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Competitive dynamics in blockchain-based supply chains under cryptocurrency volatility: a game theory approach

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ABSTRACT

The increasing integration of blockchain technology in supply chains has brought about significant challenges due to the volatility of cryptocurrencies, as it has become an essential aspect of customers' risk considerations. This study addresses the problem of managing supply chain operations amid such volatility, focusing specifically on pricing, advertising, manufacturer subsidy, and cybersecurity strategies within a manufacturer-retailer framework involving two cryptocurrency-based retailers that have higher market capitalisation compared to others: Ethereum and Bitcoin. The proposed solution employs game theory – a simultaneous game and two Stackelberg games with either retailer as the leader – to identify optimal strategies based on the corresponding parameter values. Accordingly, the study uniquely delivers blockchain-related risks by applying game theory to analyze the decision variables, providing insights into competitive pricing adjustments and leadership strategies for the cryptocurrency-based retailers under varying volatility levels. Results demonstrate that retailer pricing strategies must adapt to changes in wholesale prices and to the difference in cryptocurrency volatility. It also identifies crucial subsidy levels for manufacturers and optimal strategies for retailers under different volatility conditions to sustain profitability and demand.

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KEYWORDS
Blockchain-based supply chain; risk management; cryptocurrency volatility; pricing; advertising strategy; game theory

1. Introduction

The application of blockchain technology in the dynamic realm of contemporary business has brought about a paradigm shift in supply chain visibility, presenting unparalleled levels of transparency and security (Moretto and Macchion 2022). Blockchain-based supply chains (BSC) have received considerable attention due to their potential to enhance efficiency and traceability across various industries (Chang and Chen 2020). Amidst this transformative wave, the intersection of blockchain and cryptocurrency has facilitated the emergence of new dynamics within the retail sector (Chan et al. 2020). Retailers, recognising the potential and widespread acceptance of cryptocurrencies, are adopting digital currencies such as Ethereum and Bitcoin as viable payment methods (Harikumar et al. 2022). The attraction of borderless transactions, reduced transaction costs, and enhanced security have positioned cryptocurrencies as more than just speculative assets but as practical instruments for facilitating commerce (Corbet et al. 2019).

Nevertheless, achieving seamless transactions within the cryptocurrency domain is not devoid of its own challenges (Sabry et al. 2020). The inherent volatility of cryptocurrencies brings a layer of complexity that retailers have to navigate strategically (Baur and Dimpfl 2018). This volatility, distinguished by rapid and unpredictable price fluctuations, prompts a deeper examination of its consequences (Panagiotidis, Papapanagiotou, and Stengos 2022).

As cryptocurrencies, notably Ethereum and Bitcoin, struggle with volatility, retailers find themselves at the forefront of a unique challenge. The conventional understanding that higher volatility leads to diminished purchasing power and decreased demand comes to the fore (Corbet et al. 2019b). The nuanced exploration of this volatility effect on demand loss forms a critical ground of our inquiry as we examine the intricate relationship between cryptocurrency volatility and its impact on the supply chain.

In this particular context, the significance of demand attraction motivators becomes paramount. Retailers are compelled to use creative and inventive strategies in response to the potential downturn in demand due to cryptocurrency volatility. Scholars remark that advertising, as an effective driver for boosting demand, has great

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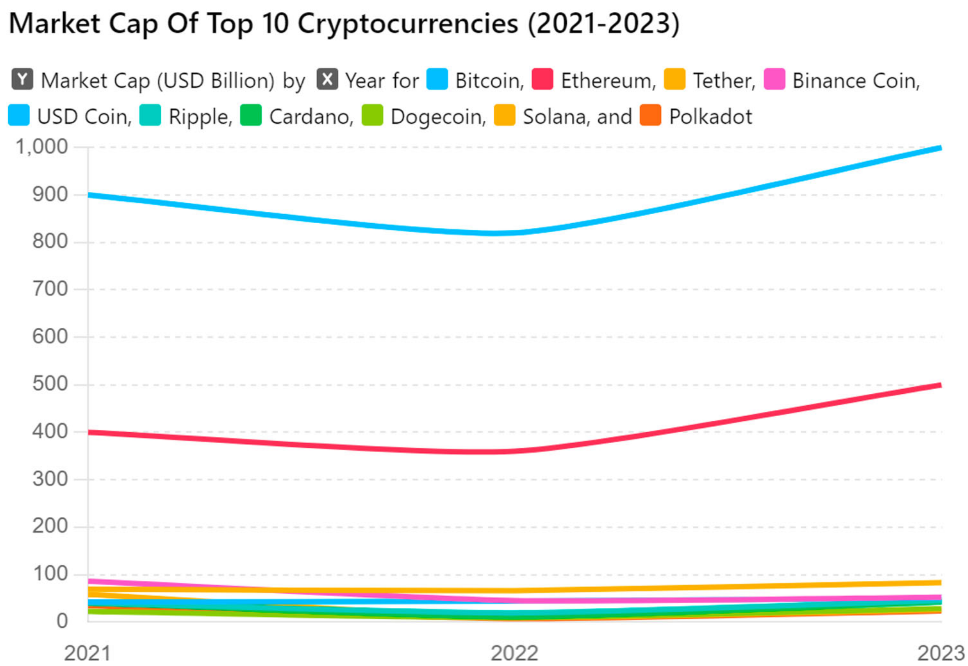

Figure 1. Market capitalisation of the 10 top cryptocurrencies from 2021 to 2023.

potential to ensure that retailers can withstand the challenges posed by volatility and emerge as resilient and competitive entities within a dynamic market (Jernej and Kovačič Batista 2018; Sakas et al. 2023). In our study, game theory is applied to analyze the complex interdependencies of supply chain decision-making.

Numerous scholars and trade journals have documented how retailers manage cryptocurrency volatility. Notable examples include Overstock and Shopify's strategies for accepting cryptocurrency payments (IvyPanda 2024). Overstock.com began accepting Bitcoin in January 2014 to attract tech-savvy customers and pioneer digital currency adoption. However, the company faced challenges as Bitcoin's value fell from $770 to $320 by the end of 2014 (Overstock.com 2024). Overstock launched campaigns targeting cryptocurrency enthusiasts, highlighting Bitcoin's security benefits and offering exclusive deals (OSTK-2015). Their experience revealed the advantages and drawbacks of integrating cryptocurrencies, such as reduced fraud and transaction fees, providing valuable insights for other companies considering similar strategies (Bradbury 2014; Lo and Wang 2014).

Additionally, our study focuses on two major top-trend cryptocurrencies, Bitcoin and Ethereum, due to their significant market presence and contrasting volatility profiles. Figure 1 presents a comparison of the market capitalisations for the top 10 cryptocurrencies from 2021 to 2023, highlighting that both Bitcoin and Ethereum consistently reached the highest market capitalisations during this period (CoinGecko 2024).

