher, with a proportion of 60% to 40%. Hence, the intercepts of certified and non-certified fresh products are set to 24 million and 16 million, respectively. The demand parameters are summarized in Table 2.7 and the demand functions are depicted in Figure 2.3. Non-certified products are defined as more price elastic, and therefore the slope is steeper compared to the certified products.

Table 2.7: Demand functions per freshness level

level (f)	$\bar{D}_i^f$	m_i^f
1	24×10^6	1.92×10^6
2	16×10^6	2.4×10^6

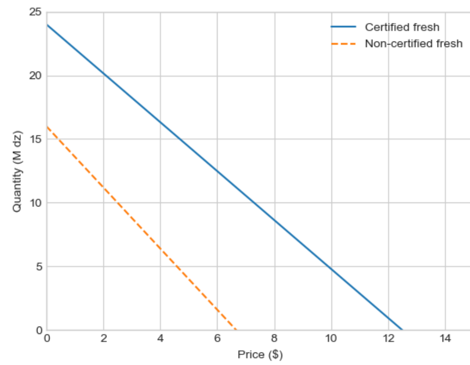


Figure 2.3: Fresh-cut flowers case study - demand curves

2.4.1 Results and insights

This section presents the results and analysis of the cut-flowers case study. The mathematical model $[BCT - SCND]$ was coded using python 3.6 and was solved using GUROBI 8.1. The optimal solution is depicted in Figure 2.4. The solution uses all three production sites, Plant 1 in the Netherlands producing 2.6 million dozen, Plant 2 in Colombia with 2.8 million dozen, and Plant 3 located in Ecuador with 6.5 million dozen. The total production is 11.9 million dozen flowers. Three out of four distribution centres are used, the ones in Halifax, Toronto, and Vancouver. All ten customer zones are served with both levels of freshness. Blockchain information is used on three links between production and distribution and seven between distribution and customers. The objective value in the optimal solution is $33.7 million and the revenue is $83.2 million. Table 2.8 summarizes the optimal production quantities.

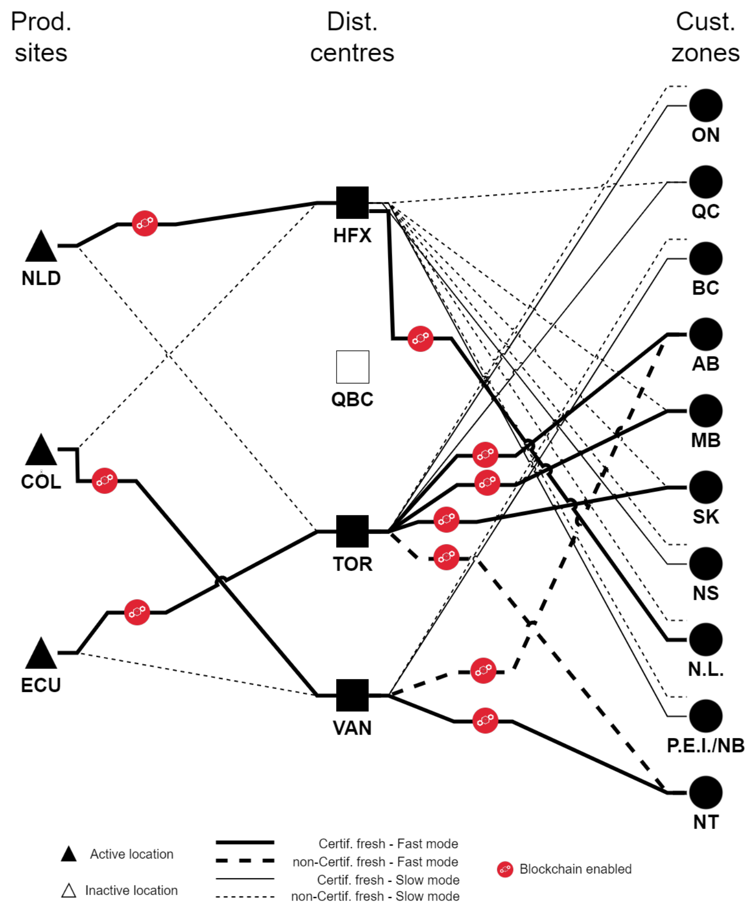


Figure 2.4: Solution diagram

Table 2.8: Quantity of flowers produced at each production site

	Production site (i)		
	NLD	COL	ECU
Quantity (M dz)	2.6 (22.0%)	2.8 (23.6%)	6.5 (54.4%)

The quantities transported between the production and distribution centres and between distribution centres and customer zones, by transportation mode and freshness levels, are represented in Tables 2.9 and 2.10, respectively. Quantities are in thousands of dozen flowers and the links where blockchain is used are marked with a star.

The optimal solution shows that the fresher products are generally two times more

Table 2.9: Quantity of flowers (K dz) transported between each production and distribution sites

Mode	Fresh		HFX	QBC	TOR	VAN
fast	certif.	NLD	⋆ 450.7	-	-	-
		COL	-	-	-	⋆ 915.1
		ECU	-	-	⋆ 5,401.5	-
fast	non certif.	NLD	-	-	-	-
		COL	-	-	-	-
		ECU	-	-	-	-
			HFX	QBC	TOR	VAN
slow	certif.	NLD	-	-	-	-
		COL	-	-	-	-
		ECU	-	-	-	-
slow	non certif.	NLD	-	-	2,169.9	-
		COL	1,896.9	-	-	-
		ECU	-	-	-	1,072.0

expensive, which is expected considering that the value of flowers drops by 15% every day (Fredenburgh, 2019). The optimal prices are summarized in Table 2.11.

The total revenue is \$83.2 million with a profit margin of 40.5%. The calculated total consumer surplus, which is the difference between how much a customer would be willing to pay minus how much they are paying, is \$17.8 million. The average age of sold products is 3.99 days and the final average market price is \$6.99 per dozen.

As a summary, the results show that blockchain can be used to monetize data through differentiated pricing of the product categories. Information is added to the blockchain for the cases where the fast transportation mode is necessary to ensure the freshness level. Market segmentation is observed by the final price, as the certified fresh products cost around twice the non-certified. It is important to note that the optimal solution has blockchain for all the links with fast transportation mode. Since the only two possibilities are fast or slow transportation mode, blockchain only adds value when used to certify the travel time of the fast mode.

Table 2.10: Quantity of flowers (K dz) transported between each distribution centre and customer zone

Mode	Fresh		ON	QC	BC	AB	MB	SK	NS	N.L.	P.E.I./NB	NT
fast	certif.	HFX	-	-	-	-	-	-	-	$\star$ 74.6	-	-
		QBC	-	-	-	-	-	-	-	-	-	-
		TOR	-	-	-	$\star$ 569.9	$\star$ 189.1	$\star$ 155.9	-	-	-	-
		VAN	-	-	-	-	-	-	-	-	-	$\star$ 14.9
fast	non certif.	HFX	-	-	-	-	-	-	-	-	-	-
		QBC	-	-	-	-	-	-	-	-	-	-
		TOR	-	-	-	-	-	-	-	-	-	$\star$ 5.8
		VAN	-	-	-	$\star$ 342.5	-	-	-	-	-	-
			ON	QC	BC	AB	MB	SK	NS	N.L.	P.E.I./NB	NT
slow	certif.	HFX	-	-	-	-	-	-	192.9	-	183.2	-
		QBC	-	-	-	-	-	-	-	-	-	-
		TOR	2,856.2	1,630.5	-	-	-	-	-	-	-	-
		VAN	-	-	900.2	-	-	-	-	-	-	-
slow	non certif.	HFX	-	1,225.9	-	-	169.1	138.9	150.4	70.7	141.9	-
		QBC	-	-	-	-	-	-	-	-	-	-
		TOR	2,164.2	-	-	-	-	-	-	-	-	-
		VAN	-	-	729.4	-	-	-	-	-	-	-

Table 2.11: Price per dozen flowers at each customer zone

Customer zone (j)	Freshness level (f) 1	2
ON	\$ 8.66	\$ 4.34
QC	\$ 8.73	\$ 4.40
BC	\$ 9.03	\$ 4.42
AB	\$ 9.95	\$ 5.44
MB	\$ 9.79	\$ 4.73
SK	\$ 9.90	\$ 4.81
NS	\$ 8.61	\$ 4.24
N.L.	\$ 9.69	\$ 4.53
P.E.I./NB	\$ 8.65	\$ 4.28
NT	\$ 10.16	\$ 5.94

Next, we introduce changes to the model to analyze two extreme cases, first when no BCT is used, and then when BCT is considered on every active link on the network.

No blockchain vs. full blockchain adoption

To evaluate the impact of blockchain on the supply chain network design, the same case study is considered under two assumptions, the first when no BCT is used and the other with BCT on every active link on the network. The no-BCT model is derived from $[BCT-SCND]$, without the term $\sum_{i,j\in A}\sum_{l\in L}\sum_{f\in F}\Gamma r_{ij}^{l}x_{ij}^{lf}$ in the objective function, given that there is no blockchain cost. Since there is no BCT certification, then one freshness level is considered, and constraints (2.8) are replaced by an upper bound on the product age, enforced by

$$\Delta_j \geq \Delta_i + t_{ij}^{l}y_{ij}^{l} \qquad \forall (i,j) \in A, l \in L.$$

The upper limit for product age is set on 6 days, instead of 3 to 9 for the partial BCT case. Only one demand curve per customer zone is necessary for the no-BCT model, as there is a single freshness level. The intercept is set to 40 million dozen. Using the real number of sold roses in 2017 and the total revenue of \$76 million, the estimated parameters of the demand curve are estimated as presented in Table 2.12.

Table 2.12: Demand function for the no blockchain model

level (f)	$\bar{D}_j^f$	m_j^f
1	40×10^6	4.5×10^6

The rest of the parameters of $[BCT-SCND]$ remain unchanged. The resulting optimal solution has flowers sourced only from Colombia, where a total of 12.3 million dozen flowers is produced. Two out of four distribution centres are used, in Halifax, and Vancouver. All ten customer zones are served. The objective value is \$32.9 million with a revenue of \$75.2

million and a profit margin of 44%. The consumer surplus is \$17.0 million. The average age of the sold flowers is 4.78 days. The market prices per customer zone are listed in Table 2.13.

Table 2.13: Price per dozen flowers at each customer zone for the no blockchain case

Customer zone (j)	Freshness level (f) 1
ON	\$ 6.05
QC	\$ 5.95
BC	\$ 6.79
AB	\$ 6.36
MB	\$ 6.36
SK	\$ 6.51
NS	\$ 5.35
N.L.	\$ 6.00
P.E.I./NB	\$ 5.39
NT	\$ 7.14

The next scenario that is evaluated is the extreme case where blockchain adoption is used on every active link of the network. This is enforced by adding the following constraint to $[BCT - SCND]$.

$$\sum_{f \in F} y_{ij}^{lf} \leq 2 * r_{ij}^{l} \qquad \forall (i,j) \in A, l \in L.$$

All parameters remain the same as the partial BCT case. In the optimal solution, flowers are sourced from all three facilities. A total of 9.3 million dozen of flowers are produced, 1.2 million from the Netherlands, 2.5 million from Colombia, and 5.6 million from Ecuador. Three out of four distribution centres are used, in Halifax, Toronto and Vancouver. All ten customer zones are served. The objective value is \$22.1 million with a revenue of \$73.7 million and a profit margin of 30%. The average age of the sold flowers is 3.52 days and the consumer surplus is \$12.0 million. Blockchain is adopted for all 26 active links. The market prices are listed in Table 2.14.

Table 2.14: Price per dozen flowers at each customer zone for the full blockchain case

Customer zone (j)	Freshness level (f) 1	2
ON	\$ 9.09	\$ 5.20
QC	\$ 9.16	\$ 5.26
BC	\$ 9.46	\$ 5.27
AB	\$ 9.95	\$ 5.87
MB	\$ 9.79	\$ 5.59
SK	\$ 9.90	\$ 5.67
NS	\$ 9.04	\$ 5.10
N.L.	\$ 9.69	\$ 5.39
P.E.I./NB	\$ 9.08	\$ 5.14
NT	\$ 10.16	\$ 6.37

With full blockchain adoption, products are differentiated based on freshness since complete information is available about product age as all travel times are tracked using blockchain. Due to the full adoption of blockchain, total cost increases, which is then reflected in higher market prices. The prices for the non-certified products are 16% more expensive compared to the partial BCT model, while the certified fresh are 2.5% higher. Table 2.15 presents a summary of the results for the three cases of BCT adoption.

The adoption of blockchain has an impact on the total number of flowers produced and market prices. With more blockchain, fewer flowers are produced, which are then sold at a higher price. Partial blockchain produces 3% fewer flowers with 2.5% more revenue compared to the no-BCT model. As full blockchain is enforced, production reduces by 21% and the revenue by 35%, relative to the partial BCT case. As blockchain cost is proportional to the quantity produced, with full blockchain it is more profitable to reduce production. This affects directly the consumers, leading to lower supply and higher prices. The freshness of products is better with more blockchain, where the average age decreases as the level of blockchain increases, going from 4.78 days with no blockchain to 3.52 with

Table 2.15: Results for different blockchain adoption

	no-BCT	BCT	full-BCT
Quantity produced (M dz)	12.3	11.9	9.3
Objective value (M $)	32.9	33.7	22.1
Revenue (M $)	75.2	83.2	73.7
Profit margin (%)	44	41	30
Average price ($)	6.12	6.99	7.91
Consumer surplus (M $)	17.0	17.8	12.0
Production sites active	1/3	3/3	3/3
Distrib. centres active	2/4	3/4	3/4
Customer zones served	10/10	10/10	10/10
Links with blockchain	-	10/26	26/26
Average product age	4.78	3.99	3.52

full-BCT. The model with partial BCT has better results than the no-BCT for consumer surplus, product age, and gross profit. The consumer surplus is 5% higher than the no-BCT case and 48% more than the full-BCT. However, the fresher and more adequate products (in terms of consumer surplus) come at the expense of the market price increase for customers and profit margin reduction for companies. Flowers are 16% fresher than the no-BCT case, but 13% older compared to the case with complete blockchain usage. The price increases when enforcing full blockchain by 2%, on average, for the certified fresh products and 14% for the non-certified. The full blockchain implementation imposes a heavy burden on total costs, dropping the profit by 53.2% in comparison to the baseline case. By strategically optimizing the BCT location, a better profit margin is achieved, in comparison to the full-BCT case, with fresher products, compared to the no-BCT case, and with the best consumer surplus among all three scenarios.

The maximum allowable product age is a key parameter in the no-BCT model. The maximum allowable age is varied between 2 and 8 days and the no-BCT model is solved. Figure 2.5 summarizes the results. By increasing the maximum age allowable, more products may be transported by slower transportation and fewer facilities become active, reducing costs, and reshaping the supply chain network.

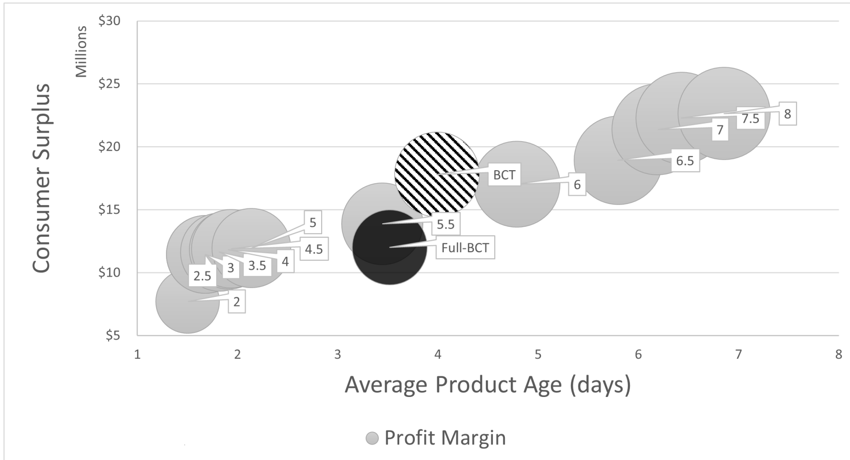


Figure 2.5: Results when changing the maximum allowable age of products for the no-BCT case.

Each circle in the diagram represents one solution of the model, with the maximum allowable age in the label. The relative circle size represents the profit margin, the y-axis is the consumer surplus and the x-axis is the average age of products. The solutions for the full-BCT and partial BCT are depicted in different colours, for comparison. The partial BCT provides fresher products compared to the no-BCT case with a maximum allowable age higher than 6 days. For all cases lower than 6 days, partial BCT has better indicators for consumer surplus and profit margin but provides products that are on average less fresh. For maximum allowable ages higher than 6 days, the use of the slow transportation modes becomes feasible for many links, allowing cost savings at the expense of less fresh products on average.

In summary, increasing the level of blockchain usage ensures better information and products with a lower average age. This however comes at the expense of a decrease in profit. Therefore, blockchain must be selected for strategic locations. The proposed formulation optimizes the blockchain usage to maximize profit.

Next, to evaluate the model's behaviour towards changes in the demand function and blockchain costs, a sensitivity analysis is conducted and the partial and full-BCT cases are compared.

Sensitivity analysis

In this section, sensitivity analysis on the blockchain cost and demand function is conducted. First, the blockchain unit transaction cost is varied. Then the impact of the demand functions is evaluated.

Blockchain cost

Blockchain costs can vary significantly depending on the type of architecture and maturity level of the implementation. Like any new technology, developments can drastically change the costs, making it a volatile parameter. The baseline model considered a unit cost of $0.858 per transaction (Ernst & Young, 2019). A multiplier factor on the cost of blockchain is applied to evaluate the impact on the model results.

As shown in Table 2.16, as the BCT cost increases, quantity produced, revenue, consumer surplus, and profit margin, all decrease. The average product age increases as the cost goes up. At a cost multiplier of 10, the quantity produced drops to one-third, the consumer surplus to one quarter, and products sold are almost twice as old, in comparison to the scenario with zero BCT cost. The production quantities for each freshness level change significantly as the BCT cost increases. The average price increases with higher costs and reaches a maximum between multipliers 3 and 5. After that, blockchain usage is reduced. More products with no information about freshness are thus available and are sold at a lower price as non-certified products. This fact shows that blockchain usage and cost determine the strategy for product mix (in terms of freshness levels) and hence the

Table 2.16: Results when varying the blockchain unit cost

BCT cost multip.	Qty prod. (M dz)	Revenue (M $)	Profit margin	Consumer surplus (M $)	Average price ($)	Average prod. age	Prod. sites active	Distrib. centres active	Customer zones served	Links with blockchain	Quantity of products with blockchain (M dz)	
											N-D	D-C
0	13.0	88.8	47%	21.6	6.82	3.86	3/3	3/4	10/10	10/26	7.8 (60%)	1.8 (14%)
0.01	13.0	88.8	47%	21.6	6.83	3.86	3/3	3/4	10/10	10/26	7.7 (60%)	1.8 (14%)
0.1	12.9	88.3	46%	21.2	6.84	3.87	3/3	3/4	10/10	10/26	7.7 (59%)	1.8 (14%)
0.5	12.5	86.2	43%	19.6	6.92	3.92	3/3	3/4	10/10	10/26	7.3 (58%)	1.6 (13%)
1	11.9	83.2	41%	17.8	6.99	3.99	3/3	3/4	10/10	10/26	6.8 (57%)	1.4 (14%)
3	9.7	68.3	33%	12.1	7.06	4.35	3/3	3/4	9/10	8/24	4.8 (49%)	0.4 (5%)
5	7.9	53.8	29%	8.7	6.79	4.85	2/3	3/4	8/10	3/19	3.1 (40%)	- (0%)
7	6.6	41.6	27%	6.5	6.29	5.48	2/3	3/4	8/10	3/19	1.8 (28%)	- (0%)
10	4.6	20.4	46%	5.3	4.39	6.88	1/3	2/4	7/10	0/9	- (0%)	- (0%)
100	4.6	20.4	46%	5.3	4.39	6.88	1/3	2/4	7/10	0/9	- (0%)	- (0%)

necessary supply chain design for profitability.

A key insight is that as the cost increases, the additional expense is not just passed on to the price. There is a point, between $2.60 and $4.30, in which the supply chain strategy changes to prioritizing non-certified over the certified fresh products and the average price goes down. When certified fresh products become no longer profitable, due to high blockchain cost, a larger share of non-certified products is sold. The price premium can no longer be exploited, and the revenue is cut in half. However, with the lower total cost from non-certified products, the profit margin is restored to levels equivalent to the zero BCT cost scenario.

Both the BCT cost multiplier and the maximum allowable age of certified fresh products are varied next. The model is solved with the maximum age for the certified fresh set between 2 to 8 days while keeping the non-certified at 9 days. The BCT cost multiplier is varied between 0 to 10. Figure 2.6 shows the change in consumer surplus for partial and full-BCT cases. The graphs show that the full-BCT is more sensitive to the cost variation than the partial BCT model. Beyond blockchain cost multiplier of 5, the consumer surplus is zero for the full BCT model, regardless of the maximum allowable age of certified fresh. This happens as no production occurs past that since it is no longer profitable. For the partial blockchain model, the consumer surplus increases as the maximum allowable age are higher, even with high blockchain costs. The impact on the profit margin is shown in Figure 2.7.

(a) Partial BCT model (b) Full-BCT model

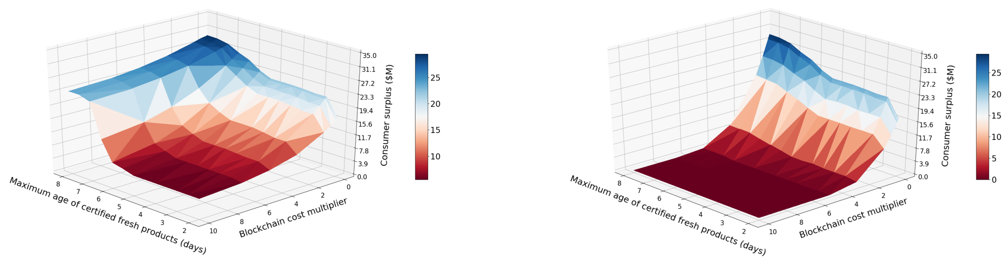


Figure 2.6: Consumer surplus when changing the maximum age for the certified fresh product and the blockchain cost multiplier

(a) Partial BCT model (b) Full-BCT model

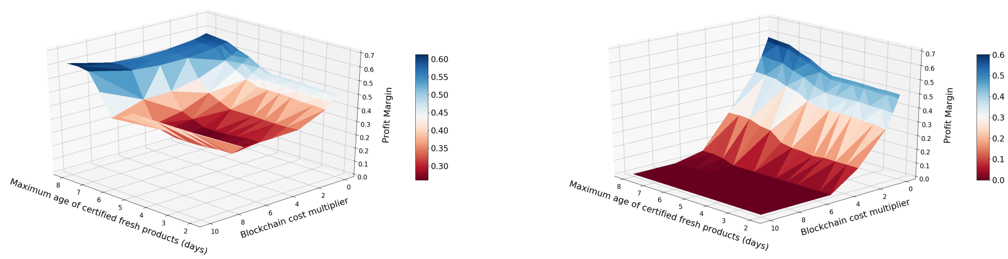


Figure 2.7: Profit margin when changing the maximum age for the certified fresh product and the blockchain cost multiplier

The profit margin exhibits a similar variation pattern as the consumer surplus, being more sensitive with the full blockchain case reaching zero profit after a cost multiplier of 5. The partial BCT model is more resistant to cost changes. After a minimum point, when the cost multiplier reaches 7, the profit margin rises again to levels similar to a cost multiplier of 1. This is due to the prioritization of non-certified products at a lower cost, as also shown by the results in Table 2.16.