Bitcoin and Ethereum are the leading cryptocurrencies by market capitalisation. Bitcoin, created in 2009 by Satoshi Nakamoto, has a market cap of about $1.29 trillion, largely due to its status as the first cryptocurrency and its adoption as a store of value (coindesk 2024; Nakamoto 2008). Ethereum, launched in 2015 by Vitalik Buterin, has a market cap of around $550 billion (Buterin 2013; coindesk 2024). It introduced smart contracts, facilitating decentralised applications and finance, boosting its market position. The differing volatilities of Bitcoin and Ethereum make them ideal for studying the effects of cryptocurrency volatility on retail strategies (CoinGecko 2024; CoinMarketCap 2024).

Our model delves into the intricate interplay between a manufacturer and its two cryptocurrency-based retailers, Ethereum and Bitcoin, who, despite offering identical products and sharing the benefits of cybersecurity investments, experience divergent paths in the face of volatility. The Ethereum-based retailer, grappling with higher volatility, strategically employs advertising and a partial return policy to mitigate its challenges and leverage the allure of potential returns. Our research analyses three different game variants regarding the information structure: a simultaneous move game that reflects imperfect information between manufacturer and retailer ('Nash-game') and two sequential games ('Stackelberg-games') which represent asymmetric information between the market actors (Bitcoin-Stackelberg-leader and Ethereum-Stackelberg-leader). The comparison of these three variants allows for unravelling optimal strategies amid fluctuating cryptocurrency values and encompasses the analysis of crucial decision variables such as retailer pricing, advertising investments, and cybersecurity levels, providing a nuanced understanding of the strategic landscape in blockchain-enabled supply chains. Accordingly, we formulate research questions by reviewing the literature on blockchain technology, cryptocurrency applications, and game theory. We identified gaps in understanding the impact of cryptocurrency volatility on retailer pricing, manufacturer subsidies, and strategy. Our questions aim to explore the interplay between advertising, return policies, cybersecurity, and wholesale pricing in blockchain-based supply chains, enhancing strategic decision-making under cryptocurrency volatility as the following:

> RQ1: How does cryptocurrency volatility affect retailer pricing strategies, and what is the interplay between advertising, return policies, and cybersecurity in shaping the performance and resilience of blockchain-based retailers?
>
> RQ2: What role does manufacturer subsidy play in supporting Blockchain-based retailers amid significant volatility, and how do critical subsidy thresholds influence their profitability, advertising investment, and response to demand fluctuations?
>
> RQ3. How does the information structure, i.e. the order of move (Nash game, Bitcoin leader, Ethereum leader) influence both strategic decisions and profitability for retailers facing cryptocurrency volatility and potential cyberattacks?
>
> RQ4. How do changes in wholesale prices interact with cryptocurrency volatility to impact retailer pricing strategies, offering insights for competitiveness and profitability in a dynamic blockchain-based supply chain?

This paper is structured as follows. Section 2 reviews the related literature. Section 3 presents notations, model descriptions, and key assumptions. Section 4 outlines the solution method, employing game theory to derive optimal decisions. Section 5 includes the presentation of numerical examples, sensitivity analyses, and managerial insights. Concluding remarks and recommendations for future studies are provided in Section 6.

2. Literature review

This section provides an in-depth analysis of the research context surrounding the key variables investigated in this study. The literature review is organised into three main categories based on the central themes of the proposed study: Blockchain in Supply Chains, Cryptocurrency Volatility in Supply Chains, and Game Theory Applications in Blockchain-Based Supply Chains. Following these categories, the literature gaps are identified to highlight the contributions of this study.

2.1. Blockchain technology in supply chains

2.1.1. Blockchain and transparency

Blockchain technology has significantly improved transparency in supply chains. Centobelli et al. (2022) highlighted that the decentralised nature of blockchain ensures secure and rapid cross-border transactions, enhancing supply chain management flexibility. Agarwal et al. (2022) also emphasised the role of blockchain in increasing the efficiency of financial transactions within supply chains. However, Zhu, Bai, and Sarkis (2022) noted that there is still a gap in understanding the full impact of blockchain on supply chain transparency. Moreover, Bai and Sarkis (2020) developed a hybrid decision model showing that decision-maker psychology critically influences the selection of blockchain technologies for sustainable supply chain transparency.

2.1.2. Blockchain and efficiency

Blockchain's ability to streamline operations is well-documented. For instance, Casino et al. (2021) presented and tested a blockchain-based traceability system for the dairy supply chain, demonstrating improved transparency, real-time monitoring, and regulatory compliance through smart contracts and decentralised data sharing. Choi (2021) compared supply chain scenarios with and without blockchain and found that blockchain significantly reduces transaction costs and enhances efficiency. Viriyasitavat, Hoonsopon, and Bi (2021) further developed a blockchain-based payment system to improve financial transaction efficiency. Additionally, Yang, Ni, and Ng (2023) remarked that blockchain-enabled traceability eliminates moral hazard in logistics, encouraging both producers and third-party firms to improve quality, and motivating outsourcing when delivery is cost-inefficient. Yet, the integration challenges and the scalability of these solutions remain underexplored.

2.1.3. Blockchain and security

Security is another critical benefit of blockchain technology. Hamledari and Fischer (2021) demonstrated how blockchain-based crypto assets can secure financial transactions by linking payments to product movements. Furthermore, Vatankhah Barenji et al. (2020) proposed a blockchain-based platform that enables secure, decentralised manufacturing for SMEs, addressing scalability, trust, and big-data challenges. Additionally, Yang et al. (2023) demonstrated that blockchain security critically influences supply chain finance outcomes, proposing an optimisation model that tailors blockchain design to fraud risk levels, showing that mismatched security levels can significantly undermine system efficiency and cost-effectiveness. However, blockchain systems' potential vulnerabilities and security risks, especially in the context of cyberattacks, require further investigation.

2.2. Cryptocurrency volatility in supply chains

2.2.1. Impact on retailer pricing strategies

Cryptocurrency volatility poses significant challenges for supply chains, particularly in developing effective retailer pricing strategies. Li and Wang (2017) explored the technological and economic determinants of Bitcoin volatility, noting that such volatility complicates pricing decisions. Similarly, Ding et al. (2022) demonstrated that volatility clustering models can mitigate uncertainty in manufacturing supply chains. Moreover, Kitamura (2022) remarked that retailers in cryptocurrency-based ecosystems face unique challenges, such as rapidly fluctuating exchange rates and reduced purchasing power, necessitating dynamic pricing models that account for market turnovers. Nevertheless, adaptive strategies, such as hedging through more stable coins or fiat currency reserves and employing dynamic pricing algorithms based on real-time market data, can help retailers navigate these challenges (Chiu 2021). These methods, coupled with tailored demand forecasting models, allow retailers to maintain profitability and customer satisfaction while enhancing resilience in blockchain-enabled supply chains.

2.2.2. Strategic responses to volatility

Retailers' strategic responses to cryptocurrency volatility are crucial. Doumenis et al. (2021) identified macroeconomic variables that correlate with cryptocurrency prices, emphasising the need for adaptive pricing strategies. Apergis (2022) highlighted how the COVID-19 pandemic exacerbated cryptocurrency volatility, suggesting that retailers need robust strategies to cope with such crises. Moreover, Mathivathanan et al. (2021) highlighted that unfamiliarity with blockchain and uncertainty about its benefits – exacerbated by perceptions shaped by cryptocurrency volatility – undermine trust in its security potential, thus acting as major barriers to adoption in supply chains (Mathivathanan et al. 2021).

2.2.3. Volatility and advertising investment

The relationship between volatility and advertising investments by retailers is complex. Khan and Hakami (2022) discussed the risks and rewards of using cryptocurrencies, suggesting that high volatility could deter investment in advertising. Gerrit, Schmidtke, and Posch (2020) evaluated Bitcoin volatility forecasting, indicating that better predictive models could support more stable advertising investments. Similarly, Osagwu and Okafor (2022) examined how advertising influences the purchase intentions of cryptocurrencies among young adults in Nigeria, revealing that advertising variables such as awareness, interest, desire, and action significantly impact consumers' decisions to purchase cryptocurrencies. The findings suggest that effective advertising strategies can enhance the adoption of cryptocurrencies within this demographic. By integrating these perspectives, this study aligns the theoretical discussion with practical approaches, illustrating the critical role of advertising as a stabilising mechanism in volatile cryptocurrency markets.

2.3. Game theory in blockchain-based supply chains

2.3.1. Strategic interactions and pricing

Game theory offers a framework for understanding strategic interactions in blockchain-based supply chains. Biais et al. (2021) reviewed game-theoretic approaches, noting their usefulness in analyzing pricing and risk management. Giovanni (2020) presented a game involving a supplier and a retailer, showing how blockchain can reduce transaction costs but requires significant initial investments. Eltoukhy et al. (2023) integrated blockchain and a Stackelberg game-theoretic model to optimise resource allocation and vehicle routing in modular construction, enhancing transparency and coordination across stakeholders. Mamoudan et al. (2024) developed a hybrid pricing model combining CNN-LSTM-GA forecasting and game theory to optimise perishable food pricing, showing that incorporating brand value and predictive pricing of competitors significantly improves profitability and coordination in the green supply chain. Additionally, Tao, Wang, and Zhu (2023) presented that blockchain adoption in platform supply chains significantly affects pricing and quality strategies, revealing that under low consumer acceptance, blockchain leads to lower prices and higher quality, but high acceptance shifts strategic advantage to competition between platforms rather than the technology itself. Zhang et al. (2024) used a biform game model to show that blockchain investment enhances coordination and profitability in supply chains under hybrid carbon trading schemes. Their findings highlight that cooperative behaviour and blockchain adoption together optimise pricing strategies and reduce emissions.

2.3.2. Collaboration and incentives

Choi, Taleizadeh, and Yue (2020) emphasised that blockchain, as an emerging technology, enhances transparency and trust in circular and sharing economy supply chains, and when combined with game theory, offers a robust framework for analyzing decentralised

Table 1. A summary of the relative literature in the case of game theory in blockchain-based supply chain.

Article	Pricing	Advertisement	Cyber security	Channel structure		Game structure	
				CRP. volatility	MAN. subsidy	Nash	Stackelberg
Biais et al. (2021)	✓	✓			✓	✓	
Giovanni (2020)	✓		✓			✓	✓
Gao et al. (2022)	✓	✓			✓		✓
Biswas et al. (2023)	✓				✓	✓	✓
Song et al. (2022)	✓		✓		✓	✓	
Bebeshko et al. (2022)	✓			✓		✓	
Tao, Wang, and Zhu (2023)	✓						✓
Mamoudan et al. (2024)	✓	✓					✓
This study	✓	✓	✓	✓	✓	✓	✓

CRP.Volatility: Cryptocurrency volatility, MAN.Subsidy: Manufacturer Subsidy.

decision-making and contract design. Gao et al. (2022) used game theory to design a blockchain framework incentivising supply chain participants' collaboration. Their model achieved a Nash Equilibrium, demonstrating blockchain's potential to foster fair collaboration. However, real-world applications and the effectiveness of these incentives in dynamic environments need further research. Additionally, Wu and Yu (2023) showed that blockchain's ability to reduce transaction costs and enhance information transparency significantly improves supply chain performance, especially when transaction costs are high, but platforms may avoid adoption if blockchain operation costs outweigh strategic benefits.

2.3.3. Risk management and security

Risk management is another area where game theory can provide insights. Biswas et al. (2023) analyzed a global supply chain using a game theory model, balancing traceability and sustainability with blockchain adoption. Song et al. (2022) used an evolutionary game model to explore blockchain's role in agricultural supply chains, highlighting its impact on long-term stakeholder interactions. The study by Bebeshko et al. (2022) utilised game theory, fuzzy logic, and neural networks to assess risks and forecast digital currency rates, optimising investment strategies under uncertainty. Accordingly, Table 1 presents a summary of the presented articles.

This study extends existing research by incorporating a dual-retailer channel structure, where the retailers operate under distinct cryptocurrency volatilities. Unlike prior works, which primarily focus on traditional pricing and advertising strategies, our game-theoretic model considers the simultaneous impacts of volatility, advertising, subsidies, and cybersecurity investments. The results reveal unique dynamics, such as the strategic interplay between retailer leadership roles and their ability to mitigate volatility effects through targeted strategies, offering insights that contrast with conventional models of supply chain coordination. These findings emphasise the critical role of cryptocurrency-specific challenges in shaping retailer and manufacturer strategies, which is a novel contribution to the literature.

Although there have been notable advancements in understanding blockchain technology and cryptocurrency volatility within supply chains, several areas remain unexplored. Specifically, the effects of advertising, return policies, cybersecurity, and wholesale pricing under cryptocurrency volatility are not well understood. Table 2 highlights critical gaps identified in relevant articles, detailing their focus, key findings, and the gaps that inspired this study. These gaps motivated the development of this article to address the existing deficiencies in the research.

3. Model description

3.1. Notation

The notations employed in this article are presented in Table 3.

3.2. Model definition

As depicted in Figure 2, the model studied in this article comprises a manufacturer and two cryptocurrency – based retailers, an Ethereum-based retailer (ER), and a Bitcoin-based retailer (BR), both of which operate online with blockchain-based payment system. In this model, the manufacturer presents identical products to the two retailers at the same wholesale price (w). To simplify, we assume the manufacturer transacts with retailers (w) using traditional (i.e. non-digital) fiat currency. Fiat-to-crypto payment gateways like CoinGate and Transak play a crucial role by enabling businesses to receive fiat payments while converting them into cryptocurrencies (Vuteva 2024). For instance, Transak's integration with

Table 2. Critical gaps identified in relevant articles.