In conclusion, the full-BCT model is very sensitive to cost changes, to the point where modifying the maximum allowable age of certified products is not sufficient to make the model profitable. The partial-BCT is more resistant and is able to optimize the BCT usage to remain profitable. Next, we present the results when varying the demand functions.

Demand for certified fresh and non-certified products

As discussed in Section 4, the demand functions of the baseline model assumed intercepts of 24 million and 16 million for certified and non-certified products, respectively. The intercept of non-certified fresh can never be higher than the certified, as this would mean that, at the same price, there is a higher demand for less fresh products, which is unlikely in practice. Table 2.17 presents the partial BCT model results when changing the intercept of the certified fresh products, $\bar{D}_j^0$, and the non-certified products, $\bar{D}_j^1$. The cumulative of both intercepts is fixed at 40 million and the elasticities are kept the same for both demand functions.

Table 2.17: Results when varying the demand intercepts

$\bar{D}_j^0, \bar{D}_j^1$ intercept (M dz)	Qty prod. (M dz)	Revenue (M \$)	Profit margin	Consumer surplus (M \$)	Average price (\$)	Average prod. age	Prod. sites active	Distrib. centres active	Customer zones served	Links with blockchain	Quantity of products with blockchain (M dz)	
											N-D	D-C
40, 0	11.3	100.5	39%	20,2	8.91	1.68	2/3	3/4	10/10	8/13	11.3 (100%)	1.7 (15%)
38, 2	11.3	98.3	39%	19,9	8.67	1.99	2/3	3/4	10/10	12/26	10.7 (94%)	1.7 (15%)
28, 12	11.7	87.6	40%	18,4	7.45	3.44	3/3	3/4	10/10	10/26	7.9 (67%)	1.4 (12%)
24, 16 (base)	11.9	83,2	41%	17,8	6.99	3.99	3/3	3/4	10/10	10/26	6.8 (57%)	1.4 (11%)
20, 20	12.1	78.9	41%	17,2	6.54	4.53	3/3	3/4	10/10	10/26	5.6 (47%)	1.33 (11%)

The blockchain usage in the first part of the supply chain (between producer and distribution) changes similarly to the intercept of the certified fresh products. As the intercept of that category is reduced, so is the blockchain usage. Revenue, price, profit margin, and consumer surplus all decrease as the total demand for fresher products is reduced. The quantity produced increases as the demand shifts to more non-certified products, with a lower market price and a higher volume. As shown in Table 2.17, it is possible to conclude that blockchain usage is more affected by the demand function of certified fresh products. As the total demand is shifted up (higher intercept and the same slope), blockchain usage becomes higher and products sold are fresher on average. Consumers are better off with more blockchain, as the usage goes up, so does the consumer surplus. Figure 2.8 shows the resulting consumer surplus while Figure 2.9 shows the resulting profit margin.

(a) Partial BCT model (b) Full-BCT model

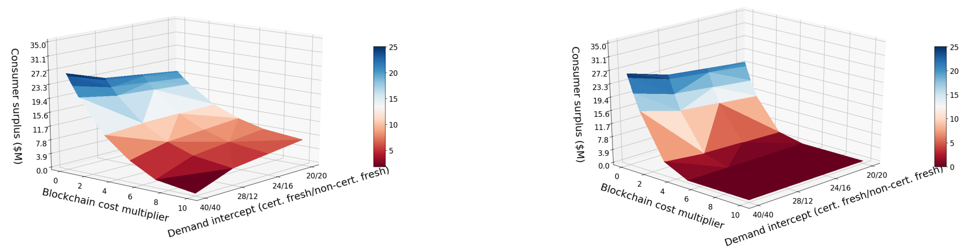


Figure 2.8: Consumer surplus when changing the demand intercepts and the blockchain cost multiplier

The full-BCT model is less impacted by the changes in the demand intercept. Not surprisingly, as shown in figures (2.8b) and (2.9b), the full-BCT is highly sensitive to blockchain cost. In the partial blockchain model, the consumer surplus becomes more sensitive to blockchain cost changes as the demand intercept of certified fresh is higher. As seen in Figure 2.9a, the profit margin sensitivity to blockchain cost is also higher for larger demand for the certified fresh product.

The key insight is that full BCT adoption leads to high sensitivity to blockchain cost.

(a) Partial BCT model (b) Full-BCT model

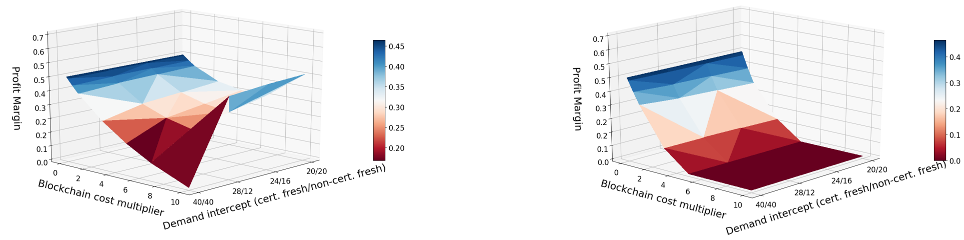


Figure 2.9: Profit margin when changing the demand intercepts and the blockchain cost multiplier

The changes in the proportion of demand from certified and non-certified products have less impact. Finally, consumers, in terms of surplus, are always better off with lower blockchain cost. In the next section, the elasticity of the demand functions are varied, first for the certified fresh demand functions and then for the non-certified products.

Elasticity of the demand for certified fresh and non-certified products

To evaluate the sensitivity of the proposed model on the elasticity of demand, a multiplier to the slope is imposed and varied for one freshness level at a time. We assume that non-certified products are always more price elastic compared to certified fresh products. Table 2.18 presents the results when varying the demand elasticity for certified fresh products, and Table 2.19 presents the results for the non-certified products.

Changes to the elasticity of the demand for certified fresh products affect all the results. The average freshness, revenue, profit margin, surplus, average price, and blockchain utilization all go down as the demand becomes more price elastic. Product age increases, meaning that products sold are less fresh on average. In summary, performance indicators are better off when the demand for fresh products is price inelastic. Next, we present the results when changing the elasticity of the demand for non-certified products.

Table 2.18: Results when varying the elasticity of the demand of the certified fresh product

Slope multiplier	Qty prod. (M dz)	Revenue (M $)	Profit margin	Consumer surplus (M $)	Average price ($)	Average prod. age	Prod. sites active	Distrib. centres active	Customer zones served	Links with blockchain	Quantity of products with blockchain (M dz)	
											N-D	D-C
0.01	17.1	7,522.8	99%	3,723.0	440.29	3.29	3/3	3/4	10/10	10/26	11.9 (70%)	2.7 (16%)
0.1	16.6	771.5	90%	348.7	46.43	3.34	3/3	3/4	10/10	10/26	11.5 (69%)	2.6 (16%)
0.5	14.5	165.6	61%	51.6	11.40	3.58	3/3	3/4	10/10	10/26	9.4 (65%)	2.0 (14%)
0.7	13.5	119.8	51%	31.7	8.89	3.72	3/3	3/4	10/10	10/26	8.3 (62%)	1.8 (13%)
1	11.9	83.2	41%	17.8	6.99	3.99	3/3	3/4	10/10	10/26	6.8 (57%)	1.4 (11%)
1.2	10.9	67.8	36%	13.0	6.24	4.21	3/3	3/4	10/10	10/26	5.7 (53%)	1.1 (10%)
1.5	9.3	50.9	32%	9.0	5.48	4.64	3/3	3/4	10/10	8/24	4.1 (45%)	0.7 (7%)

Table 2.19: Results when varying the elasticity of the demand of the non-certified product

Slope multiplier	Qty prod. (M dz)	Revenue (M $)	Profit margin	Consumer surplus (M $)	Average price ($)	Average prod. age	Prod. sites active	Distrib. centres active	Customer zones served	Links with blockchain	Quantity of products with blockchain (M dz)	
											N-D	D-C
0.7	12.8	95.8	46%	23.0	7.50	4.21	3/3	4/4	10/10	10/26	6.8 (53%)	1.5 (12%)
1	11.9	83.2	41%	17.8	6.99	3.99	3/3	3/4	10/10	10/26	6.8 (57%)	1.4 (11%)
1.2	11.3	78.0	38%	16.0	6.89	3.82	3/3	3/4	10/10	10/26	6.8 (60%)	1.2 (11%)
1.5	10.5	72.5	37%	14.3	6.92	3.54	3/3	3/4	10/10	10/26	6.8 (65%)	1.1 (10%)
3	7.2	61.2	37%	12.1	8.52	1.99	2/3	3/4	10/10	8/21	6.8 (94%)	1.0 (14%)
5	6.8	60.3	37%	12.1	8.91	1.68	2/3	3/4	10/10	8/13	6.8 (100%)	1.0 (15%)
10	6.8	60.3	373%	12.1	8.91	1.68	2/3	3/4	10/10	8/13	6.8 (100%)	1.0 (15%)

As expected, the impact on the number of products using blockchain comes from mainly changing elasticity of the demand for the certified fresh products. Almost no changes on blockchain usage, in terms of total products, are seen when varying elasticity for non-certified fresh products. Revenue, profit, and consumer surplus decrease as the elasticity decrease. As for the average product age, it decreases as the elasticity decreases, meaning that only non-certified fresh products are being sold.

2.5 Conclusion

With global and complex supply chains, the information sharing between multiple players in a network becomes a challenge. Transparency and provenance are critical factors in sensitive and regulated markets, such as pharmaceutical and food sectors. Blockchain, as an alternative to traditional centralized information systems, offers the potential to redefine supply chains, with immutable and safe records that can be shared between multiple supply chain players. This chapter focuses on the design of blockchain-enabled supply chains. We propose a mixed-integer quadratic programming model to jointly optimize the investment in blockchain technology and the design of the supply chain, along with demand and pricing decisions. The present literature that incorporates blockchain in the supply chain of fresh products focuses on game-theoretic models without other operational parameters. This work contributes to expanding the literature with an optimization model that accounts for the strategic deployment of blockchain in supply chain network design. The proposed formulation considers a three-echelon network for the supply of perishable products. We consider producers that ship fresh products to distribution centres, which then are transported to customer zones. Multiple transportation modes are available and blockchain certifies the true transportation time. Blockchain is modelled as a binary variable the indicates where in the supply chain information is stored with blockchain technology. Product freshness is modelled as discrete, with distinct demand functions for each of the freshness levels. Most importantly, the proposed framework illustrates a new form of product differentiation with data-enabled products that are sold at a premium. Through blockchain technology, data certifying certain features of the products can be monetized, leading both to increased profitability for producers and increased quality for consumers.

A case study for the global supply chain of fresh-cut flowers was built and analyzed to assess the framework. Fresh flowers are perishable, with global producers that must serve customers all around the globe, and lead time restrictions that make the case very suitable for the proposed model. We considered three suppliers that represent 90% of Canadian imports, with four distributors located in the main entry points, serving ten customer zones that cover the provinces and territories in Canada. Three scenarios were investigated, no blockchain, partial blockchain, and full blockchain adoption. It was found that an optimized strategic deployment of blockchain technology throughout the supply chain results in lower costs, data-enabled product differentiation, increased profits, and higher consumer surplus. When compared to the no-blockchain case, the optimized deployment provides fresher products and a better consumer surplus. As for the comparison with the full blockchain case, we conclude that having blockchain everywhere is costly and not necessary. The partial adoption has better profit margin and also better consumer surplus. The sensitivity analysis has shown that the optimized model is less sensitive to blockchain cost variation and demand changes. In summary, blockchain enables data certification through an optimized deployment that increases profitability and product quality.

While the proposed model extends the production distribution network design literature which inherently assumes that a single firm controls all the echelons of the supply chain, future work will consider the design of the network with multiple players. Furthermore, as products with different freshness levels may be substitutes for one another, future extensions with demand functions that account for product substitutions is also of interest. For further evaluation of the benefits of blockchain adoption, the comparison with traditional information sharing systems is a relevant extension of the present work. Finally, the proposed framework is general and can be applied in sectors, other than fresh produce including pharmaceutical drug verification, fair trade certification, and carbon footprint labelling.

Chapter 3

Strategic Blockchain Adoption to Combat Deceptive Counterfeiters

3.1 Introduction

Despite the massive efforts of public and private institutions to combat counterfeit products, recent reports estimate that the business activity involving fake products has reached more than $4.5 trillion worldwide and represents more than 3.3% of the world trade (Fontana et al., 2019; Sularia, 2020). The massive worldwide growth in the sales of counterfeit products has been fueled by the rapid rise of digital channels that facilitate the purchase and sale of goods and products through virtual channels that thrive on the premise of connecting consumers directly with manufacturers to cut down costs but provide little visibility about the origins of products. Evidently, counterfeiters capitalized on the ubiquity and anonymity of online channels to gain easy access to consumers.

Grossman and Shapiro (1986) distinguishes between two types of counterfeit products: deceptive and non-deceptive. For a deceptive product, the consumer is unable to distinguish between a counterfeit and a genuine product and therefore the consumer unknowingly purchases the counterfeit product at a market price that is usually close or the same as if the product is genuine (Stöttinger and Penz, 2017). There are certainly cases where the deceptive product functions exactly the same as the genuine product (Clover, 2016). However, it is commonly observed that while at the time of purchase the counterfeit product appears to be the same as the genuine product, the utility over the life of the counterfeit product is usually significantly lower than that of the genuine product (Staake et al., 2012). The substantial profits that can be generated from selling deceptive products entice legitimate channels to facilitate the leakage of counterfeit products into the supply of genuine products (Green and Smith, 2002; Wang et al., 2020). The pharma industry is particularly infamous for several cases where drug distributors and clinicians have facilitated the trafficking of counterfeit treatments (Cockburn et al., 2005; Mackey et al., 2015). Most recently, with the spread of COVID-19 virus, the high demand for N95 masks led to a boom of counterfeit products in the global market. At the height of the pandemic in 2020, the United States Customs and Border Protection seized over 14.6 million counterfeit face masks that were bound to enter the United States (Gillespie, 2021). Blockchain has quickly emerged as a technology to help verify the authenticity of masks and protective equipment supply chain (Orton, 2021; Wolfson, 2021).

The other category of counterfeits is non-deceptive products where the buyer is aware of the illegitimate nature of the product. For these types of products, the consumer can easily distinguish the counterfeit product and willingly purchases it at a fraction of the price of the genuine product. The primary non-deceptive products that are often purchased are luxury brands where a consumer's choice for counterfeit over genuine is often due to financial reasons (Stöttinger and Penz, 2017). Both categories of counterfeit products lead to significant social and economic loss with severe consequences to consumers as well as brand owners. Evidently though, detecting deceptive counterfeits is significantly harder due to the deceiving nature of the products as well as their infiltration to the formal distribution channels of genuine products. Blockchain presents immense opportunities to effectively distinguish and detect counterfeit products before they reach the consumers (Niu et al., 2021).

Public and private institutions, manufacturers, as well as retailers, have been aggressively investing in tools and resources to prevent the leakage of counterfeit products through the supply chain (Staake and Fleisch, 2008; Staake et al., 2009). Technological developments over recent years have presented numerous solutions that help in the tracking and detection of counterfeit products (Blaettchen et al., 2021). Radio Frequency Identification (RFID) first emerged as a tool to trace the movement of products through the supply chain (Attaran, 2012; Stevenson and Busby, 2015). Quick Response (QR) codes are another important tool used to prevent counterfeits by encoding information that can be used for validation (Liu, 2010). RFID tags and QR codes can be cloned and thus enabling traceability is an additional layer to increase the likelihood of catching counterfeit products through the supply chain before they reach consumers (Toyoda et al., 2017; Picard et al., 2021). Blockchain has emerged as a technology that can provide stakeholders with the needed capability to effectively identify counterfeit products (Hackius and Petersen, 2017; Pun et al., 2021). Blockchain provides the means for transparent end-to-end tracking in the supply chain that include all transactions that involve each product. Thus, each product can individually be tracked from production to delivery, which provides supply chain transparency and greater ability to detect fraudulent activities including the ability to identify genuine products from counterfeits. Everledger (https://www.everledger.io/) is one of many growing companies that provide such solutions to trace products from source to customer, with a secure record of a product's origin, characteristics, and ownership. The adoption of such solutions is nowadays seen in many industries including luxury goods, apparel, education, and technology among many others (Dutta et al., 2020).

The blockchain architecture enables the tracing and verification of products through a decentralized distributed database which infuses incremental trust and makes it virtually infeasible for malicious parties to tamper with the records (Gaur and Gaiha, 2020). We note that blockchain is just one flavour of distributed ledger technologies and it has its advantages and disadvantages (Li et al., 2020). While throughout this chapter we focus on using this technology in the business context of counterfeit detection, we note the significant ongoing research investigating the technical details and improving the technology itself (Maesa and Mori, 2020).

This chapter investigates the strategic implications of using blockchain as a deterrent against the sales of counterfeit products. Particularly, this chapter investigates the use of blockchain to eliminate the significant financial advantage from the sales of deceptive counterfeits. By partially preventing counterfeit products from reaching customers, the supplier of deceptive products realizes fewer profits eventually reaching a level where it is no longer economically attractive to attempt to sell counterfeits. Of course, for the brand owners, it is costly to adopt blockchain technology to allow the detection of counterfeits. Thus, this chapter investigates the important balance between the cost due to the increasing adoption of blockchain technology to suppliers/manufacturers of genuine products compared to the gain that can be realized by making it less attractive to counterfeiters. The analytical model that is proposed in this chapter highlights the existence of a "critical ratio" that is a function of the cost of manufacturing deceptive products as well as the market price of the products. A lower cost of manufacturing for deceptive products encourages the genuine manufacturer to adopt blockchain while, interestingly, the higher market price for the products discourages blockchain implementation. As such, our analysis differentiates between three types of products: regular, premium, and luxury. These three categories are distinguished based on the difference between the cost of manufacturing a genuine product and the cost of manufacturing a deceptive counterfeit. Our main counter-intuitive observation is that the attractiveness of blockchain to discourage deceptive counterfeits decreases as the product's cost increase which are in the first place the products that are most counterfeited and typically the legitimate manufacturers are interested in protecting. In an extension of the model, we include product quality which can be optimized by the genuine manufacturer where higher quality products become harder to counterfeit. The insights show that the genuine manufacturer can strategically balance between increasing the quality of its product and the adoption of blockchain to prevent deceptive counterfeits. Interestingly, our results also show that the availability of blockchain may also lead manufacturers to ignore improving the quality of their products, keeping the cost low, and alternatively invest in blockchain to combat counterfeiting, which then leads to lower quality products compared to when blockchain is not available.

Following this introductory section, the rest of the chapter is organized as follows. The literature review is presented in Section 3.2. The game-theoretic model and subsequently the equilibrium analysis are presented in Sections 3.3 and 3.4, respectively. Insights and discussions regarding the optimal blockchain strategies are presented in 3.5. An extended model that includes product quality along with the resulting insights and discussions are presented in 3.6. Finally, Section 3.7 concludes.

3.2 Literature review

Over the recent years, blockchain applications in supply chain have become mainstream (Michelman, 2017). In the operations and supply chain management literature, the focus has been on exploiting the main benefits of blockchain in terms of information sharing and increased transparency (Abeyratne and Monfared, 2016), on the reduction of paperwork and automation of processes (Hackius and Petersen, 2017), and more recently on using verifiability to signal quality and realize financial benefits (Chod et al., 2020). The ultimate promise of blockchain is to create efficient, transparent, and robust supply chains (Babich and Hilary, 2020b). Even competing firms in a supply chain have the incentive under certain conditions to use blockchain information visibility as it would benefit the profitability of the entire supply chain (Cui et al., 2020). As such, blockchain is nowadays a main counterfeiting technology to fight back against the continuously growing spread of illicit products through the supply chain (Gayialis et al., 2019).

Blockchain solutions to detect counterfeit products like prior technologies such as RFID, are based on tracking and tracing products throughout the supply chain to detect anomalies and identify illicit products (Basole and Nowak, 2018; Lee and Özer, 2007; Li and Visich, 2006). The luxury goods and pharmaceuticals industries are two main sectors that have traditionally seen significant research for the development and adoption of such technologies to detect deceptive counterfeits. For instance, the drug distribution supply chains often involve a multitude of companies that include manufacturers, distributors, wholesalers and dispensaries before reaching patients. The lack of visibility among all the involved parties along with the generally high premiums on drug sales make the drug distribution supply chains a common sector that is infiltrated by counterfeits (Saxena et al., 2020). Counterfeiters continue to find sophisticated ways to copy drug labelling and packaging to make highly deceiving counterfeits that infiltrate the legitimate supply chain (Burhouse, 2010). Similarly, luxury goods offer fertile grounds for counterfeits due to the high profit margins as well as to production outsourcing to foreign industries (Choi, 2019).

Analytical models investigating the use of blockchain to combat counterfeits in supply chains have shown that financial incentives may not always exist for manufacturers to adopt blockchain technology. Such incentives can be created through government subsidies and, under certain conditions, price signalling may be more effective to highlight product authenticity (Pun et al., 2021). However, in the case of deceptive counterfeits, it is more common that the counterfeit products get sold at the same price as authentic products particularly once the counterfeit products become part of the legitimate supply chain. In such cases, brand name and pricing are ineffective and can further promote counterfeit products (Cho et al., 2015). Both Cho et al. (2015) and Pun et al. (2021) present a sequential decision-making model that assumes a strategic counterfeiter that maximizes its profits. Cho et al. (2015) considers two types of counterfeiters: a deceptive that infiltrates a legitimate supply chain, and a non-deceptive with an illegitimate supply chain. For the case of deceptive counterfeiter, which is the focus of this chapter, Cho et al. (2015) assumes that both legitimate and counterfeit products are sold to consumers at the same market price. After observing the quality and the market price of the genuine product, the counterfeiter first decides on its product quality. In the second stage, the counterfeiter decides on the wholesale price, i.e., the price at which the counterfeit products are sold to a legitimate distributor. In the third stage, the legitimate distributor decides on a fraction of the counterfeit products to sell to consumers. The model assumes a likelihood for the distributor getting caught, which then leads to a penalty. The probability of getting caught is a function of the fraction of counterfeit products in the market as well as the quality of the counterfeit product. Pun et al. (2021) also considers a deceptive counterfeiter, however the presented model assumes different market prices for the genuine and the deceptive products. The legitimate manufacturer uses blockchain to prove that a product is genuine. In the first stage, the genuine manufacturer decides on whether or not to implement blockchain, then sets a market price for the genuine product. Finally, the counterfeiter sets the market price for its product. The presented model and insights consider two important issues; the first relates to customer's concern regarding leaving a digital footprint when acquiring a product that is supported by blockchain and the second relates to the role of government in encouraging blockchain adoption by subsidizing costs. Sumkin et al. (2021) evaluates the use of blockchain to encourage ethical sourcing with a particular focus on the diamond supply chain. In contrast to the focus of our work on deceptive counterfeits, the model presented in Sumkin et al. (2021) considers legitimate products and the value-added opportunities of blockchain certification on product resale. The model shows that under certain conditions, customers may prefer the non-certified products given an increasing belief that all non-certified products are responsibly sourced which consequently encourages the supplier to use less responsible sources.