Study	Focus	Key findings	Gaps identified
Centobelli et al. (2022)	Transparency in supply chains	Blockchain ensures secure and rapid cross-border transactions	Full impact on transparency not fully understood
Zhu, Bai, and Sarkis (2022)	Application of blockchain in supply chains	Significant potential but practical implementation lacking	Practical implementation and real-world applicability
Doumenis et al. (2021)	Macroeconomic variables and crypto prices	Need for adaptive pricing strategies	Detailed impact on supply chain dynamics
Khan and Hakami (2022)	Risks and rewards of cryptocurrencies	High volatility deters advertising investment	Long-term effects on retailer strategies
Biswas et al. (2023)	Game theory model for balancing traceability and sustainability in supply chains.	Blockchain adoption improves sustainability and economic benefits for stakeholders.	Did not address volatility and strategic retail decisions.
Mathivathanan et al. (2021)	Identifies and structures barriers to blockchain adoption in supply chains using TISM and MICMAC.	-Unfamiliarity with blockchain technology-Uncertainty about its benefits	Does not address operational strategies, crypto volatility, cybersecurity risks, or quantitative modelling in blockchain adoption.
Yang, Ni, and Ng (2023)	Blockchain traceability's effect on outsourcing and quality decisions	Resolves moral hazard, boosts outsourcing and quality under certain costs	No crypto volatility, pricing, advertising, or cybersecurity considerations
Bai and Sarkis (2020)	Blockchain evaluation for supply chain transparency using fuzzy-regret decision modelling	Transparency boosts sustainability; decision psychology affects tech choice	No crypto volatility, pricing, cybersecurity, or game-theoretic analysis
Casino et al. (2021)	Blockchain traceability system for dairy supply chains	Boosts trust, security, and regulatory compliance	No pricing, volatility, or strategic decision modelling
Song et al. (2022)	Game theory application in agriculture using evolutionary models.	Stable cooperation promotes sustainable agricultural practices, by application of Blockchain.	Focused on agriculture without addressing retail supply chains, and volatility in cryptocurrencies.

Visa Direct allows real-time conversion of crypto to fiat, facilitating immediate spending at Visa-accepting merchants worldwide, thereby enhancing the practical use of cryptocurrencies in daily transactions (Shittu 2024). Therefore, it is assumed in our paper that the manufacturer determines a defined wholesale price (w) in fiat currency, which is converted into Ethereum or Bitcoin via gateways such as CoinGate or Transak. This pricing mechanism simplifies transactions and guarantees uniformity among retailers. If retailers deploy separate gateways, w can be modified to include volatility-based risk surcharges or variations in transaction costs to ensure equity and market coherence. This method allows retailers to adjust their pricing strategies dynamically, effectively reducing demand fluctuations caused by volatility. Additionally, Each retailer then sells the products to the market at its own retail price of p^j_{ER} and p^j_{BR}, respectively. This assumption aligns with the long-standing practice of product retailers such as REEDS Jewelers and Newegg, who have integrated Bitcoin and Ethereum as accepted payment methods. For instance, REEDS Jewelers began accepting Bitcoin in 2014, reporting an increase in transactions from tech-savvy customers, with cryptocurrency purchases accounting for approximately 2% of their total sales by 2016. Similarly, Newegg has seen significant engagement with cryptocurrency payments since introducing the option in 2014, with over 15% of its online transactions in certain markets being processed in Bitcoin and Ethereum by 2021. These examples highlight the practical adoption of cryptocurrencies in retail and their potential to attract niche customer segments, demonstrating the relevance of this assumption to real-world practices (REEDS Jewelers' 2023; Newegg Knowledge Base 2023).

According to Phillip, Chan, and Peiris (2018) and Hayes (2015), different cryptocurrencies exhibit varying volatility, directly influencing customers' decision of the preferred retailer. In our study, we computed the daily volatility of the cryptocurrencies *ER* and *BR* from November 1, 2021, to November 1, 2022, using data from www.coinmarketcap.com as illustrated in Figure 3(a,b) (CoinMarketCap 2023). This calculation was based on the measure of daily volatility according to D'Amato, Levantesi, and Piscopo (2022).

$$V_d = Ln(H_d) - Ln(L_d) \tag{1}$$

In Equation (1) H_d represents the high price, and L_d stands for the low price at a given period. This method enables the measurement of daily volatility (V_d) through intraday ranges, demonstrating efficiency and consistency properties supported by the research of Alizadeh, Brandt, and Diebold (2002) and Yang and Zhang (2000).

When assessing the volatility of *ER* and *BR*, we calculate the mean and standard deviations for each during the specified period, as illustrated in Figure 4. Accordingly, Figure 4(a,b) depict the number of days beyond the standard deviation for *ER* and *BR*, respectively. It is evident that the number of days exceeding the standard deviation for *ER* (71) is significantly greater than for *BR* (59), indicating that the Ethereum-based retailer faced higher volatility.

Table 3. Overview of notations.

Category	Symbol	Definition
Nomenclatures		
	$i = \begin{cases} BR \\ ER \end{cases}$	Subscript index for Bitcoin-based retailer Subscript index for Ethereum – based retailer
	$j = \begin{cases} NE \\ BI \\ EI \end{cases}$	Superscript index for Nash equilibrium (simultaneous move game) Superscript index for Bitcoin leader (Stackelberg game) Superscript index for Ethereum leader (Stackelberg game)
Parameters	α	Market base demand dependent on volatility
	σ	Market base demand independent form volatility
	β	Own price elasticity
	γ	Rival price elasticity
	w	Wholesale price of the manufacturer
	ε	Ethereum cryptocurrency volatility rate
	θ	Basic return of products independent from refund amount
	r	Refund amount of a unit of product in *ER*
	φ	Sensitivity of returns quantity with respect to refund amount
	λ	Manufacturer subsidy coefficient
	n_i^j	The probability of successful cyber-attacks of *i* in game model *j*
	Q_i^j	The total number of platform shutdowns of *i* in game model *j*
	f	Total number of cyber-attacks
	μ_i	Sensitivity of product demand to cybersecurity level of *i*
	k_i	Cost of platform shutdown of *i*
Decision variables	A^j	The wholesale power price of the renewable power plant in scenario / strategy *j*
	Z_i^j	The wholesale power price of the fossil fuel power plant in scenario / strategy *j*
	p_i^j	The retail price of the manufacturer in scenario / mode *i* strategy *j*
Functions	D_i^j	Customer demand function in scenario / mode *i* strategy *j*
	π_i^j	Fossil fuel power plant profit function for scenario / strategy *j*

As our analysis focuses on relative volatility of one cryptocurrency with respect to a competing alternative, we normalise Bitcoin's volatility to the value zero. This normalisation analytically isolates the impact of Ethereum's cryptocurrency volatility (ε) on customers' choices of the preferred platform. Furthermore, cryptocurrency instability also results in a loss of demand for the desired product through the *ER*. To counteract this loss and attract more demand, the *ER* invests in advertising (A).

In our model, it is supposed that the *ER* provides customers with a partial refund return policy. This practice aligns with the approach commonly found in other articles, such as Taleizadeh, Soleymanfar, and Choi (2017), as illustrated below in Equation (2):

$$r(\theta + \varphi r - \lambda A^j)\varepsilon \tag{2}$$

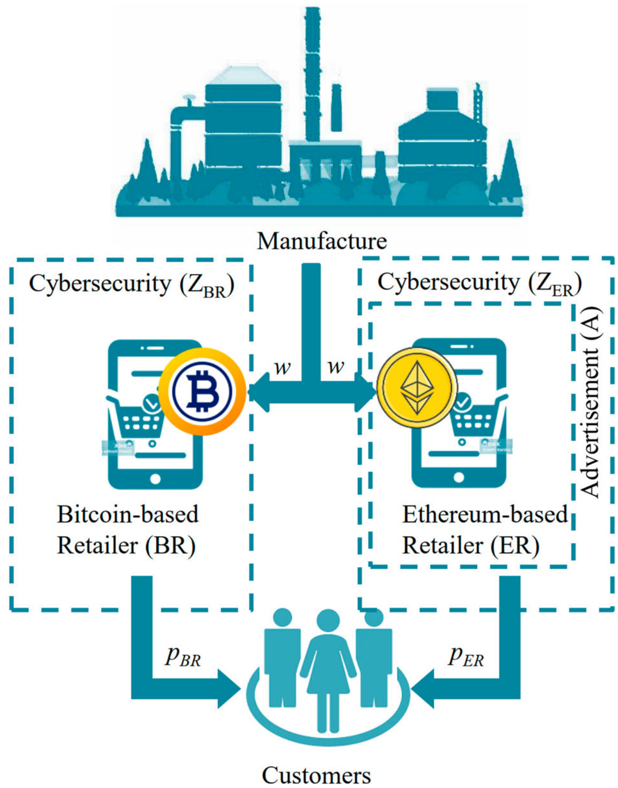

Figure 2. Basic structure of the model in this study.

The parameter θ indicates the primary return of the product that does not depend on its refund amount of the Ethereum-based retailer. Moreover, φ reflects the sensitivity of returns concerning the refund amount, and r represents the refund amount of a unit product aligned with the article Heydaryan and Taleizadeh (2017). Accordingly, φr reflects the sensitivity of returns to the refund amount. However, due to the assumed higher volatility of the Ethereum cryptocurrency, the expectation of product returns by dissatisfied customers is higher. Therefore, in this model, it is mentioned that the manufacturer supports the *ER*, which has invested in product advertising, with the subsidy factor in the product return policy (λ), as illustrated in Equation (2). This support aims to encourage more customers to purchase products through advertising and offset the negative impact of increased returns on the Ethereum platform due to its higher level of crypto volatility.

Another interesting aspect of this model comes from the extra customers who were attracted to the product through Ethereum advertisements. Due to the volatility, these customers may choose to buy the product through the Ethereum platform or switch to the Bitcoin platform.

Given that both retailers operate online using blockchain technology, the model accounts for the possibility of cyber-attacks. In our model, both platforms benefit

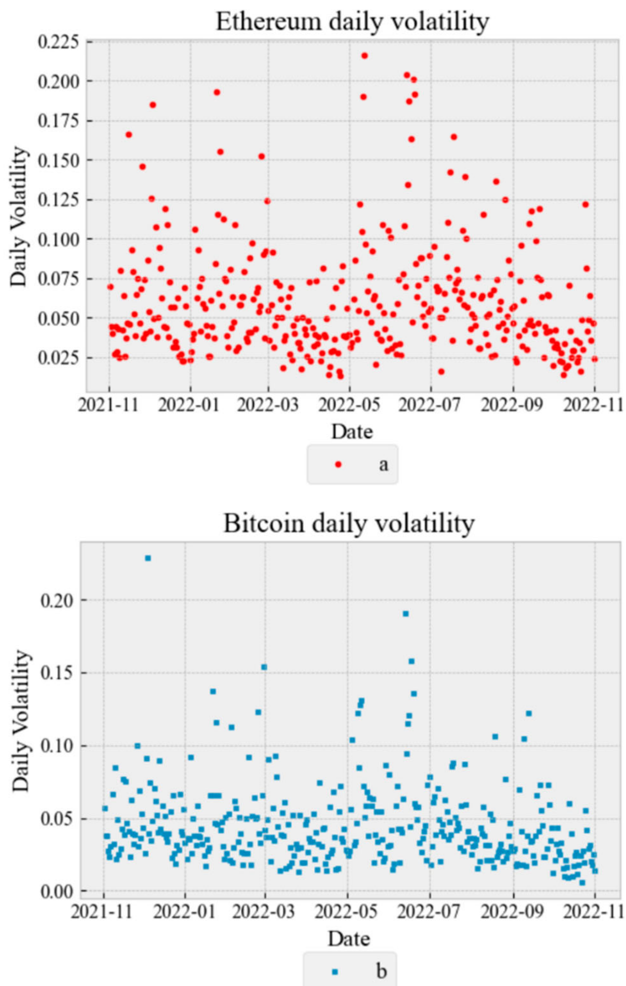

Figure 3. Daily volatility for Ethereum (a) and Bitcoin (b) from 1st Nov.2021 to 1st Nov. 2022.

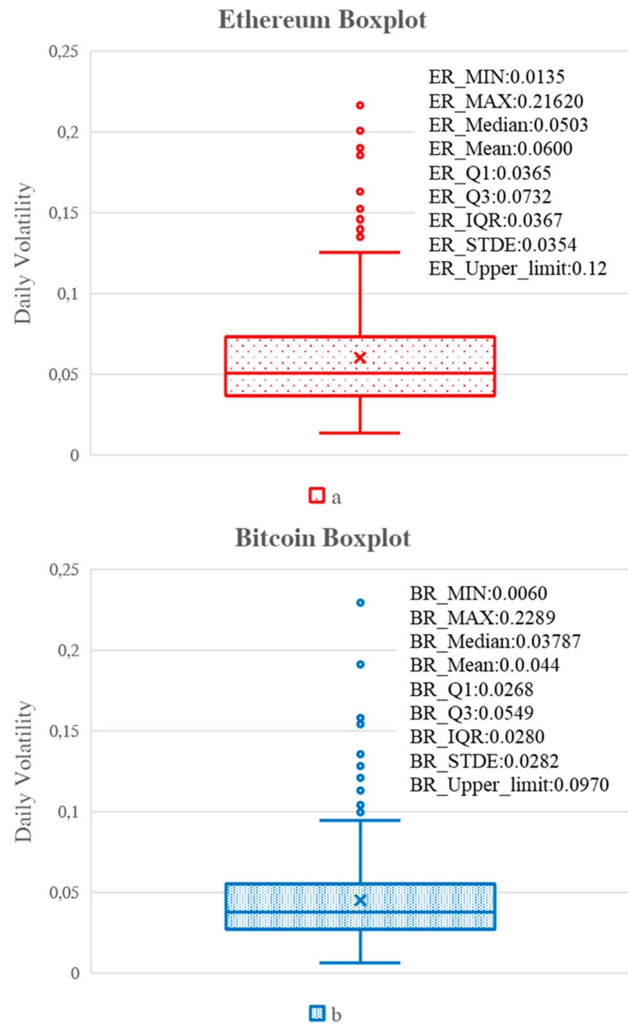

Figure 4. Achieved values of daily volatility for both cryptocurrencies ER and BR from 1st Nov.2021 to 1st Nov. 2022.