The model presented in this chapter focuses on the case of a deceptive counterfeiter that infiltrates a legitimate supply chain. Thus, contrary to Pun et al. (2021) but in line with Cho et al. (2015), we assume that the counterfeit product, being deceptive, is sold to consumers at the same market price as the genuine product (i.e., the consumers are unable to distinguish between the genuine and the deceptive counterfeit). Pun et al. (2021) assumes that blockchain is fully effective in eliminating deceptive counterfeits and thus the proposed framework as noted in their paper is essentially a case of non-deceptive counterfeit which explains price differentiation, as opposed to the case of deceptive counterfeit that is considered in our work. Furthermore, rather than assuming that the distributor is complicit with the counterfeiter as in Cho et al. (2015), the model proposed in our work considers an honest distributor that attempts to detect counterfeit products and removes them from the supply chain. The probability of detecting a counterfeit product is a function of the blockchain implementation level which is decided on by the manufacturer of the genuine product. The blockchain implementation level may denote the amount of information that is stored on the blockchain where more information increases the probability of counterfeit detection however at the expense of additional cost to the product. Chang et al. (2018) adopted a similar approach to model blockchain decisions, i.e., blockchain implementation level, though in a different context of supply chain management focusing on production, inventory, and pricing operations. It is unrealistic to believe that blockchain adoption will be 100% effective in enabling the detection of all counterfeit products. Even in the most thought after use case of blockchain, which is Bitcoin, the network has failed in several cases from preventing fraudulent activities (Bradbury, 2013; Fletcher, 2021). The main purpose of the blockchain supply chain solutions has been to offer a unified platform to acquire and store immutable data and the promise of detecting illicit activities is due to enabling the visibility of the data to the supply chain entities and consumers (Schneier, 2019). Distributed databases that enable such services existed before blockchain and have not been effective in eliminating counterfeits. However, blockchain solutions offer more mainstream decentralized visibility, which makes it more effective than prior technologies but it is a stretch to assume that blockchain can eliminate all counterfeit products. Thus, the model presented in this work assumes a detection probability that is increasing with the investment in blockchain. Accordingly, the present work focuses on evaluating the use of blockchain to discourage and deter deceptive counterfeiters from entering the market and illustrates the tradeoffs between increasing cost for the manufacturer of genuine products while increasing ability to detect illicit products in the supply chain. To our knowledge, this proposed work is the first to evaluate the motivation of balancing the investment in blockchain and subsequently its effectiveness as a tool to deter counterfeiters and to increase the capabilities of firms to detect deceptive counterfeit products that infiltrate the supply chain before reaching the customers.

3.3 Model

The proposed model considers a three echelon supply chain formed by two suppliers, a distributor, and the customers. The two suppliers are a manufacturer of genuine products denoted by α and a manufacturer of deceptive counterfeits denoted by β. We assume that each manufacturer has a per-unit production cost c^j where $j \in \{\alpha, \beta\}$ and we make the reasonable assumption that $c^\alpha > c^\beta > 0$, i.e., the cost of a genuine product exceeds the cost of a counterfeit. The larger cost for the genuine product is driven by higher quality consideration, higher labour costs, and other operational costs that counterfeiters do not incur. We note the increasing trend of counterfeiters producing high-quality products that may match genuine products (Clover, 2016), however, manufacturers of genuine products still incur additional costs such as research, development, and marketing that add up to the manufacturing cost and thus it is reasonable to assume differentiating costs $c^\alpha > c^\beta$ for the genuine and counterfeit manufacturers, respectively. Both manufacturers produce market equilibrium quantities x^α and x^β.

Besides the two manufacturers, the supply chain includes an honest distributor that intends to only source genuine products even though the counterfeiter may infiltrate the supply chain and push counterfeit products to the distributor. According to Zhang and Zhang (2015), companies can mitigate the occurrence of counterfeits by using manufacturer-owned channels. However, it is common that firms must also rely on non-exclusive distribution channels that involve other players. As the complexity of the distribution network increases, there are more opportunities for counterfeits to enter the authentic supply chain (Jamil et al., 2019). The distributor in our modelling framework represents this additional complexity that counterfeiters exploit to penetrate the supply chain. We consider that the distributor is honest and that the manufacturer's decision to replace them is not an option. Our focus is on the manufacturer's strategy to combat counterfeits and thus the potential decisions from the distributors perspective are not modelled in our framework. The distributor has a probability $r \in [0, 1]$ for identifying a counterfeit product. Thus given x^β counterfeit products that infiltrate the supply chain, the distributor is able to catch and remove rx^β products while the remaining $(1 - r)x^\beta$ proceed undetected. This probability, r, is set as the blockchain implementation level that is chosen by the genuine manufacturer. Increasing the blockchain implementation level increases the ability of the distributor to identify counterfeit products but at the expense of increasing the per-unit cost of the genuine items. We assume that the additional blockchain-related cost of each genuine item is given by $r\Gamma$. Only variable costs for blockchain usage are considered. Most manufacturers do not have the infrastructure or resources to implement their own blockchain platform, and often rely on providers operating with a variable cost model without fixed costs (Pun et al., 2021).

The distributor sells the supplied genuine products as well as the undetected counterfeit products to consumers. Since counterfeit products are deceptive, the consumers cannot distinguish between the genuine product and the counterfeit product at the time of purchase. Therefore, both types of products are sold at the same competitive market price $p > c^\alpha$ where the corresponding demand is $D > 0$. The price p corresponds to the amount received by the manufacturers, not the distributor. We assume no back-ordering cost for unmet demand and no salvage value for excess inventory. The genuine manufacturer does not produce more than the demand, but the presence of counterfeits can cause oversupply. We do not consider any penalty or costs for the excess supply.

The genuine and the counterfeit suppliers make their decisions sequentially to maximize profit. We assume that the counterfeiter enters the market after the genuine company and then decides on the production quantity x^β after observing the production quantity of the genuine manufacturer x^α and the blockchain implementation level r (i.e., the probability of a counterfeit product being detected by the distributor). All the manufactured items, genuine and counterfeit, make it to the distributor. The genuine items and the counterfeits that are undetected by the distributor are then used to satisfy demand. The genuine manufacturer is the "market leader" and optimizes its profit according to

$$f^g(r, x^\alpha, x^\beta) = \max\ ps^\alpha(x^\alpha, x^\beta) - (c^\alpha + r\Gamma)x^\alpha \tag{3.1}$$

$$\text{s.t. } 0 \leq r \leq 1 \tag{3.2}$$

$$x^\alpha \geq 0 \tag{3.3}$$

where $s^\alpha(x^\alpha, x^\beta)$ denotes that amount of genuine product sales given a market supply of x^α genuine products x^β counterfeit products. The counterfeiter is the "market follower" and optimizes its profit according to

$$f^c(r, x^\alpha, x^\beta) = \max \, ps^\beta(x^\alpha, x^\beta) - c^\beta x^\beta \tag{3.4}$$

$$\text{s.t. } \; x^\beta \geq 0 \tag{3.5}$$

where $s^\beta(x^\alpha, x^\beta)$ is the number of counterfeit product sales given a market supply of x^α and x^β. The quantities for $s^\alpha(x^\alpha, x^\beta)$ and $s^\beta(x^\alpha, x^\beta)$ are set depending on the supply exceeding or not the market demand, which will be detailed in sections 3.4.1 and 3.4.2.

3.4 Equilibrium analysis

The competition between the genuine and the counterfeiter is a leader-follower Stackelberg competition. To find the equilibrium solution of this game, we assume that the leader, i.e., the genuine manufacturer, has full knowledge of the follower which in this case is the counterfeit unit cost c^β based on its expert knowledge of the raw material needed and the manufacturing processes involved. The genuine manufacturer thus makes its decision knowing how the counterfeiter will respond. We also assume that the genuine manufacturer makes its decision sequentially by first deciding on the blockchain level r then on the production quantity x^α, which is consistent with the game sequence from the comparable literature (Pun et al., 2021). To identify the equilibrium solution, we consider two disjoint cases. First, we consider the case where the total supply does not exceed the demand and show that in an equilibrium solution, the supply should at least meet the demand. Then we consider the case where the total supply exceeds the demand and provide the equilibrium solution.

3.4.1 Realized supply does not exceed market demand

This considers the case where the total supply available to consumers does not exceed the demand. The total supply that is available to the consumers includes all the genuine products and the non-detected counterfeits and thus we evaluate the equilibrium solution when $x^\alpha + (1-r)x^\beta \leq D$.

In that case, since the supply does not exceed the demand then all the available products are sold to consumers. Thus given a market supply of x^α genuine products and x^β counterfeit products, the genuine sales are $s^\alpha(x^\alpha, x^\beta) = x^\alpha$ and the counterfeit sales are $s^\beta(x^\alpha, x^\beta) = (1-r)x^\beta$. The optimal solution of the follower problem, i.e., the counterfeiter is thus the solution of

$$\max\ p(1-r)x^\beta - c^\beta x^\beta \tag{3.6}$$

$$\text{s.t. } x^\alpha + (1-r)x^\beta \leq D \tag{3.7}$$

$$x^\beta \geq 0 \tag{3.8}$$

which is given by the following conditions.

1. If $x^\alpha = 0$, then $x^\beta = D$ (Note that if $x^\alpha = 0$ then also $r = 0$).
2. If $x^\alpha > 0$ then
   (a) if $r > 1 - \frac{c^\beta}{p}$ then $x^\beta = 0$ and therefore the optimal x^α is $x^\alpha = D$.
   (b) otherwise $x^\beta = \frac{D - x^\alpha}{1-r}$

Thus, under any condition, the equilibrium with the condition $x^\alpha + (1-r)x^\beta \leq D$ will always have a solution $x^\alpha + (1-r)x^\beta = D$. Thus the following section presents the equilibrium under the condition $x^\alpha + (1-r)x^\beta \geq D$.

3.4.2 Realized supply equals to or exceeds market demand

This section considers the case where $x^\alpha + (1-r)x^\beta \geq D$, i.e., the supply of products from the distributor exceeds the demand. Since the realized supply includes $(1-r)x^\beta$ undetected counterfeit, then a part of the demand is satisfied with counterfeit products.

Given that the counterfeits are deceptive, then at the time of purchase, a customer cannot identify which products are deceptive and which ones are genuine then the probability of a purchase being counterfeit is given by $\frac{(1-r)x^\beta}{x^\alpha+(1-r)x^\beta}$. The total amount of counterfeit products that are sold is $s^\beta(x^\alpha, x^\beta) = \frac{(1-r)x^\beta}{x^\alpha+(1-r)x^\beta} \times D$ while the total amount of genuine products that are sold is $s^\alpha(x^\alpha, x^\beta) = \frac{x^\alpha}{x^\alpha+(1-r)x^\beta} \times D$. The counterfeiter (the follower) thus optimizes

$$\max \frac{(1-r)x^\beta}{x^\alpha + (1-r)x^\beta} pD - c^\beta x^\beta \tag{3.9}$$

$$\text{s.t. } x^\alpha + (1-r)x^\beta \geq D \tag{3.10}$$

$$x^\beta \geq 0 \tag{3.11}$$

The optimal solution of the counterfeiter problem is given by the following lemma.

Lemma 1 *The optimal x^β of problem (3.9)–(3.11) is*

$$x^\beta = \begin{cases} \frac{\sqrt{c^\beta Dp(1-r)^3 x^\alpha} - c^\beta(1-r)x^\alpha}{c^\beta(1-r)^2} & \textit{if } \frac{c^\beta D}{p(1-r)} \leq x^\alpha \leq \frac{(1-r)pD}{c^\beta} \\ \frac{D-x^\alpha}{(1-r)} & \textit{if } x^\alpha < \frac{c^\beta D}{p(1-r)} \\ 0 & \textit{if } x^\alpha > \frac{(1-r)pD}{c^\beta} \end{cases}$$

Proof of Lemma 1

The counterfeiter's optimization problem is given by (3.9)–(3.11). The double derivative of the objective function (3.9) with respect to x^β is

$$-\frac{2Dp(r-1)^2x^\alpha}{(-rx^\beta + x^\alpha + x^\beta)^3} \tag{3.12}$$

which is negative for

$$x^\alpha + x^\beta > rx^\beta \rightarrow x^\alpha + (1-r)x^\beta > 0 \tag{3.13}$$

which always holds since $0 \leq r \leq 1$. Thus the objective function (3.9) is concave in x^β. Candidate optimal solutions can thus be obtained by taking the derivative with respect to x^β and setting it to zero which leads to

$$-c^\beta - \frac{Dp(r-1)x^\alpha}{(-rx^\beta + x^\alpha + x^\beta)^2} = 0. \tag{3.14}$$

The two possible solutions for x^β that satisfy (3.14) are

$$x^\beta = \frac{\sqrt{c^\beta Dp(1-r)^3x^\alpha} - c^\beta(1-r)x^\alpha}{c^\beta(1-r)^2} \tag{3.15}$$

and

$$x^\beta = \frac{-c^\beta(1-r)x^\alpha - \sqrt{c^\beta Dp(1-r)^3x^\alpha}}{c^\beta(1-r)^2} \tag{3.16}$$

Note that (3.16) is always negative given the condition $x^\alpha + (1-r)x^\beta \geq D$. Thus the only candidate optimal solution is

$$x^\beta = \frac{\sqrt{c^\beta Dp(1-r)^3 x^\alpha} - c^\beta(1-r)x^\alpha}{c^\beta(1-r)^2} \tag{3.17}$$

which is positive if $x^\alpha \leq \frac{(1-r)pD}{c^\beta}$. Thus given the concavity of (3.9), if $x^\alpha > \frac{(1-r)pD}{c^\beta}$, then $x^\beta = 0$ is the optimal solution. Furthermore, given (3.17), the condition $x^\alpha + (1-r)x^\beta \geq D$ is satisfied only if $x^\alpha \geq \frac{c^\beta D}{p(1-r)}$. Thus if $x^\alpha < \frac{c^\beta D}{p(1-r)}$, then $x^\alpha + (1-r)x^\beta < D$ and as shown in Section 3.4.1, the optimal solution is $x^\beta = \frac{D - x^\alpha}{(1-r)}$. In summary, the optimal x^β is

$$x^\beta = \begin{cases} \frac{\sqrt{c^\beta Dp(1-r)^3 x^\alpha} - c^\beta(1-r)x^\alpha}{c^\beta(1-r)^2} & \text{if } \frac{c^\beta D}{p(1-r)} \leq x^\alpha \leq \frac{(1-r)pD}{c^\beta} \\ \frac{D-x^\alpha}{(1-r)} & \text{if } x^\alpha < \frac{c^\beta D}{p(1-r)} \\ 0 & \text{if } x^\alpha > \frac{(1-r)pD}{c^\beta}. \end{cases}$$

□

Given the game sequence that is highlighted in Section 3.3, the optimal solution for the leader's problem (the genuine manufacturer) is found by backward induction where the optimal response of the counterfeiter is accounted for by the genuine manufacturer. As presented in Lemma 1, the optimal response of the counterfeiter is one of three options, which are considered independently next.

First, we consider the case where $\frac{c^\beta D}{p(1-r)} \leq x^\alpha \leq \frac{(1-r)pD}{c^\beta}$ and the optimal solution of the counterfeiter is $x^\beta = \frac{\sqrt{c^\beta Dp(1-r)^3 x^\alpha} - c^\beta(1-r)x^\alpha}{c^\beta(1-r)^2}$. The corresponding optimal quantity of genuine products is the solution of

$$\max \frac{x^\alpha}{x^\alpha + (1-r)x^\beta} pD - (c^\alpha + r\Gamma)x^\alpha \tag{3.18}$$

$$\text{s.t. } \frac{c^\beta D}{p(1-r)} \leq x^\alpha \leq \frac{(1-r)pD}{c^\beta} \tag{3.19}$$

$$0 \leq r \leq 1 \tag{3.20}$$

$$x^{\alpha} \geq 0. \tag{3.21}$$

As detailed in Section 3.3, the genuine manufacturer first decides on the blockchain level r and then on the optimal production x^{α}. Thus for a given blockchain level r, the optimal solution for problem (3.18)–(3.21) is given by the following lemma.

Lemma 2 *The optimal x^{α} of problem (3.18)–(3.21) given a blockchain level r is*

$$x^{\alpha} = \begin{cases} \frac{c^{\beta}D}{p(1-r)} & \text{if } \frac{c^{\beta}D}{p(1-r)} \geq \frac{c^{\beta}Dp}{4(1-r)(c^{\alpha}+\Gamma r)^2} \\ \frac{(1-r)pD}{c^{\beta}} & \text{if } \frac{(1-r)pD}{c^{\beta}} \leq \frac{c^{\beta}Dp}{4(1-r)(c^{\alpha}+\Gamma r)^2} \\ \frac{c^{\beta}Dp}{4(1-r)(c^{\alpha}+\Gamma r)^2} & \text{if } \frac{c^{\beta}D}{p(1-r)} \leq \frac{c^{\beta}Dp}{4(1-r)(c^{\alpha}+\Gamma r)^2} \leq \frac{(1-r)pD}{c^{\beta}}. \end{cases} \tag{3.22}$$

Proof of Lemma 2

The genuine manufacturer's optimal production x^{α} is given by (3.18)–(3.21). Replacing x^{β} in the objective function (3.18) by the optimal value $x^{\beta} = \frac{\sqrt{c^{\beta}Dp(1-r)^3x^{\alpha}} - c^{\beta}(1-r)x^{\alpha}}{c^{\beta}(1-r)^2}$ leads to

$$\frac{\sqrt{c^{\beta}Dp(1-r)^3x^{\alpha}}}{(1-r)^2} - x^{\alpha}(c^{\alpha}+\Gamma r) \tag{3.23}$$

which is concave in x^{α} (the double derivative with respect to x^{α} is always negative). Thus taking the derivative of the objective of the leader with respect to x^{α} and setting it to zero, we get

$$x^{\alpha} = \frac{c^{\beta}Dp}{4(1-r)(c^{\alpha}+\Gamma r)^2}$$

which is always positive. Furthermore, given the concavity of (3.23) and constraints (3.19), then if $\frac{c^\beta Dp}{4(1-r)(c^\alpha+\Gamma r)^2} \leq \frac{c^\beta D}{p(1-r)}$ then the optimal x^α is $x^\alpha = \frac{c^\beta D}{p(1-r)}$. Furthermore, if $\frac{c^\beta Dp}{4(1-r)(c^\alpha+\Gamma r)^2} \geq \frac{(1-r)pD}{c^\beta}$ then the optimal x^α is $x^\alpha = \frac{(1-r)pD}{c^\beta}$. In summary, the optimal x^α is

$$x^\alpha = \begin{cases} \frac{c^\beta D}{p(1-r)} & \text{if } \frac{c^\beta D}{p(1-r)} \geq \frac{c^\beta Dp}{4(1-r)(c^\alpha+\Gamma r)^2} \\ \frac{(1-r)pD}{c^\beta} & \text{if } \frac{(1-r)pD}{c^\beta} \leq \frac{c^\beta Dp}{4(1-r)(c^\alpha+\Gamma r)^2} \\ \frac{c^\beta Dp}{4(1-r)(c^\alpha+\Gamma r)^2} & \text{if } \frac{c^\beta D}{p(1-r)} \leq \frac{c^\beta Dp}{4(1-r)(c^\alpha+\Gamma r)^2} \leq \frac{(1-r)pD}{c^\beta}. \end{cases}$$

□

The objective function (3.18) is convex in r. The optimal blockchain level r is given by the following lemma.

Lemma 3 *The optimal r is*

$$r = \begin{cases} 0 & \text{if } 2c^\alpha \geq p \text{ and } \Gamma \geq p - c^\alpha \\ 1 - \frac{c^\beta}{p} & \text{if } 2c^\alpha \geq p \text{ and } \Gamma < p - c^\alpha \\ 0 & \text{if } 2c^\alpha < p \text{ and } \Gamma \geq \frac{p-c^\alpha-\frac{c^\beta p}{4c^\alpha}}{1-\frac{c^\beta}{p}} \\ 1 - \frac{c^\beta}{p} & \text{if } 2c^\alpha < p \text{ and } \Gamma < \frac{p-c^\alpha-\frac{c^\beta p}{4c^\alpha}}{1-\frac{c^\beta}{p}}. \end{cases}$$

Proof of Lemma 3

Replacing x^α in the objective function (3.18) by each of the three possible optimal solutions given in (3.22) leads to a function that is convex in r (the double derivative with respect to r is always positive). Thus the optimal r can be one of three possible solutions $r = 0$, or the largest $r \leq 1$ that satisfies the boundary conditions

$$x^\alpha \geq \frac{c^\beta D}{p(1-r)} \to r \leq 1 - \frac{c^\beta}{p}\frac{D}{x^\alpha} \tag{3.24}$$

$$x^\alpha \leq \frac{(1-r)pD}{c^\beta} \to r \leq 1 - \frac{c^\beta}{p}\frac{x^\alpha}{D}. \tag{3.25}$$

Since (3.18) is convex in r, then the best r satisfying conditions (3.24)–(3.25) is given by

$$r = \max_{x^\alpha} \min\{1 - \frac{c^\beta}{p}\frac{D}{x^\alpha}, 1 - \frac{c^\beta}{p}\frac{x^\alpha}{D}, 1\} \tag{3.26}$$

$$= 1 - \frac{c^\beta}{p}. \tag{3.27}$$

Thus there could be two possible optimal r, $r_1 = 0$ or $r_2 = 1 - \frac{c^\beta}{p}$. If $r_1 = 0$ is optimal then, the optimal x^α given by (3.22) is

$$x^\alpha = \begin{cases} \frac{c^\beta D}{p} & \text{if } \frac{c^\beta D}{p} \geq \frac{c^\beta Dp}{4(c^\alpha)^2}, \text{ i.e., } 2c^\alpha \geq p \to x^\beta = D - \frac{c^\beta D}{p}, f(r, x^\alpha, x^\beta) = c^\beta D(1 - \frac{c^\alpha}{p}) \\ \frac{pD}{c^\beta} & \text{if } \frac{pD}{c^\beta} \leq \frac{c^\beta Dp}{4(c^\alpha)^2}, \text{ i.e., } 2c^\alpha \leq c^\beta \to \text{This case does not occur given the assumption } c^\alpha > c^\beta \\ \frac{c^\beta Dp}{4(c^\alpha)^2} & \text{if } \frac{c^\beta D}{p} \leq \frac{c^\beta Dp}{4(c^\alpha)^2} \leq \frac{pD}{c^\beta}, \text{ i.e., } 2c^\alpha \leq p \to x^\beta = \frac{Dp}{2c^\alpha}(1 - \frac{c^\beta}{2c^\alpha}), f(r, x^\alpha, x^\beta) = \frac{c^\beta pD}{4c^\alpha}. \end{cases}$$

If $r_2 = 1 - \frac{c^\beta}{p}$ is optimal then $x^\alpha = D$ and $x^\beta = 0$. The optimal profit of the genuine manufacturer is $f(r, x^\alpha, x^\beta) = D(p - c^\alpha - \Gamma(1 - \frac{c^\beta}{p}))$.