from a cybersecurity level (Z_i^j), wherein this level of security differs based on platform design characteristics in blockchain technology such as consensus level, type of smart contract, etc. The model quantifies the number of cyberattacks (f) and considers the probability of a successful attack (n_i^j), in which $n_i^j = 1 - Z_i^j$. After each successful attack (Q_i^j), the system is generally shut down to prevent further damages, and the total number of shutdowns is formulated as Equations (3).

$$Q_i^j = n_i^j f \tag{3}$$

3.3. Formulation

The problem formulations are based on three main building blocks:

(1) Demand functions,
(2) Ethereum-based retailer profit function, and
(3) Bitcoin-based retailer profit function.

3.3.1. Demand functions

This model employs linear demand functions that are commonly utilised in academic studies such SeyedEsfahani, Biazaran, and Gharakhani (2011), and Jamali and Rasti-Barzoki (2018).

$$D_{ER}^j = ((1-\varepsilon)\alpha + \sigma - \beta p_E^j + \gamma p_B^j + (1-\varepsilon)A^j - Q_E^j \mu_E) \tag{4}$$

$$D_{BR}^j = (\varepsilon\alpha + 1 - \sigma - \beta p_B^j + \gamma p_E^j + \varepsilon A^j - Q_B^j \mu_B) \tag{5}$$

The parameter α shows the market base demand dependent on volatility while σ refers to independent ones. In both equations β and γ demonstrate the sensitivity of product demand to the own and rival´s prices, respectively, and μ_i represents the sensitivity of product demand to cybersecurity levels. Moreover, another noteworthy aspect of this model is the inclusion of surplus customers attracted to the product through Ethereum advertising. These customers may choose to purchase the manufactured product through the Ethereum platform ($(1-\varepsilon)A$) or shift to the Bitcoin platform (εA), due to cryptocurrency volatility in *ER*.

3.3.2. Ethereum-based retailer profit function

The profit function of the Ethereum-based retailer, denoted as π^j_{ER}, encompasses various aspects of the retailer's financial performance and can be expressed as follows:

$$\pi^j_{ER} = (p^j_E - w)D^j_{ER} - r(\theta + \varphi r - \lambda A^j)\varepsilon - (Q^j_E K_E) - \frac{A^{j2}}{2} - \frac{Z^{j\,2}_E}{2} \tag{6}$$

This equation includes five key components that reflect different elements of the retailer's profit and loss. The first component, $(p^j_E - w)D^j_{ER}$, represents the revenue from selling new products. Here, p^j_E is the retail price, w presents the wholesale price paid to the manufacturer, and D^j_{ER} is the demand for the products. This term calculates the gross profit by subtracting the wholesale cost from the retail price and then multiplying by the quantity sold, which provides the core revenue generated from product sales. The second component, $r(\theta + \varphi r - \lambda A^j)\varepsilon$, accounts for the loss through partial refunds. In this term, r is the refund amount per unit product, θ represents the base rate of product returns, and φ reflects the sensitivity of returns to the refund amount. The term λA^j represents the manufacturer's subsidy for advertising, and ε captures the volatility of Ethereum. This component quantifies the financial impact of product returns, which increase with higher refund amounts and greater volatility. The subsidy from the manufacturer is intended to offset some of these costs by supporting advertising efforts. A pertinent case is Coca-Cola's cooperative advertising programs. Through these initiatives, Coca-Cola collaborates with retailers by sharing advertising costs to promote its products, thereby supporting retailers' marketing efforts and ensuring consistent brand presence across various markets. This strategy not only alleviates the financial burden on retailers but also aligns marketing objectives between the manufacturer and retailers, fostering a unified promotional approach (Oliver et al. 2022).

Expenses due to system shutdowns from cyber-attacks are captured in the third component, $Q^j_E K_E$, where Q^j_E represents the number of system shutdowns and K_E is the cost per shutdown. This term highlights the operational costs related to maintaining the platform's security and dealing with disruptions, emphasising the importance of cybersecurity.

The fourth and fifth components, $\frac{A^{j2}}{2}$ and $\frac{Z^{j\,2}_E}{2}$, reflect the costs associated with advertising and cybersecurity investments, respectively. The term A^j represents the investment in advertising, and the quadratic form of the cost function, $\frac{A^{j2}}{2}$, indicates increasing marginal costs for higher levels of advertising. Similarly, Z^j_E denotes the investment in cybersecurity, and $\frac{Z^{j\,2}_E}{2}$ represents the increasing costs of enhancing the platform's security. These quadratic terms are standard in economic modelling to show the increasing marginal costs associated with scaling up investments.

The profit function is constructed to provide a comprehensive view of the retailer's financial performance by including both revenue and various cost factors influenced by internal and external variables relevant to decision-problem. The inclusion of costs related to refunds, system shutdowns, advertising, and cybersecurity investments underscores the complex nature of managing a blockchain-based retailer, where both operational efficiency and external market factors like cryptocurrency volatility play crucial roles.

This modelling approach is grounded in established economic literature and (in particular) industrial economic's applications, as evidenced by its use in previous studies by Yu, Huang, and Liang (2009); Assarzadegan, Hejazi, and Rasti-Barzoki (2023); Cachon and Netessine (2006). These references provide a foundation for understanding the dynamics of supply chain management, pricing strategies, and the impact of volatility on financial performance, thereby validating the structure and components of the profit function used in this analysis.

3.3.3. Bitcoin-based retailer profit function

Similarly, the Bitcoin-based retailer's profit function, denoted as π^j_{BR}, also comprises various components that collectively reflect the retailer's financial performance. The profit function is expressed as:

$$\pi^j_{BR} = (p^j_B - w)D^j_{BR} - (Q^j_B K_B) - \frac{Z^{j\,2}_B}{2} \tag{7}$$

The initial component, $(p^j_B - w)D^j_{BR}$, represents the Bitcoin retailer's earnings generated from the sale of new products to its customers, whereas the second part, $(Q^j_B K_B)$, considers the expenses associated with system shutdowns resulting from attacks across the entire Bitcoin platform. In Equation 7, the third component, $\frac{Z^{j\,2}_B}{2}$, encompasses the costs related to enhancing the security level of the Bitcoin platform.