Next, we consider the case where $2c^\alpha \geq p$. If $\Gamma \geq p - c^\alpha$, then $c^\beta D(1 - \frac{c^\alpha}{p}) \geq D(p - c^\alpha - \Gamma(1 - \frac{c^\beta}{p}))$ and the optimal strategy is $r = 0$, $x^\alpha = \frac{c^\beta D}{p}$, and $x^\beta = D - \frac{c^\beta D}{p}$. Otherwise, the optimal strategy is $r = 1 - \frac{c^\beta}{p}$, $x^\alpha = D$, and $x^\beta = 0$.

Finally, we consider the case where $2c^\alpha < p$. If $\Gamma \geq \frac{p - c^\alpha - \frac{c^\beta p}{4c^\alpha}}{1 - \frac{c^\beta}{p}}$, then $c^\beta D(1 - \frac{c^\alpha}{p}) \geq D(p - c^\alpha - \Gamma(1 - \frac{c^\beta}{p}))$ and the optimal strategy is $r = 0$, $x^\alpha = \frac{c^\beta D}{p}$, and $x^\beta = D - \frac{c^\beta D}{p}$. Otherwise, the optimal strategy is $r = 1 - \frac{c^\beta}{p}$, $x^\alpha = D$, and $x^\beta = 0$. □

A summary of the optimal strategy and the profits of the genuine manufacturer and counterfeiter is as follows.

- If $2c^{\alpha} \geq p$
  - If $\Gamma \geq p - c^{\alpha}$, then
    - $r = 0$, $x^{\alpha} = \frac{c^{\beta}D}{p}$, $x^{\beta} = D - \frac{c^{\beta}D}{p}$, $f(r, x^{\alpha}, x^{\beta}) = c^{\beta}D(1 - \frac{c^{\alpha}}{p})$.
  - Else
    - $r = 1 - \frac{c^{\beta}}{p}$, $x^{\alpha} = D$, $x^{\beta} = 0$, $f(r, x^{\alpha}, x^{\beta}) = D(p - c^{\alpha} - \Gamma(1 - \frac{c^{\beta}}{p}))$.
- Else
  - If $\Gamma \geq \frac{p - c^{\alpha} - \frac{c^{\beta}p}{4c^{\alpha}}}{1 - \frac{c^{\beta}}{p}}$, then
    - $r = 0$, $x^{\alpha} = \frac{c^{\beta}Dp}{4(c^{\alpha})^2}$, $x^{\beta} = \frac{Dp}{2c^{\alpha}}(1 - \frac{c^{\beta}}{2c^{\alpha}})$, $f(r, x^{\alpha}, x^{\beta}) = \frac{c^{\beta}pD}{4c^{\alpha}}$.
  - Else
    - $r = 1 - \frac{c^{\beta}}{p}$, $x^{\alpha} = D$, $x^{\beta} = 0$, $f(r, x^{\alpha}, x^{\beta}) = D(p - c^{\alpha} - \Gamma(1 - \frac{c^{\beta}}{p}))$.

Finally, we note that the cases given by $x^{\alpha} < \frac{c^{\beta}D}{p(1-r)}$ and $x^{\alpha} > \frac{(1-r)pD}{c^{\beta}}$ do not lead to an optimal policy for the genuine manufacturer, which is detailed in the following section.

3.4.3 Optimal supply of the genuine manufacturer

In this section, we show that the optimal supply x^{α} by the genuine manufacturer satisfies $\frac{c^{\beta}D}{p(1-r)} \leq x^{\alpha} \leq \frac{(1-r)pD}{c^{\beta}}$. First, we show that $x^{\alpha} < \frac{c^{\beta}D}{p(1-r)}$ cannot be optimal, then, we show that $x^{\alpha} > \frac{(1-r)pD}{c^{\beta}}$ cannot be optimal.

If $x^\alpha < \frac{c^\beta D}{p(1-r)}$

In this case, following Lemma 1, $x^{\beta*} = \frac{D-x^\alpha}{(1-r)}$, i.e., $x^\alpha = D - (1-r)x^\beta$. The optimization problem of the genuine manufacturer thus becomes

$$\max p \times [D - (1-r)x^\beta] - (c^\alpha + r\Gamma)[D - (1-r)x^\beta] \tag{3.28}$$

$$\text{s.t. } 0 \leq r \leq 1 \tag{3.29}$$

$$x^\beta \geq 0. \tag{3.30}$$

The optimal solution of problem (3.28)–(3.30) is given by $(1-r)x^\beta = 0 \rightarrow x^\beta = 0$. Thus $x^\alpha = D$ given the condition $x^\alpha < \frac{c^\beta D}{p(1-r)}$ then $r > 1 - \frac{c^\beta}{p}$. Obviously this cannot be the optimal solution for the original problem (3.9)–(3.11) since, the solution $r = 1 - \frac{c^\beta}{p}$, $x^\alpha = D$, and $x^\beta = 0$ is feasible to problem (3.9)–(3.11) and achieves a better objective function value.

If $x^\alpha > \frac{(1-r)pD}{c^\beta}$

In this case, following Lemma 1, $x^{\beta*} = 0$. The optimization problem of the genuine manufacturer thus becomes

$$\max p \times \min\{x^\alpha, D\} - (c^\alpha + r\Gamma)x^\alpha \tag{3.31}$$

$$\text{s.t. } x^\alpha > \frac{pD(1-r)}{c^\beta} \tag{3.32}$$

$$0 \leq r \leq 1 \tag{3.33}$$

$$x^\alpha \geq 0. \tag{3.34}$$

If $\min\{x^\alpha, D\} < D$, then $\frac{p(1-r)}{c^\beta} < 1 \rightarrow r > 1 - \frac{c^\beta}{p}$. Clearly, such a solution cannot be optimal since r can be decreased by ϵ which increases x^α by $\frac{pD}{c^\beta}\epsilon$ and improves the objective function value. Thus the optimal solution will have $\min\{x^\alpha, D\} = D$ and thus $x^\alpha = D$ and $r > 1 - \frac{c^\beta}{p}$. Obviously, this cannot be the optimal solution of problem (3.9)–(3.11) since the solution $r = 1 - \frac{c^\beta}{p}$, $x^\alpha = D$, and $x^\beta = 0$ is feasible to problem (3.9)–(3.11) and achieves a better objective function value.

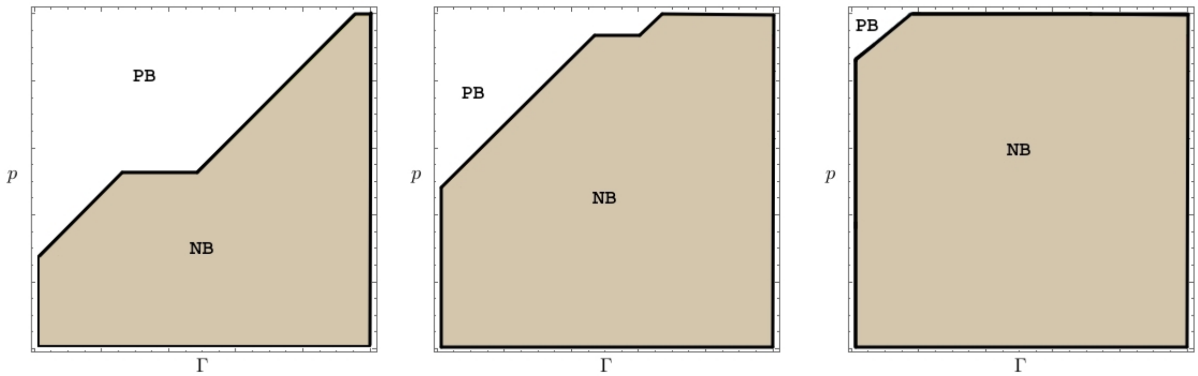
In Table 3.1, we summarize the optimal policy for the genuine manufacturer and identify the conditions and the profit for the genuine manufacturer and the counterfeiter. We denote the two optimal blockchain strategies as Partial Blockchain (PB) which refers to the case where $r = 1 - \frac{c^\beta}{p}$ and No Blockchain (NB) which refers to the case where $r = 0$.

Case	Blockchain Strategy	Condition 1	Condition 2	r	x^α	x^β	Genuine Manufacturer Profit $f^g(r, x^\alpha, x^\beta)$	Counterfeiter Profit $f^c(r, x^\alpha, x^\beta)$
1	NB	$2c^\alpha \geq p$	$\Gamma \geq p - c^\alpha$	0	$\frac{c^\beta D}{p}$	$D - \frac{c^\beta D}{p}$	$c^\beta D(1 - \frac{c^\alpha}{p})$	$(p - c^\beta)D(1 - \frac{c^\beta}{p})$
2	PB	$2c^\alpha \geq p$	$\Gamma < p - c^\alpha$	$1 - \frac{c^\beta}{p}$	D	0	$D(p - c^\alpha - \Gamma(1 - \frac{c^\beta}{p}))$	0
3	NB	$2c^\alpha < p$	$\Gamma \geq \frac{p - c^\alpha - \frac{c^\beta p}{4c^\alpha}}{1 - \frac{c^\beta}{p}}$	0	$\frac{c^\beta Dp}{4(c^\alpha)^2}$	$\frac{Dp}{2c^\alpha}(1 - \frac{c^\beta}{2c^\alpha})$	$\frac{c^\beta pD}{4c^\alpha}$	$pD(1 - \frac{c^\beta}{2c^\alpha})$
4	PB	$2c^\alpha < p$	$\Gamma < \frac{p - c^\alpha - \frac{c^\beta p}{4c^\alpha}}{1 - \frac{c^\beta}{p}}$	$1 - \frac{c^\beta}{p}$	D	0	$D(p - c^\alpha - \Gamma(1 - \frac{c^\beta}{p}))$	0

Table 3.1: Summary of the optimal manufacturing quantities, blockchain strategies, and profits for the competing genuine and counterfeit manufacturers.

3.5 Insights and discussions

As discussed in the previous section and summarized in Table 3.1, the manufacturer's optimal strategy is to either adopt a partial blockchain strategy (PB) and deter the counterfeiter from entering the market or decide not to implement blockchain and compete with the counterfeiter on sales. This optimal decision is based on four factors that affect the profitability of the manufacturer, the market price p for the product, the cost of manufacturing the genuine product c^α, the cost of manufacturing the counterfeit product c^β, and finally the blockchain cost Γ.



(a) Production costs of the genuine product and the counterfeit are similar.

(b) Production cost of the genuine product is larger that the counterfeit cost.

(c) Production cost of the genuine product is significantly larger that the counterfeit cost.

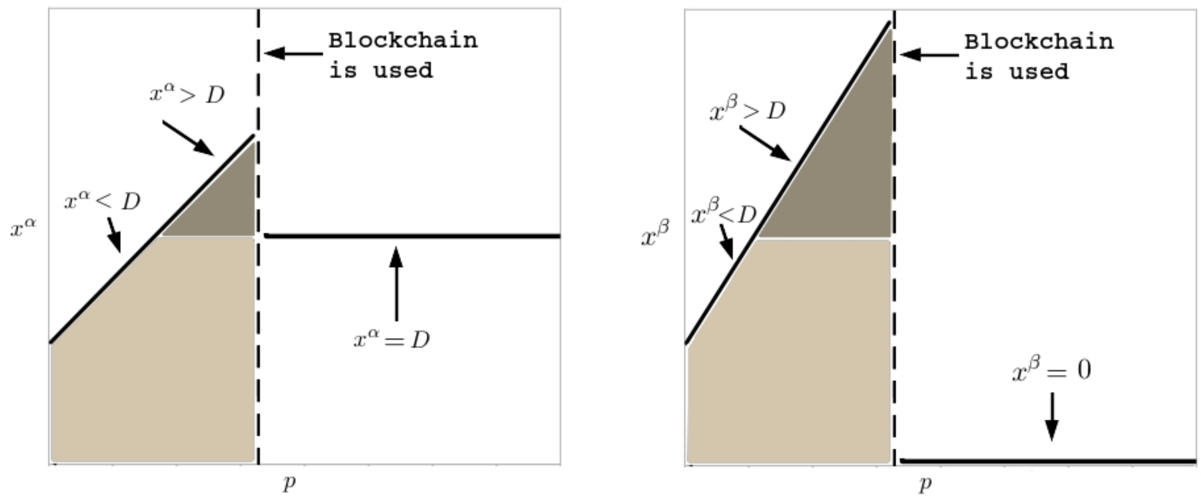
Figure 3.1: Optimal blockchain strategy with changes in blockchain cost Γ and product market price p.

3.5.1 Optimal Blockchain Strategy by Product Type

We can distinguish between three types of products. Regular products are those whose cost of manufacturing is almost identical whether they are authentic or counterfeit ($c^{\alpha} \gtrsim c^{\beta}$). These are basically the products that will have similar quality and functionality, i.e., the same cost of production whether produced by the genuine manufacturer or a counterfeiter. Typical regular products are those that have little differentiation and are used in day-to-day activities such as certain food and non-brand named clothes for example. The second type of products are premium products characterized by a higher manufacturing cost due to the premium product quality and functionality while a counterfeiter does not offer the same product quality nor delivers the same functionality and thus the manufacturing cost of the counterfeit is lower ($c^{\alpha} \gg c^{\beta}$). Such products are commonly counterfeited due to the large consumer base and high profit margin for the counterfeiter and include products such as electronics, toys, and pharmaceuticals. Finally, luxury products are those whose cost of manufacturing is significantly higher for the genuine manufacturer compared to the counterfeiter ($c^{\alpha} \ggg c^{\beta}$) due to the highly sophisticated manufacturing requirements and brand cost. Such products include jewelry and luxury clothing which are also commonly counterfeited due to the significant profit margins to the counterfeiter.

Figure 3.1 shows the optimal strategy as a function of the blockchain cost Γ and the market price p. Not surprisingly, the genuine manufacturer is more persuaded to adopt blockchain when the blockchain cost is low and the market price for the product is high, thus the cost of investment can be easily recovered by the sold products. However, the counter-intuitive observation is that the manufacturer of the genuine product is much less likely to adopt blockchain for luxury products (Figure 3.1c) compared to premium (Figure 3.1b) and regular products (Figure 3.1a). The initial intuition behind adopting blockchain is to protect against counterfeiting for premium and luxury products where the counterfeit product has significantly less value and functionality compared to a genuine product and thus it is important to discourage counterfeiting for these products to protect the consumers. For luxurious products, however, we notice that the genuine manufacturer has an incentive to adopt blockchain only if the blockchain cost is very low. The reason for this lack of incentive to adopt blockchain is that the cost of manufacturing a counterfeit product is significantly smaller than the cost of manufacturing a genuine product and since the market price is significantly high (luxury or premium product), the profit margin for a counterfeit is very high. Consequently, the counterfeiter has strong incentives to flood the market with non-genuine products. In response, the genuine manufacturer needs to have a high blockchain implementation level ($r = 1 - \frac{c^\beta}{p} \backsimeq 1$) to discourage and eliminate counterfeits, which then becomes very costly. The other extreme is for regular products where the market price and the costs of the genuine and counterfeit products are very close. Arguably, for these products the impact on the consumer is less, as from a quality and functionality perspective, both types are very similar. While it is still very important to eliminate counterfeiting for these types of products, it is less critical from a consumer impact perspective, however as Figure 3.1a shows, the genuine manufacturer has the incentives to adopt blockchain unless the blockchain cost is very high and/or the market price for the product is low. The reason for this strategy is that for the regular products the counterfeiter has little incentive to flood the market with products due to the low profit margins and thus the genuine manufacturer only needs to have a low blockchain implementation level ($r = 1 - \frac{c^{\beta}}{p} \backsimeq 0$) to discourage and eliminate counterfeiting. It is important to note that, Figure 3.1 has a small region (low prices and blockchain costs close to zero, including $\Gamma = 0$), where the optimal strategy is Partial Blockchain (PB). These values fall under cases 2 and 4 (according to Condition 2) from Table 3.1.

The main outcome from analyzing the optimal blockchain adoption strategy for a genuine manufacturer is the observation that it is not always financially beneficial to implement blockchain to discourage counterfeiting and more importantly it becomes a less attractive option as the products become more premium and luxurious which are in the first place the products that are most commonly counterfeited. Thus to incentivize manufacturers to adopt blockchain, the cost should remain minimal which necessitates subsidy. Governments already invest significantly in anti-counterfeiting strategies and thus subsidizing novel measures to combat counterfeiting such as blockchain may be an effective approach for governments to further improve their capabilities. Prior work such as Cho et al. (2015) and Pun et al. (2021) evaluated the impact of government efforts on preventing counterfeiting. Our insights complement those of Pun et al. (2021) which analyzed the role of government from a consumer standpoint based on the observation that adopting blockchain may increase the demand for counterfeits due to the increasing price of genuine products (the analysis is based on non-deceptive counterfeits where genuine and counterfeits have different prices). Thus our analysis complements Pun et al. (2021) in demonstrating the need for government subsidy from the manufacturers' perceptive, particularly in the case of deceptive counterfeits, which is the focus of this Chapter.



(a) Genuine Manufacturer. (b) Counterfeiter.

Figure 3.2: Supply by the genuine manufacturer and the counterfeiter given the market price.

3.5.2 Blockchain Adoption, Production Planning, and Profitability

As discussed in the prior section, the motivation of the genuine manufacturer to adopt blockchain is driven by the ability of the counterfeiter to inject counterfeited products at profit in the supply chain. As products become more premium, counterfeiters are attracted by the higher profit margins. Furthermore, the additional cost of implementing blockchain may make it more attractive for the genuine manufacturer to ignore blockchain adoption and compete by optimizing the number of genuine products introduced into the market. As shown in Figure 3.2, when the market price of the product is low, i.e., does not recover the investment in blockchain, the genuine manufacturer does not invest in blockchain and instead competes with the counterfeiter through optimizing the supply of genuine products. Not surprisingly, as shown in Figures 3.2a and 3.2b, the supply of the genuine and counterfeit products increases as the market price increases, i.e., as the profitability increases. While as discussed in Section 3.4.1, the total supply of products to the market is always at least the demand, Figure 3.2 shows that the individual supply by the genuine manufacturer and the counterfeiter is below the total demand until a certain price level where the suppliers increase the market availability of their products beyond the demand despite their knowledge of the market demand. Thus, although both suppliers will end up with excess supply, the optimal strategy by both counterparts is to increase the availability of their products to compete and achieve optimal profit. More importantly, the result shows that at certain price levels, the genuine manufacturer is better off competing by optimizing the production/supply of genuine products to the market rather than by adopting blockchain. It is only when the market price is large enough to compensate the cost of blockchain adoption that the genuine manufacturer adopts blockchain, which then makes it less attractive to the counterfeiter to compete due to the increasing amount of counterfeit products that are detected and eliminated. Once blockchain is adopted, the market becomes less attractive to the counterfeiter which then stops the supply of counterfeits and the genuine manufacturer lowers its supply of genuine products to match the market demand. The key insight is that despite the potential of blockchain technology to deter deceptive counterfeiting, not surprisingly, eliminating counterfeits through blockchain adoption in supply chain is only optimal from a profitability perspective to the genuine manufacturer when accompanied by increasing prices to consumers. Thus as argued earlier, subsidies are critical as part of the counterfeiting prevention efforts by governments in order to enable genuine producers to maintain profitability without transferring the cost to consumers.

3.6 Accounting for product quality

As quality plays an important role in combating counterfeiting (Cho et al., 2015), we investigate the interplay between quality differentiation and blockchain technology and evaluate the incentives of the genuine manufacturer to adopt these approaches to discourage illicit production. We analyze two cases. First, we assume that the quality of the genuine product is exogenously determined. Then, we consider the case of endogenous product quality where the genuine manufacturer optimizes both the quality of its products as well as the level of blockchain adoption.

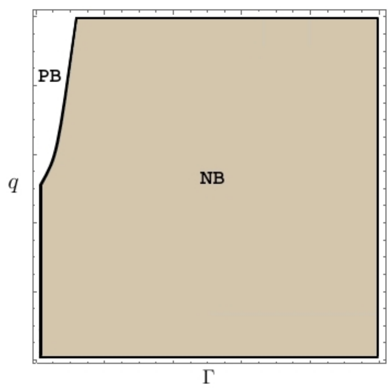
3.6.1 Exogenously determined quality

In this section, we consider product quality that is exogenously determined. Particularly, we assume that the genuine manufacturer produces the original products with quality q. While it is not expected that the counterfeiter will match the exact quality of the original product, we assume that the counterfeiter will need to adjust the quality of its production to remain deceptive. As such, as the quality of the original product increases, the counterfeiter will incur increasing production costs to ensure that the counterfeited products remain deceptive to the consumers. Particularly instead of the per-unit production cost c^β that is used in (3.4)–(3.5), we assume that the per-unit production cost is $c^\beta + c_q^\beta q^2$. Similarly, the genuine manufacturer incurs a per-unit cost $c_q^\alpha q^2$ to produce with a quality q. We make the reasonable assumptions that $p > c^\alpha + c_q^\alpha q^2$ as well as $c_q^\alpha > c_q^\beta$, i.e., the market price is more than the cost of production of the genuine items and the counterfeit product quality cost is less than that of the original product.

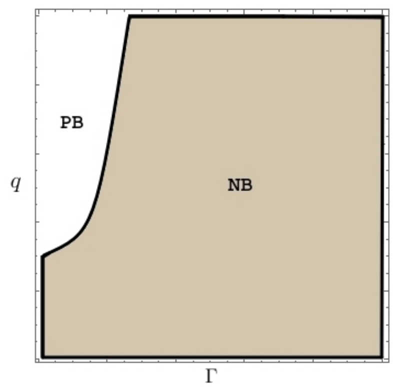
Since q is exogenous, then the optimality conditions which are summarized in Table 3.2, follow those obtained in Section 3.4 with the only change being the replacement of c^α by $c^\alpha + c_q^\alpha q^2$ and c^β by $c^\beta + c_q^\beta q^2$. Figure 3.3 shows the optimal blockchain strategy as a function of the blockchain cost Γ and the product quality q. As expected, the optimal blockchain strategy depends on the quality of the genuine product. For higher quality products, the genuine manufacturer is willing to accept a higher price for the blockchain implementation.

Case	Blockchain Strategy	Condition 1	Condition 2	r	x^{α}	x^{β}
1	NB	$2(c^{\alpha}+c_q^{\alpha}q^2) \geq p$	$\Gamma \geq p-(c^{\alpha}+c_q^{\alpha}q^2)$	0	$\frac{(c^{\beta}+c_q^{\beta}q^2)D}{p}$	$D-\frac{(c^{\beta}+c_q^{\beta}q^2)D}{p}$
2	PB	$2(c^{\alpha}+c_q^{\alpha}q^2) \geq p$	$\Gamma < p-(c^{\alpha}+c_q^{\alpha}q^2)$	$1-\frac{(c^{\beta}+c_q^{\beta}q^2)}{p}$	D	0
3	NB	$2(c^{\alpha}+c_q^{\alpha}q^2) < p$	$\Gamma \geq \frac{p-(c^{\alpha}+c_q^{\alpha}q^2)-\frac{(c^{\beta}+c_q^{\beta}q^2)p}{4(c^{\alpha}+c_q^{\alpha}q^2)}}{1-\frac{(c^{\beta}+c_q^{\beta}q^2)}{p}}$	0	$\frac{(c^{\beta}+c_q^{\beta}q^2)Dp}{4((c^{\alpha}+c_q^{\alpha}q^2))^2}$	$\frac{Dp}{2(c^{\alpha}+c_q^{\alpha}q^2)}(1-\frac{(c^{\beta}+c_q^{\beta}q^2)}{2(c^{\alpha}+c_q^{\alpha}q^2)})$
4	PB	$2(c^{\alpha}+c_q^{\alpha}q^2) < p$	$\Gamma < \frac{p-(c^{\alpha}+c_q^{\alpha}q^2)-\frac{(c^{\beta}+c_q^{\beta}q^2)p}{4(c^{\alpha}+c_q^{\alpha}q^2)}}{1-\frac{(c^{\beta}+c_q^{\beta}q^2)}{p}}$	$1-\frac{(c^{\beta}+c_q^{\beta}q^2)}{p}$	D	0

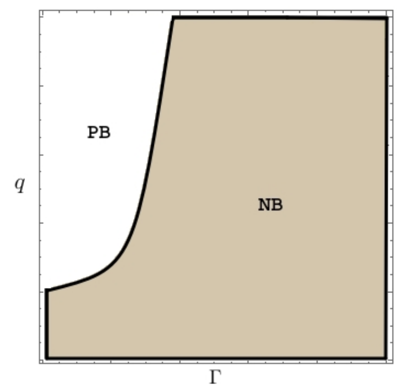
Table 3.2: Optimality conditions considering product quality.



(a) Regular products ($c^{\alpha} \gtrsim c^{\beta}$).



(b) Premium products ($c^{\alpha} \gg c^{\beta}$).



(c) Luxury products ($c^{\alpha} \ggg c^{\beta}$).

Figure 3.3: Effect of product quality and blockchain cost on optimal strategy.

Furthermore, as illustrated by the differences in Figures (3.3a)–(3.3c), as the products become more premium and luxurious, the genuine manufacturer is more willing to invest in blockchain compared to regular products. For instance for luxury products, the optimal strategy is to invest in blockchain for a larger range of product quality and for a higher range of blockchain cost compared to premium and regular products. On the other hand, for regular products, the optimal policy is to invest in blockchain only if the quality is high and the blockchain cost is low.

3.6.2 Endogenously determined quality

Similar to blockchain, product quality can be used as a deterrent against deceptive counterfeits. For instance, genuine manufacturers can produce their products with a quality that is high enough to make it very costly for counterfeiters to produce deceptive counterfeits. As observed in practice, for luxury products that are typically of very high quality, the counterfeits are often non-deceptive and consumers can identify a counterfeit from a genuine product. This section thus analyzes the case where the genuine manufacturer can optimize both the blockchain implementation level as well as the product quality to prevent counterfeiting. For that, we focus on the cases where the optimal strategy of the genuine manufacturer involves blockchain implementation (Cases 2 and 4) in Table 3.2. The optimal blockchain level for these cases is given by

$$r = 1 - \frac{(c^{\beta} + c_q^{\beta} q^2)}{p} \tag{3.35}$$

which indicates that the blockchain implementation is inversely proportional to the product quality (See Figure 3.4). This relationship indicates that as the quality of the products increases, there is less need to implement blockchain to prevent deceptive counterfeits since it becomes more costly for the counterfeiter to produce deceptive products. We note though that this does not mean that a counterfeiter exits the market. In such cases, the counterfeiter may then start producing non-deceptive products rather than deceptive products (See Pun et al. (2021) for an analysis of the case of the non-deceptive counterfeit).

The genuine manufacturer's optimal strategy to deter deceptive counterfeits thus balances between blockchain implementation and product quality. Making the reasonable assumption that quality can be set within the lower and upper limits $\underline{q}$ and $\overline{q}$ (minimum and maximum possible product quality), respectively, the optimal quality and subsequently, the optimal blockchain implementation levels are given by the following lemma (Proof in

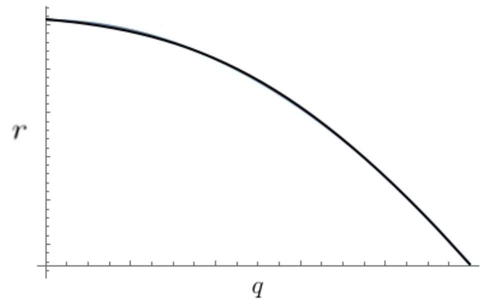


Figure 3.4: Relation between blockchain implementation and product quality.

Appendix 3.6.2). We consider quality and blockchain decisions sequentially to better analyze the isolated effects of both parameters. This assumption is consistent with the game sequence from the comparable literature (Pun et al., 2021), with blockchain and other operational decision defined sequentially. The consideration of simultaneously deciding on quality and blockchain could be considered in an extension to the present work.

Lemma 4 *The optimal product quality and blockchain implementation level are*

$$q = \begin{cases} \overline{q} & \text{if } c_q^\alpha - \frac{c_q^\beta}{p}\Gamma \leq 0 \\ \underline{q} & \text{if } c_q^\alpha - \frac{c_q^\beta}{p}\Gamma \geq 0, \end{cases}$$

$$r = \begin{cases} 1 - \frac{c^\beta + c_q^\beta \overline{q}^2}{p} & \text{if } c_q^\alpha - \frac{c_q^\beta}{p}\Gamma \leq 0 \\ 1 - \frac{c^\beta + c_q^\beta \underline{q}^2}{p} & \text{if } c_q^\alpha - \frac{c_q^\beta}{p}\Gamma \geq 0. \end{cases}$$

Proof of Lemma 4

The objective function of the genuine manufacturer is

$$\max \frac{x^\alpha}{x^\alpha + (1-r)x^\beta} pD - (c^\alpha + r\Gamma + c_q^\alpha q^2)x^\alpha. \tag{3.36}$$

Replacing r by its optimal value $r = 1 - \frac{c^\beta + c_q^\beta q^2}{p}$, objective (3.36) becomes

$$\max \frac{x^\alpha}{x^\alpha + (1-r)x^\beta} pD - \left[c^\alpha + (1 - \frac{c^\beta}{p})\Gamma + (c_q^\alpha - \frac{c_q^\beta}{p}\Gamma)q^2 \right] x^\alpha.$$

Since the quality is bounded by an upper and a lower bound $\underline{q} \leq q \leq \overline{q}$, then the optimal solution is

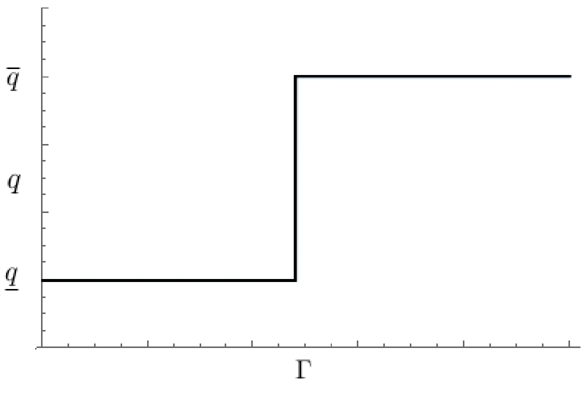
$$q = \begin{cases} \overline{q} & \text{if } c_q^\alpha - \frac{c_q^\beta}{p}\Gamma \leq 0 \\ \underline{q} & \text{if } c_q^\alpha - \frac{c_q^\beta}{p}\Gamma \geq 0. \end{cases}$$

Equivalently, the optimal blockchain implementation level is

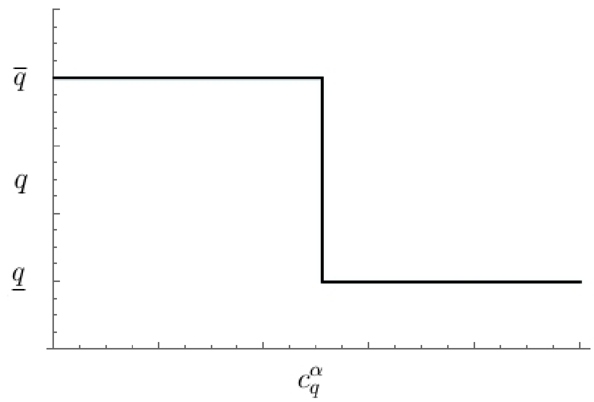
$$r = \begin{cases} 1 - \frac{c^\beta + c_q^\beta \overline{q}^2}{p} & \text{if } c_q^\alpha - \frac{c_q^\beta}{p}\Gamma \leq 0 \\ 1 - \frac{c^\beta + c_q^\beta \underline{q}^2}{p} & \text{if } c_q^\alpha - \frac{c_q^\beta}{p}\Gamma \geq 0. \end{cases}$$

□

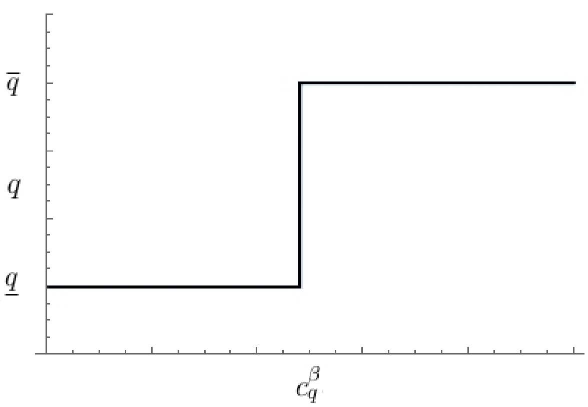
Lemma 4 indicates that the genuine manufacturer's strategy is to either produce at the lowest possible product quality with a high blockchain level or alternatively produce at the highest possible product quality with a lower blockchain level. The choice between those two strategies is based on the cost of blockchain, the cost of producing at higher quality for both the genuine and the counterfeiter, and finally the market price of the product. Evidently, higher blockchain cost motivates the genuine manufacturer to increase the quality (Figure 3.5a) and reduce the blockchain level (Figure 3.6a) while the opposite is true if the cost of increasing quality for the genuine manufacturer is high (Figures 3.5b and 3.6b). Alternatively, as the cost of increasing quality gets larger for the counterfeiter, the genuine manufacturer is more inclined to increase the quality of the product (Figure 3.5c) rather than invest in blockchain (Figure 3.6c). This is due to the fact that larger quality cost for the counterfeiter negatively impacts the counterfeiter's profitability and thus the ability to compete with deceptive counterfeits. Therefore, it becomes more cost-effective for the genuine manufacturer to produce higher quality products that are harder to deceptively imitate rather than invest in blockchain. Finally, Lemma 4 indicates that blockchain is more effective at higher market prices where the genuine manufacturer's preference is to increase the blockchain implementation as the market price increases (Figure 3.6d) while lowering product quality (Figure 3.5d). This insight is particularly interesting as it demonstrates that, with the availability of blockchain, for higher market price products, manufacturers are less interested in improving the quality of their products to differentiate them from counterfeits and alternatively rely on the availability of blockchain technology to eliminate the threat of counterfeits. Subsequently, consumers will receive lower quality products despite being genuine and at a high price.



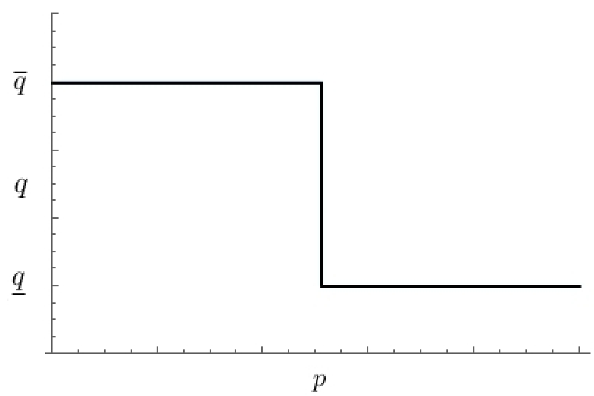
(a) Blockchain cost (Γ).



(b) Genuine manufacturer quality cost (c_q^α).

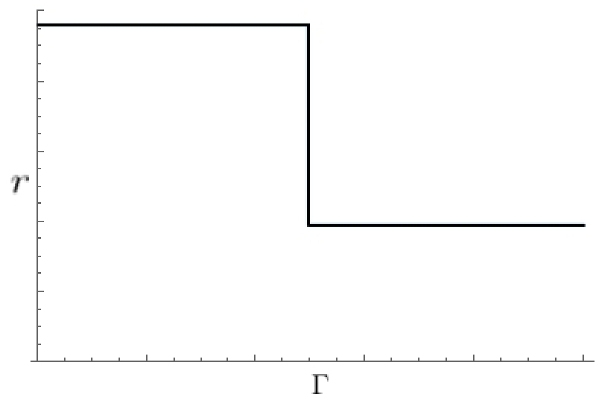


(c) Counterfeiter quality cost (c_q^β).

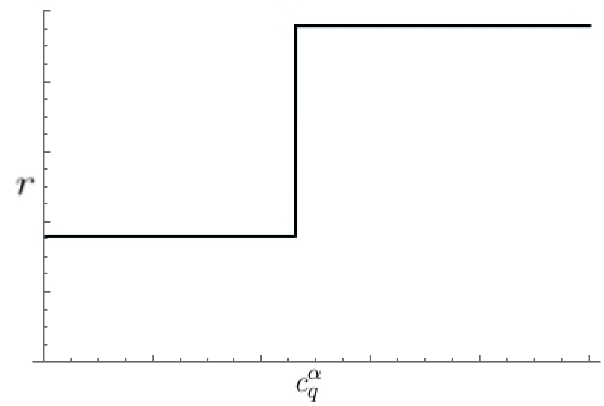


(d) Market price (p).

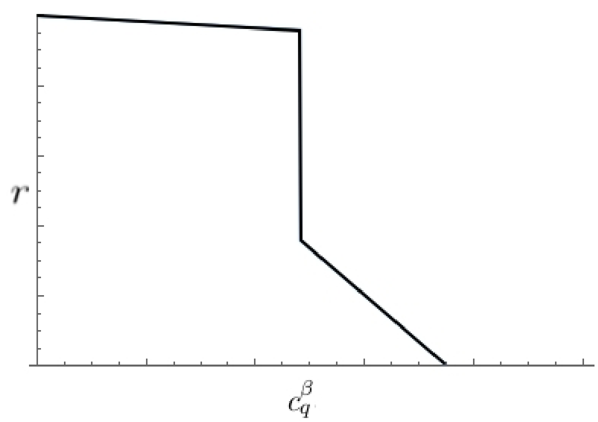
Figure 3.5: Optimal product quality.



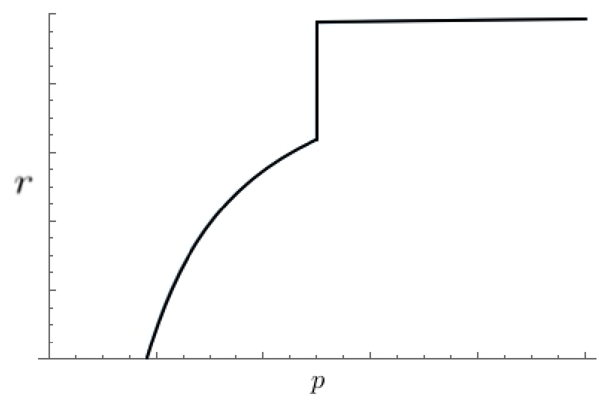
(a) Blockchain cost (Γ).



(b) Genuine manufacturer quality cost (c_q^α).



(c) Counterfeiter quality cost (c_q^β).



(d) Market Price (p).

Figure 3.6: Optimal blockchain level in the presence of quality.

3.7 Concluding remarks

Counterfeiting constitutes a massive business that threatens the world economy. Over the recent years, the sale of counterfeited goods has accelerated dramatically given the advancement of copying technologies as well as with the immense growth of e-commerce markets which altogether made fake products widely accessible and harder to distinguish. Law enforcement agencies across the globe continue to increase their efforts to discover and eliminate illicit manufacturing and counterfeit products relying on the evolving intellectual property laws, close collaboration with e-commerce firms, and most importantly anti-counterfeit technology such as QR codes, RFID, holograms, and most recently blockchain.

The most challenging counterfeits to detect and arguably the most dangerous to consumers and the economy are deceptive counterfeits that get leaked to genuine supply chains and reach the consumers that buy them typically at the same market prices of genuine products without any knowledge of their illicit nature. Not only that the consumers end up paying a premium for a fake product, but these products often lack the functionality of the genuine counterpart and may pose immense health risks such as in the case of the thriving industry of pharmaceuticals counterfeits. These illicit products find their way to the supply chain of genuine products with the help of legitimate supply chain parties that facilitate their leakage given the premium profits that can be made from the sales of counterfeits. The introduction of blockchain technology has facilitated the ability to detect counterfeits through the various layers of the supply chain and even by the consumers given the promise of full data visibility from source to consumer. Traditionally, detecting counterfeits gets harder as they become part of the supply chain of legitimate products and particularly as these products reach retail (or even worse when the retailer is complicit), however with the availability of blockchain, virtually anyone can check the authenticity of a particular product by reviewing its history that is stored on the blockchain. Evidently this ability to detect is driven by the investment of genuine producers in blockchain, the amount of information that is stored on the blockchain, and the frequency of verifying the authenticity of each product in the supply chain among other factors all of which come at an increasing cost to producers of genuine products. We introduced a model that captures this ability to detect counterfeits through a design decision, the blockchain level, and evaluate the incentives of genuine manufacturers to facilitate the detection of illicit products through strategic investment in blockchain technology. While the previous literature has considered the case of deceptive counterfeits that become non-deceptive due to blockchain, our model explicitly considers the competing supply of both genuine products and deceptive counterfeits and evaluates the market equilibrium. The proposed model enabled us to evaluate the strategic decisions of genuine manufactures and their incentives to compete with deceptive counterfeiters through a careful balance between investing in blockchain and storming the market with genuine products to reduce the sales of counterfeits. In our analysis, we distinguish among three different product types, regular products, premium products, and luxury products. The main insight from our analysis is that the attractiveness of blockchain to discourage deceptive counterfeits decreases as the products become more premium and luxurious (higher cost), which are practically the products that are most commonly counterfeited. Introducing product quality to potentially decrease the ability of counterfeiters to produce deceptive products shows that genuine manufacturers can strategically balance between their product quality and the investment in blockchain to combat deceptive counterfeits. However, our insights show that with the availability of blockchain, genuine manufacturers may become less interested in improving the quality of their products to differentiate from counterfeiters, but rather rely on blockchain to prevent the sale of counterfeits. Subsequently, genuine products with lower quality are passed to the consumer, though with blockchain authenticity certification.In summary, for the two proposed models, with and without quality consideration, manufacturers would direct more investment in blockchain when product costs are lower.

In future research, it would be interesting to investigate the impact of product quality on the sales of genuine and deceptive counterfeit products. Particularly, one would expect that a higher quality genuine product will offer more distinctive clues to consumers that would increase their ability to identify counterfeits, which would increase the probability of choosing genuine products from a pool of products containing deceptive counterfeits. We decided to model the blockchain implementation as a continuous scale between zero and one. This decision allows for the derivation and analysis of equilibrium states by exploring the concavity of the functions. However, an interesting extension would be the consideration of discrete levels and how this is translated into practical implementation of counterfeit detection systems. Also, testing alternative blockchain cost functions, such as quadratic or exponential, would be important to evaluate the model's robustness. Additionally, future research should also investigate the potential joint use of different anti-counterfeiting technologies such as RFID, QR codes, and holograms in addition to blockchain and evaluate the added benefits and equivalent costs.

Chapter 4

Blockchain Adoption in Competitive Supplier Selection Under Carbon Emission Restrictions

4.1 Introduction

Over the recent years, companies have recognized that environmental aspects can be strategic in supply chain management (Diabat and Govindan, 2011; Ansari and Moghadam, 2016; Fu and Su, 2020). It is of great importance that corporations raise take action concerning the environmental impact of their business, particularly with tighter regulations in place, and well-informed customers that seek sustainable products (Chiou et al., 2011; Lee et al., 2015; Seman et al., 2019). Firms need to redesign their supply chains and modify how they fulfill supply and manage production to minimize their impact on climate change (Ahmed and Sarkar, 2018). In addition, when considering competition and dynamic demand, organizations need to identify and adopt environmental measures that create competitive advantage (Green et al., 2012; Plambeck, 2012; Seman et al., 2019). Supply chain practices that incorporate green measures can also bring direct benefits by improving product quality, lowering production costs through innovation, generating new sources of revenue, and differentiating products (Chiou et al., 2011). For the effective management of the supply chain, reliable information is not only relevant but imperative for success.

Supply chain decision-making is becoming more reliant upon real-time and accurate data, most likely delivered by some sort of tracking system, and companies want to explore the benefits of data-driven visibility to gain competitive advantage, satisfying customers and regulators (Basole and Nowak, 2018). Currently, greenhouse gas (GHG) emission is the main indicator to monitor and control green supply chains, and considering that 45% of total emissions are due to the production and transportation of goods (Metz et al., 2007; Ahmed and Sarkar, 2018), a reliable emission accounting system is necessary.

The use of databases and tables to estimate emissions is well established in industrial and agricultural activities. The Intergovernmental Panel on Climate Change (IPCC), a body from the United Nations, is responsible for assessing the science of climate change and for proposing methods and tools to reduce impacts and mitigate risks. They were responsible for the establishment of a Database on GHG Emission Factors, EFDB (IPCC, 2020). The guide provides the users with well-documented emission factors and other relevant parameters for gas emission calculation. However, traditional calculation of carbon emissions can lead to inaccurate accounting due to the lack of standardization, different geographical locations, incomplete data, and incorrect user input (Couwenberg, 2011; Wang et al., 2015; Zhang et al., 2017; Rodrigo et al., 2020; Peng et al., 2020). With calculations based on rough estimates and averages, carbon emission calculations are today at the point that financial accounting was forty years ago, but to be relevant and transferable emissions must shift from organization-level to product-level data (Spiller, 2021). This requires the collaboration between multiple players sustained by reliable and accurate calculationmeasurement systems. This is where Blockchain can become a differential tool, increasing transparency, providing accurate and validated emission factors (Shakhbulatov et al., 2019) while securely sharing data between players along the supply chain.