The first component, $(p_B^j - w)D_{BR}^j$, represents the revenue generated from selling new products. Here, p_B^j is the retail price at which the Bitcoin-based retailer sells its products, w is the wholesale price paid to the manufacturer, and D_{BR}^j is the demand for these products. This term calculates the retailer's gross profit by subtracting the wholesale cost from the retail price and multiplying the result by the quantity sold, thus providing a measure of the earnings from product sales. The second component, $Q_B^j K_B$, considers the expenses associated with system shutdowns caused by attacks on the Bitcoin platform. In this term, Q_B^j denotes the number of system shutdowns, and K_B represents the cost per shutdown. This component highlights the operational costs incurred due to disruptions in the platform's functionality, which can significantly impact the retailer's overall performance.

The third component, $\frac{Z_B^{j\,2}}{2}$, encompasses the costs related to enhancing the security level of the Bitcoin platform. Here, Z_E^j reflects the investment in cybersecurity measures. The quadratic nature of this cost function indicates that the costs increase at an increasing rate as more resources are allocated to improving security. This term underscores the importance of investing in cybersecurity to protect the platform from potential threats, which, although costly, is essential for maintaining operational integrity and customer trust.

Together, these components provide a comprehensive view of the Bitcoin-based retailer's financial performance, accounting for both revenue generation and the various costs associated with maintaining and securing the platform. This model reflects the intricate balance that the retailer must maintain between generating revenue through sales and managing the costs related to system security and stability. By considering these elements, the profit function illustrates the critical factors that influence the retailers profitability in a volatile and risk-prone cryptocurrency market.

3.4. Decision support perspective for model applications

The suggested game-theoretic model serves as an effective decision support mechanism for stakeholders in blockchain-integrated logistics and production systems. It empowers manufacturers and retailers to make educated, data-driven choices on essential operational factors such as pricing, advertising, refund policies, and cybersecurity investments amid digital currency volatility. The system simulates strategic interactions using a simultaneous Nash game and two Stackelberg leadership scenarios, reflecting typical hierarchical connections in supply chains. This framework assists companies in evaluating the implications of leading posture and asymmetric volatility exposure, providing direction on ideal subsidy levels, demand-side incentives, and investment thresholds to ensure profitability stability. The approach is designed to be versatile across industries using blockchain for transaction transparency and decentralisation, hence facilitating diverse production and logistical decision-making scenarios. Accordingly, key novelties of the Proposed Model:

- Volatility as Operational Risk: Introduces cryptocurrency volatility as a production-relevant uncertainty affecting pricing, demand, and profitability.
- Cybersecurity as a Decision Lever: Models cybersecurity investment as a strategic variable to mitigate cyberattack-related disruptions.
- Dual-Retailer Game Structure: Incorporates a two-retailer Stackelberg framework with asymmetric volatility exposure (Ethereum vs. Bitcoin).
- Integrated Strategy Variables: Combines pricing, advertising, return policy, and manufacturer subsidies in a unified decision model.

Equilibrium Insights: Compares Nash and Stackelberg outcomes to guide decision-making under different market and leadership scenarios.

4. The game models and optimal values

In this study, we use a game-theoretic approach, which provides a robust framework for examining how supply chain participants make decisions and interact, taking into account their personal motivations and the potential for conflicts. Our primary analysis involves three different game variants, and we begin with an analysis of the simultaneous move game between two mentioned retailers as a whole (in short: Nash game). Subsequently, we examine BR as a leader, which turns the model into a Stackelberg game. Lastly, we investigate a second Stackelberg variant where ER acts as a leader.

This type of analysis is commonly employed in numerous studies, allowing for a comprehensive strategic examination across various game theoretic models (Kumar, Basu, and Avittathur 2018; Rajabzadeh and Babazadeh 2022). Notably, the Stackelberg games in this study are solved using a backward induction approach based on dynamic optimisation principles as outlined by John (2021). The proofs for all lemmas and propositions can be found in Appendix 1.

4.1. Equilibrium values of decision variables in the Nash game

In the initial game, we conducted a Nash equilibrium analysis by examining the concavity of each profit function with respect to their decision variables, ultimately determining the optimal values for each profit function.

Lemma 4.1: *The profit function of ER exhibits concavity in its own decision variables under the condition presented in Appendix 1.*

Lemma 4.2: *The profit function of BR shows concavity in its own decision variables under the circumstances outlined in Appendix 1.*

Proposition 4.1: *The optimal outcomes for the decision variables of both retailers in the Nash game are as follows.*

$$A^{NE*} = \frac{N_2 + f^4\lambda\varepsilon r\mu_B^2\mu_E^2 + f^4\varepsilon k_E\mu_B^2\mu_E - 2\beta f^2\lambda\varepsilon\mu_B^2 r - f^4 k_E\mu_B^2\mu_E}{N_1} \quad (8)$$

$$Z_{ER}^{NE*} = \frac{f(N_3 + f^2\lambda\varepsilon^2\mu_E\mu_B^2 r - f^2\lambda\varepsilon\mu_E\mu_B^2 - \alpha f^2\varepsilon\mu_E\mu_B^2 + \beta f^2 w\mu_E\mu_B^2)}{N_1} \quad (9)$$

$$Z_{BR}^{NE*} = \frac{f(N_4 - f^2\lambda\varepsilon^2\mu_B\mu_E^2 r - \alpha f^2\varepsilon\mu_B\mu_E^2 + \beta f^2 w\mu_B\mu_E^2 + f^3\mu_B^2\mu_E^2)}{N_1} \quad (10)$$

$$p_{ER}^{NE*} = \frac{N_5 + f^4 w\mu_B^2\mu_E^2 - f^4 k_E\mu_E\mu_B^2 - f^2\lambda\varepsilon^2 r\mu_B^2 + f^2 w\varepsilon^2\mu_B^2}{N_1} \quad (11)$$

$$p_{BR}^{NE*} = \frac{N_6 + f^4 w\mu_B^2\mu_E^2 - f^4 k_B\mu_B\mu_E^2 - f^2\lambda\varepsilon^2 r\mu_E^2 + f^2 w\varepsilon^2\mu_B^2}{N_1} \quad (12)$$

The values of N_1 to N_6 are presented in Appendix 1.

4.2. Equilibrium values of decision variables in the Stackelberg game with *BR* leadership

As a second variant, we conduct an equilibrium analysis of the Stackelberg game with *BR* taking the leadership role. Firstly, the optimal values for *ER* as the follower are determined after ensuring that the concavity conditions are held.