According to a report from McKinsey, two-thirds of a company's sustainability footprint lies with suppliers (Cherel-Bonnemaison et al., 2021). Companies must adopt a global view over their supply chains by improving not only their emissions but also the emissions from their suppliers and customers (Plambeck, 2012). However, having the necessary supply chain transparency is a challenge, and most companies have no visibility over their second or third-tier suppliers (Abeyratne and Monfared, 2016). To shed light on that, blockchain can offer supply chain management visibility, aggregation, validation, automation, and resilience (Babich and Hilary, 2020a). Information can be shared in real-time among all players in the supply chain, increasing transparency and product traceability. With reliable data, suppliers can plan and better estimate demand, and customers can make more informed buying decisions.

Motivated by the necessity of greener supply chains, and by the fact that suppliers are critical in the overall supply chain carbon emissions, we propose a supplier competition model to investigate the strategic deployment of blockchain under carbon emission restrictions. We consider suppliers that offer components to a manufacturer, which has to comply with emission targets for its final product. The manufacturer, in turn, can award the suppliers bonuses to foster greener components. We note that, blockchain with mining-based consensus architecture, such as Bitcoin, have very high energy consumption which itself has an environmental impact. In the present work, we assume permissioned blockchain architectures, where this elevated environmental impact is not a concern (Sedlmeir et al., 2020).

We propose a Stackelberg game-theoretic framework where the supplier's and manufacturer's problems are modelled as mixed-integer programs in a bi-level optimization problem. By deriving the optimality conditions for the suppliers, we can reformulate the problem as a mixed-integer program. To our knowledge, this is the first work to optimize blockchain implementation as a variable along with other operational decisions, in a competition setting under carbon emission restrictions. The remainder of this chapter is organized as follows. A literature review is presented in Section 4.2. The supplier competition model is presented in Section 4.3, followed by computational results in Section 4.4, and a conclusions in Section 4.5.

4.2 Literature review

Blockchain has the potential to transform supply chain functions by improving operational efficiency, transparency, provenance, responsiveness, and data management. This disruptive potential is confirmed by an exponential increase in the related published research (Dutta et al., 2020), and applications with sustainability considerations are of great significance. The strengths of blockchain are that records become immutable, transparent, trustworthy, and can be shared by different players and stakeholders (Saberi et al., 2019), besides, becoming the foundation for applications in sustainability. The ability to provide private and public keys allows for better supplier selection and development (Kouhizadeh and Sarkis, 2018; van Hoek, 2019) where emissions, carbon assets, and certifications can be registered and validated in complex and heterogeneous supply chains, using blockchain. Also related to the shareability of data, blockchain allows for a more effective product tracking and life cycle control, enabling intelligent waste management and recycling programs (Kouhizadeh and Sarkis, 2018; Kouhizadeh et al., 2019; Xu et al., 2019; Saberi et al., 2019), which opens the possibility of tokens awarded to the customer as an incentive for product return at the end of their life cycle (Kouhizadeh et al., 2019). Blockchain acts as an enabler for other disruptive technologies, for instance, Physical Internet – which proposes digital, physical, and operational interconnectivity for logistic systems. According to Meyer et al. (2019), simulation-based Physical Internet provided a 30% cost reduction and emissions that are 60% lower, sustained by the functionalities of blockchain. Additionally, carbon trading platforms are an effervescent research topic in blockchain that is gaining a lot of attention, particularly when combined with decentralized energy production or cryptocurrencies and tokens (Al Kawasmi et al., 2015; Imbault et al., 2017; Khaqqi et al., 2018; Pan et al., 2019; Kim and Huh, 2020; Zhao and Chan, 2020; Richardson and Xu, 2020). Saberi et al. (2019) highlight that blockchain offers enormous potential for environmental sustainability projects and could be associated with the U.N.'s sustainable development goals (SDGs) to study blockchain-enabled supply chain effectiveness. Motivated by this potential, in the present work we investigate the strategic relation between blockchain implementation and the development and competition of suppliers, aiming at products with lower emission, while keeping the cost perspective at sight. We focus on a limited number of papers that provide a quantitative approach to emission tracking and optimization in supply chains, with blockchain consideration.

Liu et al. (2019) propose a blockchain-based framework to calculate, store and share carbon footprint information between players in a determined supply chain. The model is comprised of three layers, the calculation layer, where they combine traditional footprint inventory and data from sensors and IoT; the blockchain layer, to register and validate the emission information; and the integration layer, where supply chain players and external stakeholders can visualize the data. The framework introduces the idea of a combined emission calculation, using both traditional methods and automatically collected data, which is consistent with our approach of partial blockchain implementation. Our work takes the idea one step further with the proposition of a model that optimizes blockchain adoption level together with other operational decisions, in a supplier competition setting.

Manupati et al. (2020) present a blockchain-based framework to jointly optimize total costs and carbon emissions in a supply chain. The model considers a three-echelon supply chain accounting for inventory, transportation, ordering and manufacturing costs. The proposed blockchain architecture is based on smart contracts, registering the flow of physical items and carbon assets. Emissions are converted into financial costs for the optimization, by the multiplication of a carbon tax. The blockchain records can track emissions that can be identified at a product level. Our approach differs from the one presented by the authors on the blockchain adoption choice. We consider the decision and cost of blockchain adoption as a part of the optimization model, so the deployment level is optimized along with the other operational decisions. In summary, the frameworks from Liu et al. (2019) and Manupati et al. (2020) present blockchain systems that are well detailed in terms of functionalities and data flow, however, they are not at the core of the optimization and rather working in parallel. Manupati et al. (2020) convert the carbon emissions into a financial cost, which are accounted for in the global cost optimization. In contrast, our approach places the blockchain adoption decision at the core of the strategic and operational decisions, and the final solution presents an optimized deployment that is in line with the supplier's overall competitive strategy.

Supplier selection is well studied in supply chain management, with consolidated research and a broad spectrum of solution approaches (as reviewed by Weber et al., 1991, De Boer et al., 2001, Aissaoui et al., 2007, and Chai et al., 2013). Supplier competition and sourcing strategies are significant aspects to be considered that can highly impact the companies' profitability and service level (Qi et al., 2015). Price is the main component considered in procurement decisions but there are additional relevant parameters that must be considered in the decision process, as product quality (Bergman and Lundberg, 2013; Abdolshah, 2013), lead time (Babich, 2006; Noori-Daryan et al., 2019), reliability (Tomlin and Wang, 2005; Wang et al., 2010; Qi et al., 2015), and information sharing (Yang et al., 2012; Li and Wan, 2017; Li, 2020). The inclusion of additional criteria, such as sustainability metrics, makes the decision models more complex and requires rethinking some of the traditional and established approaches (Govindan et al., 2015). From the thirty-three papers related to green supplier evaluation and selection, reviewed by Govindan et al. (2015), only one paper presents a mathematical programming formulation, the focus of the present work. Yeh and Chuang (2011) propose a multi-objective model to optimize total cost, transportation time, product quality, and a green appraisal score. The authors solve the model using a genetic algorithm offering a set of Pareto-optimal solutions for supplier selection. The paper incorporates sustainability factors in a decision-making model, however, our work differs from the author's in the sense that we directly account for product emissions and use bonuses to foster more efficient products, altering the procurement structure towards a balanced final product.

In conclusion, publications on blockchain application for sustainable supply chains are increasing exponentially in the past years. However, the vast majority of the papers are dedicated to reviewing current initiatives or discussing opportunities and future research avenues. The present work is among the first, if not the first, to jointly optimize blockchain adoption, supplier selection, and manufacturing costs in a competitive setting under carbon regulation.

4.3 Proposed framework and problem formulation

Consider a setting where a manufacturer, M, has to acquire the main component for its product, and the component is offered by two suppliers, denoted by S1 and S2. Being conscious of its environmental impact, the manufacturer ensures that its final product has total emissions that are below the market standard, denoted by $\bar{e}$. The manufacturer informs suppliers of the standard wholesale price, $\bar{w}$, and the desired emission level for the component, denoted by $\underline{e}$. The suppliers can be rewarded with a bonus, on top of the price, in case the offered product is below the desired emission $\underline{e}$. The suppliers decide on the technology used to produce the parts, which defines the cost and total emissions that would determine order allocation. The manufacturer then decides on the allocation of orders, the technology used, and the bonus awarded to the suppliers. The game sequence is defined as follows.

1. The leader, the manufacturer, defines the wholesale price and the desired target emission for the component.
2. Each supplier defines the technology adopted, which sets the corresponding cost and emission level.
3. Considering the suppliers' emission level, the manufacturer defines the technology adopted, allocates orders, and sets the bonuses.

The application of a bonus is intended to foster competition, aiming at components with lower emission levels. The manufacturer and the suppliers are assumed to seek profit maximization. A network representation of the framework, along with notation, is depicted in Figure (4.1).

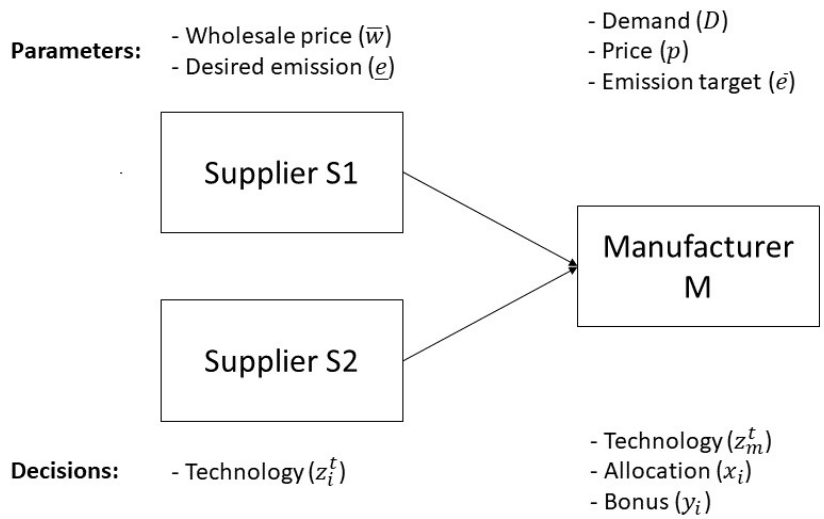


Figure 4.1: Supply chain representation of supplier selection with blockchain consideration

4.3.1 Baseline model

The proposed setting considers supplier competition for order allocation, aiming at profit maximization. Considering that both the bonus and the allocation are defined by the manufacturer, the suppliers select their technology to maximize their profit. The proposed formulation uses indices $i \in I$ for suppliers and $t \in T_i$ for technology choices. Given $\bar{w}$, the wholesale price for components that the manufacturer pays, the bonus y_i paid based on the supplier's emission level with bonus multiplier b, x_i the quantity allocated to supplier i by the manufacturer, $\underline{e}$ target emission level for the components, as well as c_i^t and $\bar{\epsilon}_i^t$, the cost and emission level of supplier i when adopting technology t, respectively, the supplier decides on:

$$z_i^t = \begin{cases} 1, & \text{if supplier } i \text{ adopts technology } t \\ 0, & \text{otherwise} \end{cases}$$

e_i : emission level of the components offered by supplier i.

Each supplier i maximizes profit by solving:

$$
\begin{aligned}
[S_i] : \max\ & (\bar{w} + y_i - \sum_{t \in T_i} c_i^t z_i^t) x_i \\
\text{s.t. } & \sum_{t \in T_i} z_i^t = 1 && (4.1) \\
& \bar{w} + y_i - \sum_{t \in T_i} c_i^t z_i^t \geq 0 && (4.2) \\
& e_i = \sum_{t \in T_i} \bar{\epsilon}_i^t z_i^t && (4.3) \\
& e_i \leq \underline{e} - \frac{y_i}{b} && (4.4) \\
& z_i^t \in \{0, 1\}, \quad t \in T_i
\end{aligned}
$$

The objective function maximizes the profit. Constraint (4.1) specify that the supplier must adopt only one technology. Constraint (4.2) ensures that the bonus and wholesale price from the manufacturer are sufficient for the supplier's profitability. Constraint (4.3) calculates the emission level according to the technology adopted, while constraint (4.4) sets the relation between the bonus and emission level.

The manufacturer also seeks to maximize its profits and considers the emission level from the suppliers as inputs to decide on the allocation, bonus, and technology which adds to the final emission level. The manufacturer's problem considers the following parameters: market price, p, market emission level, $\bar{e}$, maximum demand for products, D, as well as the manufacturer's cost when adopting technology $t \in T_m$, c_m^t, and emission level when adopting technology $t \in T_m$, $\underline{\epsilon}_m^t$. The manufacturer decides on:

$$
\begin{aligned}
x_i &: \quad \text{order quantity allocated to supplier } i. \\
y_i &: \quad \text{bonus to supplier } i.
\end{aligned}
$$

$$
z_m^t = \begin{cases} 1, & \text{if the manufacturer adopts technology } t \\ 0, & \text{otherwise.} \end{cases}
$$

The optimization problem for the manufacturer is:

$$
\begin{aligned}
[M] : \max\ & D(p - \bar{w}) - \sum_{i \in I} y_i x_i - \sum_{t \in T_m} D c_m^t z_m^t \\
\text{s.t.}\ & \sum_{i \in I} x_i = D && (4.5) \\
& \sum_{i \in I} e_i x_i + \sum_{t \in T_m} D \underline{\epsilon}_m^t z_m^t \leq D \bar{e} && (4.6) \\
& y_i \geq (\underline{e} - e_i) b, \quad i \in I && (4.7) \\
& \sum_{t \in T_m} z_m^t = 1 && (4.8) \\
& x_i, y_i \geq 0, \quad i \in I,\ z_m^t \in \{0, 1\}, \quad t \in T_m
\end{aligned}
$$

The objective function maximizes the manufacturer's profit. Constraint (4.5) ensures the total allocation satisfies the market demand. Constraint (4.6) calculates the total emission level, based on the emissions from the suppliers and technology adopted by the manufacturer. Constraint (4.8) ensures that exactly one technology is adopted. Constraints (4.7) define the bonus paid to supplier i.

The problem we propose has an inherent hierarchy, with the manufacturer acting as the leader and the suppliers as followers in Stackelberg game, resulting in a bi-level optimization problem:

$$
\begin{aligned}
[BL-M]: \max\ & D(p-\bar{w}) - \sum_{i \in I} y_i x_i - \sum_{t \in T_m} D c_m^t z_m^t \\
\text{s.t.}\ & \sum_{i \in I} x_i = D \\
& \sum_{i \in I} e_i x_i + \sum_{t \in T_m} D \underline{\epsilon}_m^t z_m^t \leq D\bar{e} \\
& y_i \geq (\underline{e} - e_i) b, \quad i \in I \\
& \sum_{t \in T_m} z_m^t = 1 \\
& x_i, y_i \geq 0, \quad i \in I,\ z_m^t \in \{0,1\}, \quad t \in T_i \\
(e_i, z_i^t) = & \arg\max\ (\bar{w} + y_i - \sum_{t \in T_i} c_i^t z_i^t) x_i, \qquad i \in I \\
& \text{s.t.}\ \sum_{t \in T_i} z_i^t = 1 \\
& \quad \bar{w} + y_i - \sum_{t \in T_i} c_i^t z_i^t \geq 0 \\
& \quad e_i = \sum_{t \in T_i} \bar{\epsilon}_i^t z_i^t \\
& \quad e_i \leq \underline{e} - \frac{y_i}{b}, \\
& \quad z_i^t \in \{0,1\}, \quad t \in T_i.
\end{aligned}
$$

The next section presents the linearization of the bilevel problem $[BL-M]$.

4.3.2 Linearization of the bi-level formulation

Let us consider the suppliers' problem:.

$$
\begin{aligned}
[S_i] : \max\, & (\bar{w} + y_i - \sum_{t \in T_i} c_i^t z_i^t) x_i \\
\text{s.t.}\ & \sum_{t \in T_i} z_i^t = 1 \\
& \bar{w} + y_i - \sum_{t \in T_i} c_i^t z_i^t \geq 0 \\
& e_i = \sum_{t \in T_i} \bar{\epsilon}_i^t z_i^t && (4.9) \\
& e_i \leq \underline{e} - \frac{y_i}{b} && (4.10) \\
& z_i^t \in \{0, 1\}, \quad t \in T_i
\end{aligned}
$$

By replacing e_i from constraint (4.9) into (4.10) and considering that $\bar{w}$, y_i, and x_i are fixed quantities, the problem becomes:

$$
\begin{aligned}
\min\ & \sum_{t \in T_i} c_i^t z_i^t \\
\text{s.t.}\ & \sum_{t \in T_i} \bar{\epsilon}_i^t z_i^t \leq \underline{e} - \frac{y_i}{b} && (4.11) \\
& \sum_{t \in T_i} c_i^t z_i^t \leq \bar{w} + y_i && (4.12) \\
& \sum_{t \in T_i} z_i^t = 1 \\
& z_i^t \in \{0, 1\}, \quad t \in T_i
\end{aligned}
$$

Considering that only one technology is chosen, (4.11) can be replaced by $\bar{\epsilon}_i^t z_i^t \leq \underline{e} - \frac{y_i}{b}$

and constraint (4.12) can be replaced by $c_i^t z_i^t \leq \bar{w} + y_i$ which leads to:

$$
\begin{aligned}
\min \ & \sum_{t \in T_i} c_i^t z_i^t \\
\text{s.t. } & \bar{\epsilon}_i^t z_i^t \leq \underline{e} - \frac{y_i}{b}, \quad t \in T_i \\
& c_i^t z_i^t \leq \bar{w} + y_i, \quad t \in T_i \\
& \sum_{t \in T_i} z_i^t = 1 \\
& z_i^t \in \{0, 1\}, \quad t \in T_i,
\end{aligned}
$$

which is equivalent to the bounded binary knapsack problem:

$$
\begin{aligned}
\min \ & \sum_{t \in T_i} c_i^t z_i^t \\
\text{s.t. } & \sum_{t \in T_i} z_i^t = 1 \\
& 0 \leq z_i^t \leq \frac{\bar{w} + y_i}{c_i^t} \\
& 0 \leq z_i^t \leq (\underline{e} - \frac{y_i}{b}) \frac{1}{\bar{\epsilon}_i^t} \\
& z_i^t \in \{0, 1\}, \quad t \in T_i
\end{aligned}
$$

This is, intern, equivalent to:

$$
\begin{aligned}
[PO_i] : \min \ & \sum_{t \in \tau_i} c_i^t z_i^t \\
\text{s.t. } & \sum_{t \in \tau_i} z_i^t = 1 \\
& z_i^t \in \{0, 1\}, \quad t \in \tau_i \subseteq T_i,
\end{aligned}
$$

where $\tau_i \subseteq T_i$ only includes the technologies for which $(\underline{e} - \frac{y_i}{b})\frac{1}{\bar{\epsilon}_i^t} \geq 1$ and $\frac{\bar{w}+y_i}{c_i^t} \geq 1$. The previous problem $[PO_i]$ can be solved as a linear program by relaxing the binary requirement on z_i^t and the optimal solution can be characterized by the primal-dual optimality conditions:

$$\Omega_i \leq c_i^t, \quad t \in \tau_i$$
$$\Omega_i = \sum_{t \in \tau_i} c_i^t z_i^t$$
$$\sum_{t \in \tau_i} z_i^t = 1$$
$$0 \leq z_i^t \leq 1, \quad t \in \tau_i$$

The latter conditions and the characterization of τ_i can be written explicitly as:

$$\Omega_i \leq c_i^t + M(1 - u_i^t), \quad t \in T_i$$
$$\Omega_i = \sum_{t \in T_i} c_i^t z_i^t$$
$$z_i^t \leq u_i^t, \quad t \in T_i$$
$$\sum_{t \in T_i} z_i^t = 1$$
$$(\underline{e} - \frac{y_i}{b})\frac{1}{\bar{\epsilon}_i^t} \geq u_i^t, \quad t \in T_i \tag{4.13}$$
$$M u_i^t \geq (\underline{e} - \frac{y_i}{b})\frac{1}{\bar{\epsilon}_i^t} - 1, \quad t \in T_i \tag{4.14}$$
$$\frac{\bar{w} + y_i}{c_i^t} \geq u_i^t, \quad t \in T_i \tag{4.15}$$
$$M u_i^t \geq \frac{\bar{w} + y_i}{c_i^t} - 1, \quad t \in T_i, \tag{4.16}$$

where u_i^t is a binary decision variables, defined as:

$$u_i^t = \begin{cases} 1, \text{ if } (\underline{e} - \frac{y_i}{b})\frac{1}{\bar{\epsilon}_i^t} \geq 1 \text{ and } \frac{\bar{w}+y_i}{c_i^t} \geq 1 \\ 0, \text{ otherwise.} \end{cases}$$

Note that (4.13) and (4.14) are equivalent to $y_i \leq b(\underline{e} - \bar{\epsilon}_i^t u_i^t)$ and $y_i \geq b(\underline{e} - \bar{\epsilon}_i^t(Mu_i^t + 1))$, and (4.15) and (4.16) are equivalent to $y_i \geq c_i^t u_i^t - \bar{w}$ and $y_i \leq Mc_i^t u_i^t - \bar{w} + 1$. By substituting the linearized equations into the bi-level problem, we obtain:

$$[BL - M - PO] : \max D(p - \bar{w}) - \sum_{i \in I} m_i - \sum_{t \in T_m} Dc_m^t z_m^t$$

$$\text{s.t. } y_i x_i \leq m_i, \quad i \in I \tag{4.17}$$

$$\sum_{i \in I} x_i = D$$

$$\sum_{i \in I} \sum_{t \in T_i} \bar{\epsilon}_i^t s_i^t + \sum_{t \in T_m} D\underline{\epsilon}_m^t z_m^t \leq D\bar{e} \tag{4.18}$$

$$s_i^t \geq x_i - M(1 - z_i^t), \qquad i \in I, t \in T_i \tag{4.19}$$

$$s_i^t \leq x_i, \qquad i \in I, t \in T_i \tag{4.20}$$

$$y_i \geq (\underline{e} - e_i)b, \quad i \in I$$

$$\sum_{t \in T_m} z_m^t = 1$$

$$x_i, y_i, m_i \geq 0, \quad i \in I$$

$$s_i^t \geq 0, \quad i \in I, t \in T_i$$

$$z_m^t \in \{0, 1\}, \quad t \in T_m$$

$$\Omega_i \leq c_i^t + M(1 - u_i^t), \quad i \in I$$

$$\Omega_i = \sum_t c_i^t z_i^t, \quad i \in I$$

$$z_i^t \leq u_i^t, \quad i \in I$$

$$\sum_{t \in T_i} z_i^t = 1, \quad i \in I$$

$$y_i \leq b(\underline{e} - \bar{\epsilon}_i^t u_i^t), \quad i \in I, t \in T_i$$

$$y_i \geq b(\underline{e} - \bar{\epsilon}_i^t (M u_i^t + 1)), \quad i \in I, t \in T_i$$

$$y_i \geq c_i^t u_i^t - \bar{w}, \quad i \in I, t \in T_i$$

$$y_i \leq M c_i^t u_i^t - \bar{w} + 1, \quad i \in I, t \in T_i$$

$$u_i^t, z_i^t \in \{0, 1\}, \quad i \in I, t \in T_i$$

The new variable m_i is introduced to remove the non-linearity from the objective function, with the addition of the second-order cone constraints (4.17). Constraint (4.18) is the linearization of constraint (4.6) by the introduction of a new variable s_i^t and constraints (4.19) and (4.20).

4.3.3 Blockchain adoption

We now present the bi-level formulation when blockchain adoption is considered. Blockchain certifies the true emission value. Without blockchain, the supplier calculates the emissions based on tables and averages. We consider a continuous blockchain implementation variable that ranges from zero, no blockchain adopted, to one, full blockchain. This choice allows for a strategic deployment of blockchain that represents in practice the percentage of production processes that have the emissions certified using blockchain, versus traditional average-based methods. Let us consider the supplier's problem $[S_i - BCT]$ with blockchain consideration.

$$
\begin{aligned}
[S_i - BCT] : \max \ & \left(\bar{w} + y_i - \sum_{t \in T_i} \left(c_i^t z_i^t + c^B r_i^t \right) \right) x_i \\
\text{s.t. } e_i = & \sum_{t \in T_i} \left(\underline{\epsilon}_i^t r_i^t + \bar{\epsilon}_i^t (1 - r_i^t) - \bar{\epsilon}_i^t (1 - z_i^t) \right) \\
& e_i \leq \underline{e} - \frac{y_i}{b} \\
& \sum_{t \in T_i} z_i^t = 1 \\
& \bar{w} + y_i - \sum_{t \in T_i} \left(c_i^t z_i^t + c^B r_i^t \right) \geq 0 \\
& r_i^t \leq z_i^t, \quad t \in T_i \\
& 0 \leq r_i^t \leq 1, \quad t \in T_i \\
& z_i^t \in \{0, 1\}, \quad t \in T_i
\end{aligned}
$$

Where the blockchain adoption level is given by $r_i^t = \sum_{t \in T_i} r_i^t z_i^t$. Given that $\sum_{t \in T_i} z_i^t = 1$, it is essentially $\max_{t \in T_i} r_i^t$. As $\bar{w}$, y_i, and x_i are fixed, the previous problem is equivalent to:

$$
\begin{aligned}
\min \ & \sum_{t \in T_i} \left(c_i^t z_i^t + c^B r_i^t \right) \\
\text{s.t. } & \sum_{t \in T_i} \left(\underline{\epsilon}_i^t r_i^t + \bar{\epsilon}_i^t (1 - r_i^t) - \bar{\epsilon}_i^t (1 - z_i^t) \right) \leq \underline{e} - \frac{y_i}{b} \\
& \sum_{t \in T_i} z_i^t = 1 \\
& \sum_{t \in T_i} \left(c_i^t z_i^t + c^B r_i^t \right) \leq \bar{w} + y_i \\
& r_i^t \leq z_i^t, \quad t \in T_i \\
& 0 \leq r_i^t \leq 1, \quad t \in T_i
\end{aligned}
$$

$$z_i^t \in \{0,1\}, \quad t \in T_i$$

If technology t is chosen by supplier i, so that $z_i^t = 1$, the problem, is reduced to:

$$\begin{aligned}
&\min c^B r_i^t \\
&\text{s.t. } \underline{\epsilon}_i^t r_i^t + \bar{\epsilon}_i^t (1 - r_i^t) \leq \underline{e} - \frac{y_i}{b} \\
&\quad r_i^t \leq \frac{\bar{w} + y_i - c_i^t}{c^B} \\
&\quad 0 \leq r_i^t \leq 1
\end{aligned} \tag{4.21}$$

Constraint (4.21) can be rearranged to:

$$r_i^t \geq \frac{\bar{\epsilon}_i^t + \frac{y_i}{b} - \underline{e}}{\bar{\epsilon}_i^t - \underline{\epsilon}_i^t},$$

and the optimal blockchain is given by:

$$r_i^{t*} = \frac{b\bar{\epsilon}_i^t + y_i - b\underline{e}}{b(\bar{\epsilon}_i^t - \underline{\epsilon}_i^t)},$$

when

$$\begin{cases} 0 \leq \frac{b\bar{\epsilon}_i^t + y_i - b\underline{e}}{b(\bar{\epsilon}_i^t - \underline{\epsilon}_i^t)} \leq 1 \\ \text{and } \frac{b\bar{\epsilon}_i^t + y_i - b\underline{e}}{b(\bar{\epsilon}_i^t - \underline{\epsilon}_i^t)} \leq \frac{\bar{w} + y_i - c_i^t}{c^B}, \end{cases}$$

which is equivalent to:

$$\begin{cases} \bar{\epsilon}_i^t \geq \underline{e} - \frac{y_i}{b} \quad \text{and} \quad \underline{\epsilon}_i^t \leq \underline{e} - \frac{y_i}{b} \\ c^B(b\bar{\epsilon}_i^t + y_i - b\underline{e}) \leq b(\bar{\epsilon}_i^t - \underline{\epsilon}_i^t)(\bar{w} + y_i - c_i^t). \end{cases} \tag{4.22}$$

The latter is equivalent to:

$$(b(\bar{\epsilon}_i^t - \underline{\epsilon}_i^t) - c^B)y_i \geq c^B b(\bar{\epsilon}_i^t - \underline{e}) - b(\bar{\epsilon}_i^t - \underline{\epsilon}_i^t)(\bar{w} - c_i^t).$$

Under these conditions and as $r_i^t \leq z_i^t$ enforces $r_i^t = 0$ for $z_i^t = 0$, one can write:

$$r_i^t = \frac{b\bar{\epsilon}_i^t + y_i - b\underline{e}}{b(\bar{\epsilon}_i^t - \underline{\epsilon}_i^t)} z_i^t.$$

So the constraint:

$$\sum_{t \in T_i} \left(\underline{\epsilon}_i^t r_i^t + \bar{\epsilon}_i^t (1 - r_i^t) - \bar{\epsilon}_i^t (1 - z_i^t) \right) \leq \underline{e} - \frac{y_i}{b}$$

reduces to:

$$\begin{aligned}
&\sum_{t \in T_i} \left[\left(\underline{\epsilon}_i^t - \bar{\epsilon}_i^t \right) \frac{b\bar{\epsilon}_i^t + y_i - b\underline{e}}{b(\bar{\epsilon}_i^t - \underline{\epsilon}_i^t)} + \bar{\epsilon}_i^t \right] z_i^t \leq \underline{e} - \frac{y_i}{b} \\
\Rightarrow &\sum_{t \in T_i} \left(\underline{e} - \frac{y_i}{b} \right) z_i^t \leq \underline{e} - \frac{y_i}{b},
\end{aligned}$$

which is always satisfied as $\sum_{t \in T_i} z_i^t = 1$. And the supplier's problem with blockchain consideration, $[S_i - BCT]$, reduces to:

$$\begin{aligned}
[S_i - BCT] : \min &\sum_{t \in \tau_i} \left[c_i^t + c^B \frac{b\bar{\epsilon}_i^t + y_i - b\underline{e}}{b(\bar{\epsilon}_i^t - \underline{\epsilon}_i^t)} \right] z_i^t \\
\text{s.t.} &\sum_{t \in \tau_i} z_i^t = 1 \\
&z_i^t \in \{0, 1\}, t \in \tau_i \subseteq T_i
\end{aligned}$$

for $t \in \tau_i \subseteq T_i$ where $\bar{\epsilon}_i^t \geq \underline{e} - \frac{y_i}{b}$, and $\underline{\epsilon}_i^t \leq \underline{e} - \frac{y_i}{b}$, and $(b(\bar{\epsilon}_i^t - \underline{\epsilon}_i^t) - c^B)y_i \geq c^B b(\bar{\epsilon}_i^t - \underline{e}) -$

$b(\bar{\epsilon}_i^t - \underline{\epsilon}_i^t)(\bar{w} - c_i^t)$.

To characterize the optimal solution, we define additional variables and use primal-dual optimality conditions as in the previous sections. For that, we define new binary variables:

$$v_i^t = \begin{cases} 1, \text{ if } \bar{\epsilon}_i^t \geq \underline{e} - \frac{y_i}{b} \text{ and } \underline{\epsilon}_i^t \leq \underline{e} - \frac{y_i}{b} \text{ and } (b(\bar{\epsilon}_i^t - \underline{\epsilon}_i^t) - c^B)y_i \geq c^B b(\bar{\epsilon}_i^t - \underline{e}) - b(\bar{\epsilon}_i^t - \underline{\epsilon}_i^t)(\bar{w} - c_i^t). \\ \\ 0, \text{ otherwise,} \end{cases}$$

and characterize the optimal solution using the following equations:

$$\Omega_i \leq \left[c_i^t + c^B \frac{b\bar{\epsilon}_i^t + y_i - b\underline{e}}{b(\bar{\epsilon}_i^t - \underline{\epsilon}_i^t)} \right] + M(1 - v_i^t), \quad t \in T_i$$

$$\Omega_i = \sum_{t \in T} \left[c_i^t + c^B \frac{b\bar{\epsilon}_i^t + y_i - b\underline{e}}{b(\bar{\epsilon}_i^t - \underline{\epsilon}_i^t)} \right] z_i^t$$

$$z_i^t \leq v_i^t, \quad t \in T_i$$

$$\sum_{t \in T_i} z_i^t = 1$$

$$\underline{e} - \frac{y_i}{b} \leq \bar{\epsilon}_i^t + M(1 - v_i^t), \quad t \in T_i$$

$$\underline{e} - \frac{y_i}{b} \geq \underline{\epsilon}_i^t v_i^t, \quad t \in T_i$$

$$(b(\bar{\epsilon}_i^t - \underline{\epsilon}_i^t) - c^B)y_i \geq c^B b(\bar{\epsilon}_i^t - \underline{e}) - b(\bar{\epsilon}_i^t - \underline{\epsilon}_i^t)(\bar{w} - c_i^t) - M(1 - v_i^t), \quad t \in T_i$$

$$z_i^t, v_i^t \in \{0, 1\}, \quad t \in T_i.$$

By including these constraints, the definition of e_i, the variable m_i to represent the lump-sum bonus, and the optimal value for r_i^t into the bi-level problem, we obtain:

$[BL - M - PO{-}BCT]$:

$$\max D(p - \bar{w}) - \sum_{i \in I} m_i - \sum_{t \in T_m} Dc_m^t z_m^t$$

$$\text{s.t. } y_i x_i \leq m_i, \quad i \in I$$

$$\sum_{i \in I} x_i = D$$

$$\sum_{i \in I} \left(\underline{e} x_i - \frac{y_i}{b} m_i \right) + \sum_{t \in T_m} D \underline{\epsilon}_m^t z_m^t \leq D\bar{e}$$

$$s_i^t \geq x_i - M(1 - z_i^t), \quad i \in I, t \in T_i$$

$$s_i^t \leq x_i, \quad i \in I, t \in T_i$$

$$\sum_{t \in T_m} z_m^t = 1$$

$$x_i, y_i \geq 0, \quad i \in I$$

$$s_i^t \geq 0, \quad i \in I, t \in T$$

$$z_m^t \in \{0, 1\}, \quad t \in T_m$$

$$\Omega_i \leq \left[c_i^t + c^B \frac{b\bar{\epsilon}_i^t + y_i - b\underline{e}}{b(\bar{\epsilon}_i^t - \underline{\epsilon}_i^t)} \right] + M(1 - v_i^t), \quad t \in T_i$$

$$\Omega_i = \sum_{t \in T} \left[c_i^t + c^B \frac{b\bar{\epsilon}_i^t + y_i - b\underline{e}}{b(\bar{\epsilon}_i^t - \underline{\epsilon}_i^t)} \right] z_i^t$$

$$z_i^t \leq v_i^t, \quad t \in T_i$$

$$\sum_{t \in T_i} z_i^t = 1$$

$$\underline{e} - \frac{y_i}{b} \leq \bar{\epsilon}_i^t + M(1 - v_i^t), \quad t \in T_i$$

$$\underline{e} - \frac{y_i}{b} \geq \underline{\epsilon}_i^t v_i^t, \quad t \in T_i$$

$$(b(\bar{\epsilon}_i^t - \underline{\epsilon}_i^t) - c^B) y_i \geq c^B b(\bar{\epsilon}_i^t - \underline{e}) - b(\bar{\epsilon}_i^t - \underline{\epsilon}_i^t)(\bar{w} - c_i^t) - M(1 - v_i^t), \quad t \in T_i$$

$$z_i^t, v_i^t \in \{0, 1\}, \quad t \in T_i.$$

In the next section, we present computational results for the blockchain model $[BL - M - PO - BCT]$ when considering two suppliers and one manufacturer.

4.4 Computational results

Let us consider a test instance with two suppliers, denoted by 1 and 2. Supplier 1 is considered to have more efficient processes and therefore lower emissions, while supplier 2 offers a lower cost with higher emissions. Supplier 1 has a baseline cost of $50 and provides a product with a total emission of 65 units. A reduction of 10% in emissions is achieved with a cost 15% higher. Supplier 2 has a baseline cost of $48 and an emission of 67 units and has a 10% reduction with a 20% cost increase. After acquiring the components, the manufacturer uses additional processes with the corresponding technology to manufacture the final product. This increases the final emission and costs levels for the product. The costs and emission levels for each of the three technologies available are presented in Table (4.1).

	Manufacturer			Supplier 1			Supplier 2		
Cost	$35	$45	$60	$50	$57	$66	$48	$57	$69
Emission	35	27	21	65	59	53	67	61	54

Table 4.1: Cost and emission levels for the manufacturer and suppliers 1 and 2.

The suppliers have the option to adopt blockchain and certify the true value of emissions. The use of blockchain leads to a cost, c_B, per blockchain transaction. The emission levels when adopting blockchain are presented in the Table 4.2.

	Supplier 1			Supplier 2		
Emission with BCT	62	56	50	64	57	51

Table 4.2: Emission levels for suppliers 1 and 2 with blockchain certification

We consider a fixed demand, price, and product emission that are determined by the market. The manufacturer sets in advance the wholesale price, the target emission for the components, and the bonus multiplier. The model's general parameters are presented in the Table 4.3.

D	p	$\bar{w}$	$\bar{e}$	$\underline{e}$	b	c_B
1000	130	65	87	65	2	5

Table 4.3: General parameters

The problem has multiple optimal solutions, 67 for this specific instance. The manufacturer can choose different combinations of bonuses and allocation, changing the response from the suppliers while complying with the total emissions set by the market. To analyze the solution from the supplier perspective, we define contribution as the marginal profit made by the suppliers, according to $(\bar{w} + y_i - \sum_{t \in T_i} c_i^t z_i^t)$. Table (4.4) presents the average results.

	Manufacturer	Supplier 1	Supplier 2
Profit ($)	20000.0	5286.0	11702.9
Emission	27.0	59.3	59.0
Allocation (units)	-	302.5	697.5
Blockchain level	-	0.50	0.45
Bonus per unit ($)	-	12.0	12.4
Total bonus ($)	-	2470.7	7529.3
Contribution ($)	-	18.6	16.9

Table 4.4: Average results for the multiple optimal solutions

To assess the supplier's profit we compare each supplier's profit against the average profit of each, over the 67 solutions. Considering all solutions, supplier 1 has profit above the average in 31 cases and supplier 2 does better than the average in 37 occasions. There is only one case where both suppliers, together, have profits above the average (See Table (4.5)). Figures (4.2a) and (4.2b) depict the profit values for each of the solutions and average line denotes the average profit given all of the possible solutions.

	Manufacturer	Supplier 1	Supplier 2
Profit ($)	20000	5625	11875
Emission	27	65	57
Allocation (units)	-	375	625
Blockchain level	-	0.0	1.0
Bonus per unit ($)	-	0	16
Total bonus ($)	-	0	10000
Contribution ($)	-	15	19

Table 4.5: Results for the case where both suppliers perform above their average profit.

(a) Supplier 1 (b) Supplier 2

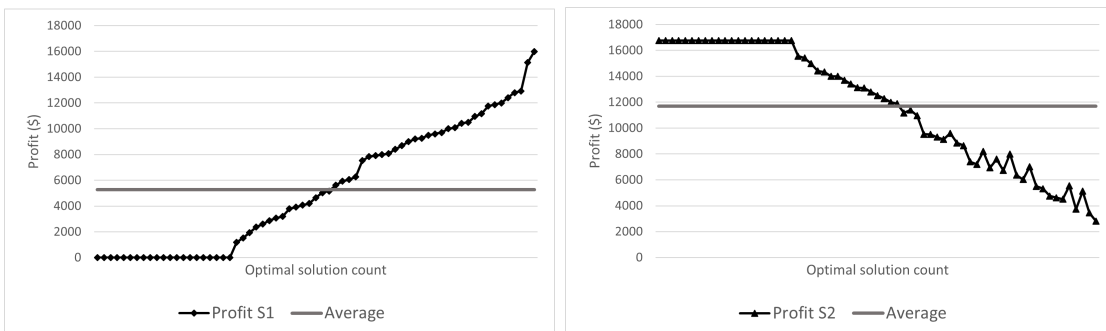


Figure 4.2: Supplier's profit and average for the multiple optimal solutions

In summary, the objective function for the manufacturer is indifferent to the profit of suppliers or emission improvements beyond the market target. As the total bonus is fixed, the supplier does not have any preference on its split between suppliers. The existence of one solution where both suppliers perform better than their averages while maintaining optimal profit for the manufacturer and complying with the market emission target indicates that, with a modified policy, all players could be better off. In Figures (4.3a) and (4.3b) we showcase how blockchain technology is used by the suppliers to improve the marginal profit contribution, until the point where they are forced to switch to a more efficient, and more expensive, technology to comply with the market emission target. The technological changes are marked by a jump in the contribution and a decrease in the blockchain implementation level (see Figure (4.3a)). Blockchain technology offers to suppliers the possibility to improve emissions by better reporting. With that, the suppliers can make incremental investments and keep competitiveness. Blockchain can postpone the necessity of technological upgrades, creating intermediate levels inside each technology.

(a) Supplier 1 (b) Supplier 2

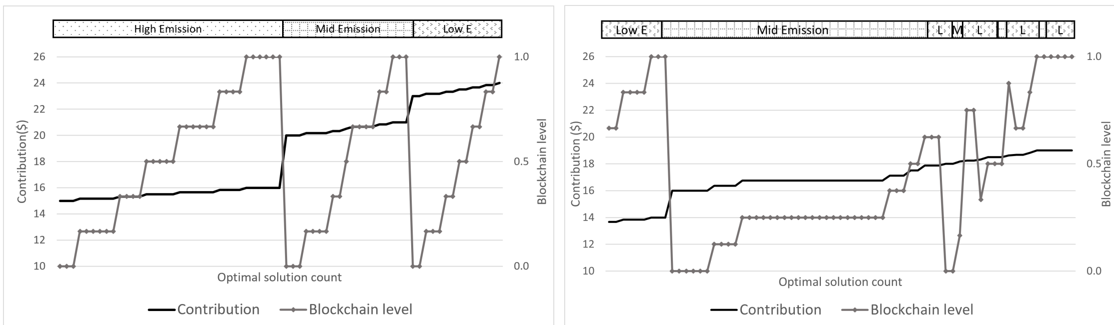


Figure 4.3: Contribution and blockchain implementation level for the multiple optimal solutions

The blockchain implementation level is crucial to ensure that the emission target is achieved in a cost-optimal way, creating intermediary steps before a technological upgrade becomes necessary. It adds a continuous aspect to the technology adoption, balancing the allocation and blockchain implementation level to comply with the market emission requirement. The main insight is that the manufacturer can choose bonuses and allocations that can bring higher profit to all participants in the supply chain, but the manufacturer has no incentive to do that. To foster higher profits and better emission levels for all participants in the supply chain, the decision policy must change. In the next section, we investigate the effect of blockchain cost and explore possible decision policies beyond the manufacturer's profit maximization.

4.4.1 Blockchain cost variation

Blockchain usage incurs additional costs for the suppliers, and therefore its variation impact must be evaluated towards the other operational decisions. We solved the model with c_B ranging from 0 to 100. Considering that multiple optimal solutions occur for each cost value, we analyze the results under two conditions. For the first, we assume that the manufacturer chooses the solution where both suppliers perform better than their profit average. In the second, we assume the manufacturer chooses the solution with the highest total profit. Figure (4.4) depicts the number of multiple optimal solutions per blockchain cost.

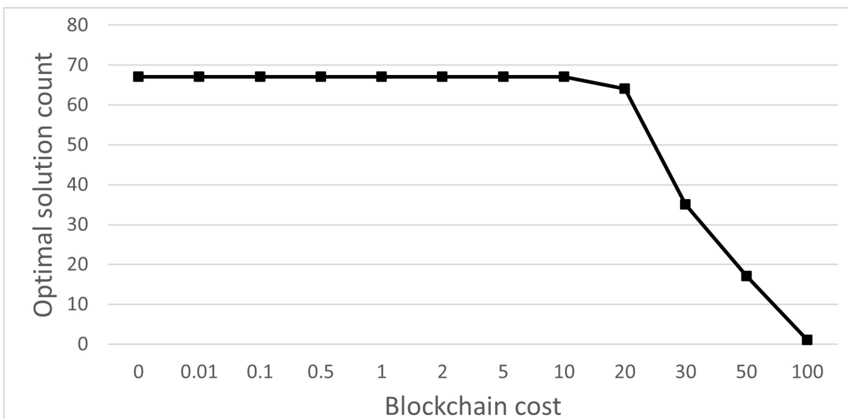


Figure 4.4: Number of multiple optimal solutions as the blockchain cost varies.

Solutions where suppliers perform better than their average profit

After obtaining all the multiple optimal solutions for a given blockchain cost, the best solution among the ones where suppliers perform better than their average profit is selected. With this filter, we compare solutions that are equivalent and capture more accurately the effects of blockchain cost variation. First, the total, suppliers, and manufacturer profits are presented in Figure (4.5a). Then, we present how the allocation changes with the blockchain cost in Figure (4.5b). Lastly, Figures (4.6a) and (4.6b) present the suppliers' marginal profit contribution and the blockchain implementation level, respectively.

(a) Profit for the suppliers and manufacturer as the blockchain cost varies

(b) Order allocation as the blockchain cost varies

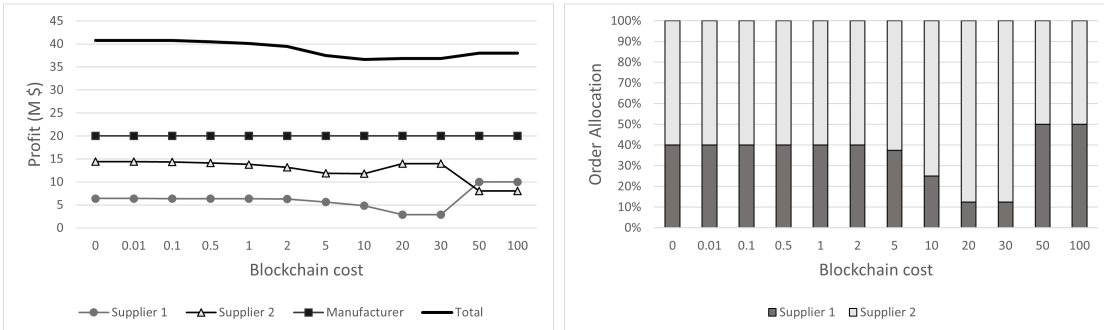
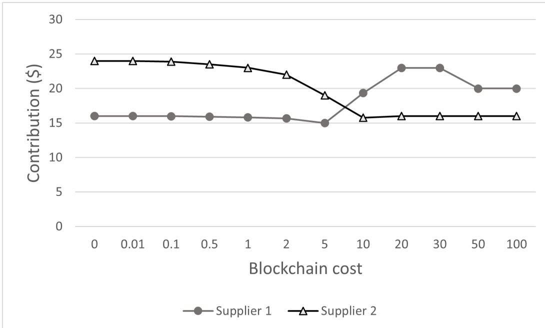


Figure 4.5: Profit and order allocation for with blockchain cost variation when considering the cases with profit above average for all suppliers

Both the manufacturer's profit and the total bonus awarded are constant and independent from the blockchain cost. As the cost increases, supplier 2 suffers a higher profit reduction, as they adopt full blockchain as opposed to partial adoption from supplier 1. The strategy adopted by supplier 1 is the same regardless of the blockchain chain cost, a medium emission strategy. Supplier 2 changes strategy, from high to medium emissions, as the cost reaches 5. The change is reflected by the increase in the marginal profit contribution, as seen in (4.6a). Both suppliers do not adopt blockchain if the cost is higher than 20. The total profit is reduced and then rises again after the cost passes 50. This happens when there is a shift between the suppliers, and supplier 1 exceeds supplier 2 in absolute profit.

(a) Marginal profit contribution for the suppliers as the blockchain cost varies



(b) Blockchain implementation level as the blockchain cost varies

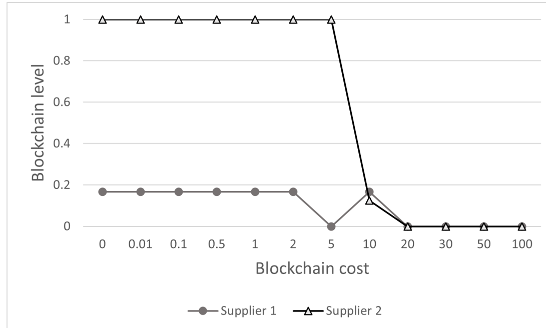


Figure 4.6: Marginal profit contribution and blockchain implementation when considering the cases with profit above average for all suppliers

In summary, as the manufacturer's performance is independent of the blockchain cost variation, the burden falls entirely on the suppliers. For this section, we considered the alternative where suppliers perform better than their average profit. Being the manufacturer driven by cost and emission only, the outcome may not be the best for the suppliers. With a different decision policy, for instance, as discussed in this section, the suppliers could be better off without any loss to the manufacturer. As the blockchain cost burden falls only on suppliers, to foster lower emissions, governmental subsidies might be a good alternative or a profit-sharing arrangement between suppliers and manufacturers. Next, we analyze an alternative policy, where the best total profit is selected among the multiple optimal solutions.

Solutions with maximum total profit

We now evaluate the cases where the solution with the highest total profit, among the multiple optimal solutions, is selected. For this scenario, the solutions are more homogeneous, the same solution is optimal between 0 and 2, and another between 10 and 100. For a cost of 5, supplier 1 changes its blockchain level to zero while supplier 2 keeps it at 1, giving supplier 1 a significant profit advantage, as can be seen in (4.7a).

(a) Profit for the suppliers and manufacturer with blockchain cost variation (b) Order allocation with blockchain cost variation

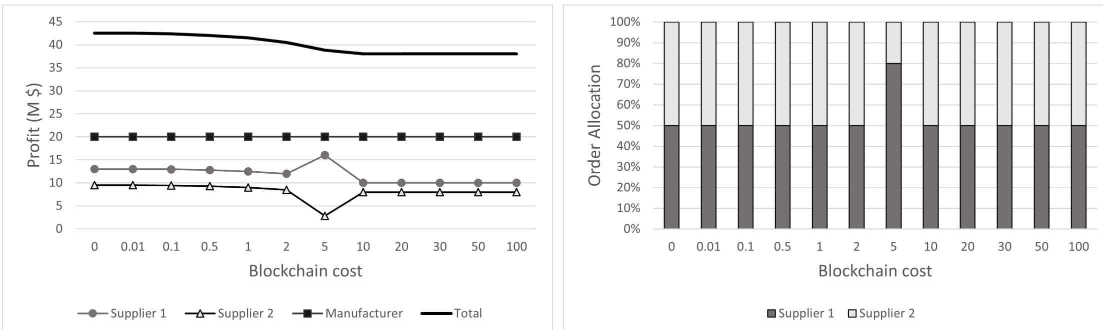


Figure 4.7: Profit and order allocation for with blockchain cost variation when considering the cases with maximum total profit

(a) Marginal profit contribution for the suppliers with blockchain cost variation (b) Blockchain implementation level with blockchain cost variation

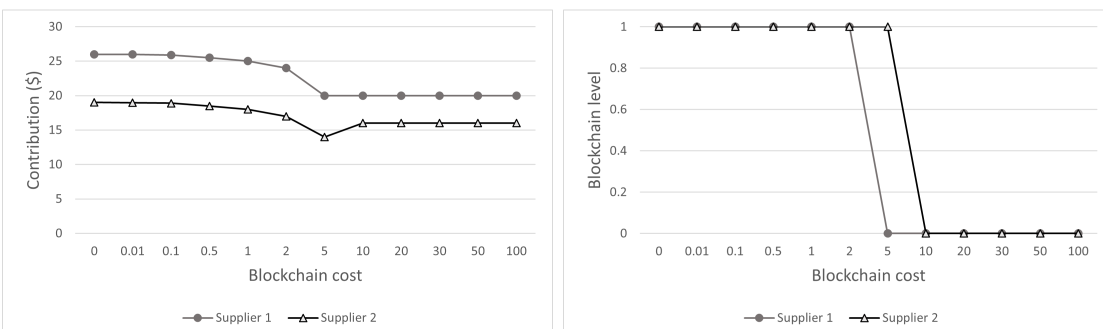


Figure 4.8: Marginal profit contribution and blockchain implementation when considering the cases with maximum total profit

In conclusion, when considering the maximum total profit policy, the optimal solution is homogeneous with little variation. The effect of cost increase is clearly observed, with suppliers turning the blockchain level directly from one to zero when it is not economically attractive. There is a defined hierarchy between suppliers, with supplier 2 always performing better than 1. Again, the manufacturer has no natural incentive to improve the supplier's profit, and this maximum total profit shows a consistent way to prioritize one supplier over the other, without affecting the manufacturer's profit. Next, we investigate the impact of changing the bonus multiplier and its effects on the competition and profit.

4.4.2 Bonus multiplier variation

The bonus multiplier is the instrument used by the manufacturer to incentivize lower emission components from suppliers. Hence, it is important to evaluate how the changes in the bonus impact the performance of all players in the supply chain. We varied the bonus multiplier from 10E-6 to 10. Similar to the analysis on the blockchain cost, we obtained multiple optimal solutions for each bonus multiplier value. We first present the best solution in terms of the supplier's average profit, then we analyze the best total profit among all multiple solutions.

(a) Profits as the bonus multiplier varies

(b) Contribution as the bonus multiplier varies

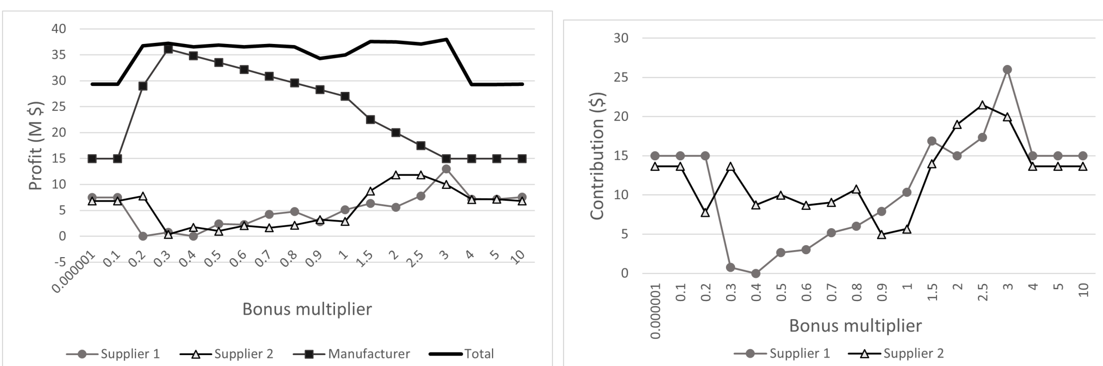


Figure 4.9: Results when considering the cases with profit above average for the suppliers

The bonus multiplier has a direct impact on the profit of all players in the supply chain. If the bonus is too low, the suppliers have no incentive to improve their products and the manufacturer profit is constant. As the bonus increases, it becomes attractive to the suppliers. The manufacturer's highest profit happens with a low bonus and decreases as the bonus increases. When the bonus multiplier becomes too high, it is not profitable for the manufacturer to award bonuses, and the profit becomes constant again. The suppliers' marginal profit contribution increases as the bonus multiplier is higher.

(a) Profits as the bonus multiplier varies

(b) Contribution as the bonus multiplier varies

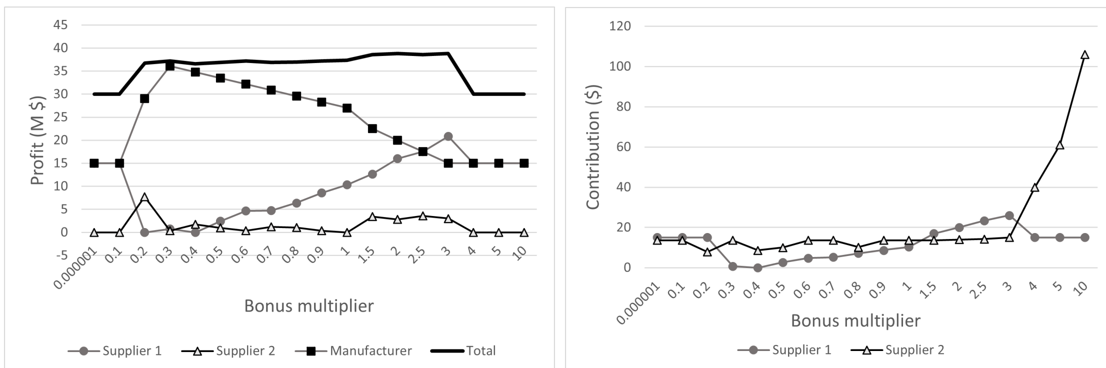


Figure 4.10: Results when considering the cases with the best total profit

If the solution with the highest total profit is selected, from the multiple optimal solutions, the difference is that supplier 1 concentrates most of the allocation and has its profit increasing consistently with the increase in the bonus multiplier, as seen in Figure (4.10). The contribution factor also follows the increase in the bonus multiplier, and for a very high bonus multiplier, supplier 2 attempts to offer a product with very low emission to collect a high bonus (high contribution) but is receives no allocation and has no realized profit.

Figure (4.11) showcases the effectiveness of the bonus in fostering lower emission components from the suppliers. When the bonus is too low, it is not attractive for suppliers to invest in technology and therefore the manufacture has to compensate with the lowest possible emission to satisfy the market requirements. As the bonus becomes attractive, suppliers invest in technology and the manufacturer is able to satisfy the market target with a high emission technology. Now, as the bonus multiplier increases, the manufacturer limits the bonuses, which become expensive. The suppliers do not have the incentive to lower their emissions and now the manufacturer is forced to change their technology, to medium emission and later to low emissions.

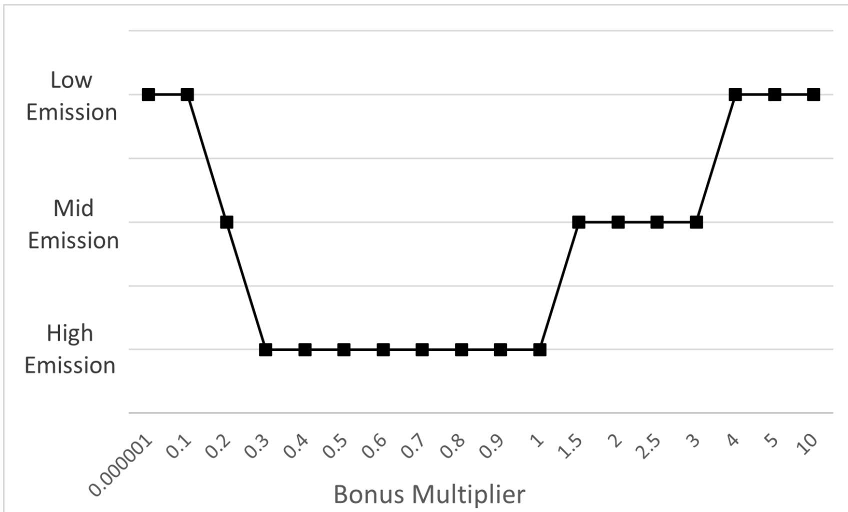


Figure 4.11: Manufacturer's emission strategy as the bonus multiplier varies

In summary, the results show that the bonus is effective in incentivizing lower emission components from the suppliers. As the bonus multiplier increases, the bonus becomes financially attractive to suppliers and they reduce their emissions, allowing the manufacturer to rely on cheaper technologies. If the manufacturer optimizes their profit based on the bonus multiplier, this may not be the best situation for the suppliers. This indicates that, if the manufacturer is concerned about the economic sustainability of their suppliers, they must adapt their bonus policy to contemplate profit sharing among all players in the supply chain.

4.5 Concluding remarks

With pressing concerns from customers and stakeholders, companies have recognized the importance of the environmental impact in supply chains. Greenhouse gas emission is an important measure of product sustainability, and firms must have good accounting and tracking systems to control and reduce it. With suppliers accounting for a significant share of the emissions and companies being held accountable for actions beyond their operations, transparency and information trust are crucial. Blockchain offers the potential to integrate information in the supply chain and provide better carbon tracking systems.

In this chapter, we investigate the strategic deployment of blockchain to track carbon emissions in competitive supplier selection. We propose a bi-level optimization model that captures the hierarchical game structure between suppliers and a manufacturer. The manufacturer seeks to maximize its profit while complying with carbon emission restrictions defined by the market. That manufacturer can award suppliers with bonuses to foster lower emissions. The suppliers decide on the technology level and blockchain adoption, to maximize their profit. A case study with one manufacturer and two suppliers show that the model has multiple optimal solutions. The resulting solutions have several combinations of allocation, technology and blockchain decisions that comply with the emission targets while maximizing the manufacturer's profit. It turns out that the total incentives paid by the manufacturer, as well as their profit, are fixed with respect to individual allocations. The results also show that blockchain offers the suppliers flexibility to explore emission reductions either by better reporting or technological upgrades. Blockchain creates intermediate levels inside each technology and allows for the supplier to keep competitiveness before the necessity of a technological upgrade. Furthermore, the bonus incentive is effective in fostering greener products from the suppliers, allowing the manufacturer to rely on cheaper technologies.

In the present work, we decided to consider both fixed demand and price. This assumption simplifies the model and allows for better exploration of the blockchain and technology-level decisions. The consideration of demand as a function of both price and emission levels is an interesting extension but the resulting models may be more challenging to solve. In addition, for future research, it would be worth exploring the effect of a third party fostering lower emissions, for example with a subsidy policy from a governmental agency. The current framework attributes the blockchain cost to the suppliers, with the manufacturer indifferent to the supplier's individual profits. By subsidizing blockchain costs, the government can help suppliers maintain profitability while going for greener components. Finally, extending the model beyond a single period would help account for strategic green technology investment and the impact of lower emissions on demand.

Chapter 5

Conclusions and future work

In this thesis, we investigated blockchain adoption in supply chain, specifically addressing questions related to the strategic deployment of blockchain technology in supply chain operations. We proposed quantitative models for three distinct problems: blockchain adoption in perishable products supply chain, blockchain to combat counterfeiting, and blockchain in green supplier selection.

In Chapter 2, we proposed a framework that integrates blockchain technology in the supply chain network design of perishable products. Our approach, based on a mixed-integer quadratic programming formulation, jointly optimizes the investment in blockchain technology along with network design and pricing decisions. Blockchain enables data certification of product freshness which leads to increased profitability for producers and better product quality for consumers. The proposed framework shows that blockchain not only brings transparency to the supply chain by tracking products, but it allows for certification, adding value to the supply chain operation overall.

In Chapter 3, we introduced a framework to use blockchain in deterring counterfeits. The model evaluates the incentives of genuine manufacturers to facilitate the detection of illicit products through strategic investment in blockchain technology. In the proposed framework, we envision that information that ensures authenticity would be shared between supply chain players. This would include certificates, audit reports, ownership transfer data, inventory data, and tracking info. The main insight from our analysis is that the attractiveness of blockchain to deter counterfeits decreases as the products become more expensive. Furthermore, with the introduction of product quality as an alternative to deter counterfeits, we show that genuine manufacturers can strategically balance between their product quality and the investment in blockchain to combat deceptive counterfeits.

In Chapter 4, we presented a bi-level optimization problem to model competitive supplier selection by a manufacturer. We introduced blockchain as an alternative for the exact tracking of carbon emissions, which enables suppliers to balance between more accurate accounting or better technology to achieve lower emissions. Testing showed that bonuses are effective in fostering greener products from suppliers.

The originality of this work stems from the integration of blockchain deployment decisions with other supply chain operational and tactical decisions. In addition, blockchain-enabled supply chains create value to consumers from certified data and offer an opportunity to monetize information, leading to data-enabled products that are sold at a premium to consumers who are careful about product sourcing information.

While we presented specific future research opportunities in the previous chapters, we identify some commonalities. For instance, as most supply chains involve many stakeholders, questions related to blockchain network management and cost are very relevant. The blockchain cost attributions need to be addressed when designing a model. For our fresh-produce application, the cost is absorbed by consumers, but the framework can differentiate products so that customers are willing to pay for the information are served. For the counterfeit application, the cost is absorbed by the manufacturer, while suppliers bear the cost for the green supplier selection application. Alternative cost structures can be explored, where a player at a higher level subsidizes part of the cost and be responsible for the blockchain network operation and management. Also, there is potential to explore blockchain adoption in other supply chains, for example in circular economy and waste management, controlled goods and protected materials, and other certified products such as organic or fair trade. It is also important to further investigate the implications of information sharing between players in a supply chain using blockchain, focusing on the type of information and its impact on the decisions and strategy. Finally, the use of hybrid models, where blockchain is associated with other systems such as RFID tags, QR codes is worth exploring.

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APPENDICES

Summary of notations

Notation used in Chapter 2

I :	set of production sites
J :	set of distribution centres
K :	set of customer zones
L :	set of transportation modes
F :	set of freshness levels
A :	set of transportation links
i, j :	index for facilities; $i, j \in I \cup J \cup K$
f :	index for freshness level; $f \in F$
l :	index for transportation mode; $l \in L$
Γ :	blockchain usage unit cost
c_i :	per unit production cost at site i; $i \in I$
g_i :	fixed cost for operating location i; $i \in I \cup J \cup K$
τ^l_{ij} :	per unit transportation cost between facilities i and j using mode l; $(i, j) \in A, l \in L$

t_{ij}^l : transportation time between facilities i and j using mode l; $(i,j) \in A, l \in L$

$\bar{t}_{ij}$: maximum transportation time between facilities i and j (i.e., $\max_l\{t_{ij}^l\}$); $(i,j) \in A$

$\bar{\Delta}^f$: maximum allowable product age for freshness level f; $f \in F$

$\underline{\Delta}_i$: storage and processing time before shipping at production site i; $i \in I$

$D_i^f(p_i^f)$: demand at customer zone i for products of freshness level f;$i \in K, f \in F$

x_{ij}^{lf} : decision variable for the quantity of products with freshness level f shipped between i and j using transportation mode l; $(i,j) \in A, l \in L, f \in F$

q_i : decision variable for the quantity produced at production site i; $i \in N$

p_j^f : decision variable for the price at customer zone j for products of freshness level f; $j \in C, f \in F$

Δ_j^f : decision variable for the age of products of freshness level f sold at customer zone j; $j \in C, f \in F$

r_{ij}^l : decision variable for the travel time information of link (i,j) using mode l is stored on the blockchain; $(i,j) \in A, l \in L$

y_{ij}^{lf} : decision variable for the mode l used to transport products of freshness level f on link (i,j); $(i,j) \in A, l \in L, f \in F$

z_i : decision variable for the location i used; $i \in I \cup J \cup K$

w_{ij}^{lf} : linearization variable for the term $r_{ij}^l x_{ij}^{lf}$

Notation used in Chapter 3

α :	manufacturer of genuine products
β :	manufacturer of deceptive counterfeits
c^j :	per-unit production cost; $\quad j \in \{\alpha, \beta\}$
x^j :	market equilibrium quantities; $\quad j \in \{\alpha, \beta\}$
r :	blockchain implementation level
Γ :	blockchain-related cost
p :	market price
D :	market demand
q :	product quality
c_q^j :	per-unit production cost for quality q; $\quad j \in \{\alpha, \beta\}$

Notation used in Chapter 4

I : set of suppliers

T : set of technologies

i : index for suppliers; $i \in I$

t : index for technologies; $t \in T$

M : manufacturer

S_i : supplier i; $i \in I$

c_i^t : cost of supplier i when adopting technology t; $i \in I, t \in T$

$\bar{\epsilon}_i^t$: emission level of supplier i when adopting technology t; $i \in I, t \in T$

$\bar{w}$: wholesale price for components that the manufacturer pays

y_i : bonus paid by the manufacturer based on the supplier's i emission level; $i \in I$

b : bonus multiplier

x_i : quantity allocated to supplier i by the manufacturer; $i \in I$

$\underline{e}$: target emission level for the components

p : market price

$\bar{e}$: market emission level target

D : maximum demand for products

c_m^t : manufacturer's cost when adopting technology t; $t \in T$

$\underline{\epsilon}_m^t$: manufacturer's emission level when adopting technology t; $t \in T$

z_i^t : technology adoption decision from the supplier; $i \in I, t \in T$

e_i : emission level of the components offered by supplier i; $i \in I$

z_m^t : technology adoption decision from the manufacturer; $t \in T$