Lemma 4.3: *The profit function of ER exhibits concavity in its own decision variables subject to the conditions stated in the first Appendix 1.*

Proposition 4.2: *The optimal solutions for the decision variables of ER in the second scenario are as follows.*

$$A^{Bl} = \frac{f^2\lambda\varepsilon\mu_E^2 r_E + f^2\varepsilon k_E\mu_E - 2\beta\lambda\varepsilon r_E - f^2 k_E\mu_E - \beta w\varepsilon - f\varepsilon\mu_E + \gamma\varepsilon p_B + \alpha\varepsilon + \beta w + \mu_E f - \gamma p_B - \alpha}{f^2\mu_E^2 + \varepsilon^2 - 2\beta - 2\varepsilon + 1} \quad (13)$$

$$p_{ER}^{Bl} = \frac{f^2 w\mu_E^2 - f^2 k_E\mu_E + \lambda\varepsilon^2 r_E - r_E\lambda\varepsilon + w\varepsilon^2 - \beta w + \mu_E f - \gamma p_B - 2w\varepsilon - \alpha + w}{f^2\mu_E^2 + \varepsilon^2 - 2\beta - 2\varepsilon + 1} \quad (14)$$

$$Z_{ER}^{Bl} = \frac{f(\lambda\varepsilon^2 r_E\mu_E - \lambda\varepsilon r_E\mu_E + \beta w\mu_E + f\mu_E{}^2 - \gamma\mu_E p_B + \varepsilon^2 k_E - \alpha\mu_E - 2\beta k_E - 2\varepsilon k_E + k_E)}{f^2\mu_E^2 + \varepsilon^2 - 2\beta - 2\varepsilon + 1} \quad (15)$$

By substituting the optimal values of A^{Bl}, Z_{ER}^{Bl}, and p_{ER}^{Bl} into the profit function of *BR*, the concavity conditions are confirmed and the optimal values for *BR*'s decision variables are obtained.

Lemma 4.4: *The profit function of BR exhibits concavity in decision variables under Appendix 1's condition.*

Proposition 4.3: *The optimal, profit-maximising choice of both retailers in the second scenario are derived as follows.*

$$Z_{BR}^{Bl*} = \frac{f(2wX2\mu_B + X1\mu_B - 2X2k_B)}{f^2\mu_B^2 + 2X2} \quad (16)$$

$$p_{BR}^{Bl*} = \frac{f^2 w\mu_B^2 - f^2 k_B\mu_B - X1}{f^2\mu_B^2 + 2X2} \quad (17)$$

Furthermore, by substituting the obtained values from Equations (16) and (17) into Equations (13), (14), and (15), the ultimate optimal values could be attained.

The values of $X1$ *and* $X2$ are presented in Appendix 1.

4.3. Equilibrium values of decision variables in the Stackelberg game with *ER* leadership

In the third game, *ER* is assumed to be the Stackelberg-leader. Accordingly, this yields as key findings to following Lemma 4.5 and Proposition 4.4.

Lemma 4.5: *The profit function of the BR shows concavity in decision variables when the conditions in Appendix 1 are met.*

Proposition 4.4: *The optimal value for the decision variables of BR in the third scenario are outlined below.*

$$Z_{BR}^{El} = \frac{(A\varepsilon - \beta w + \gamma p_E + \alpha)\mu_B + 2\beta k_B)f - f\mu_B^2}{f^2\mu_B^2 - 2\beta} \tag{18}$$

$$p_{BR}^{El} = \frac{\begin{matrix} f^2 w\mu_B^2 + (-f^2 k_B + f)\mu_B \\ -A\varepsilon - \beta w - \gamma p_E - \alpha \end{matrix}}{f^2\mu_B^2 - 2\beta} \tag{19}$$

It can easily be verified that the concavity conditions hold. We derived the optimal values for *ER*'s decision variables by plugging in the optimal values for Z_{BR}^{El}, and p_{BR}^{El} into *ER*'s profit function.

Lemma 4.6: *The profit function of ER displays concavity in its own decision variables subject to the conditions described in Appendix 1.*

Proposition 4.5: *For the third game variant, the optimal solutions for the decision variables are given as the follows.*

$$A^{El*} = \frac{\begin{matrix} f^2 wY1\mu_E^2 - f^2 Y1 k_E \mu_E - f^2 Y2 \mu_E^2 \\ -Y1Y3 - 2Y2Y4 \end{matrix}}{f^2\mu_E^2 + Y1^2 + 2Y4} \tag{20}$$

$$Z_{ER}^{El*} = \frac{\begin{matrix} f(Y1^2 k_E - wY1^2\mu_E - 2wY4\mu_E + Y1Y2\mu_E \\ -Y3\mu_E + 2Y4k_E) \end{matrix}}{f^2\mu_E^2 + Y1^2 + 2Y4} \tag{21}$$

$$p_{ER}^{El*} = \frac{f^2 w\mu_E^2 - f^2 k_E \mu_E + Y1Y2 - Y3}{f^2\mu_E^2 + Y1^2 + 2Y4} \tag{22}$$

Furthermore, by substituting the obtained values from Equations (20), (21), and (22) into the Equations (19) and (20), the ultimate optimal values could be attained.

The values of $Y1$ *to* $Y4$ are presented in Appendix 1.

5. Sensitivity analysis

5.1. Numerical example

In this section, we employ a numerical example and carry out a sensitivity analysis to compare optimal solutions, given the complexity of the equations and resulting solutions. Following the approach used by various articles such as Zhang et al. (2021), the parameters are set as follows in Table 4.

Regarding the concavity conditions presented in Lemmas 4.1–4.6, the mentioned numerical values are only valid for a volatility of at least 0.4. Therefore, the provided numerical examples in Table 4 are considered to satisfy the conditions, and the volatility is set at 0.4.

Table 4. Numerical value used in this study.

Parameters	Allocated values	Parameters	Allocated values
α	0.5	f	1
σ	0.6	φ	0.05
β	0.3	λ	0.08
γ	0.08	k_{BR}	0.009
w	0.5	μ_{ER}	0.06
ε	0.4	k_{ER}	0.005
θ	0.2	μ_{BR}	0.09
r	0.8		

5.2. Simultaneous effect of changes in Ethereum crypto volatility and wholesale price on the retailers' prices

The initial analysis includes examinations of changes in ε and w, considering the effects on the decision variable p_i^j for each game model.

As presented in Table 5 for all game models with increasing Ethereum crypto volatility (ε), the presented prices (p_i^j) of both retailers decline significantly to avoid the demand loss; clearly, as the value of ε rises, a decrease in the retailer price on the Ethereum platform (p_{ER}^j) can be expected, accompanied by a decline in demand (D_{ER}^j) (Anisiuba et al. 2021). An interesting insight can be drawn from Table 5 regarding the impact of (w) and volatility levels on the pricing strategies of the Ethereum-based retailer. At medium and high volatility levels, an increase in w leads to higher prices (P_j^i) set by the retailers. This trend reflects the necessity to compensate for the increased wholesale costs in environments where volatility already affects demand stability. However, at lower levels of volatility, the Ethereum-based retailer opts to reduce its retail price (P_j^{ER}). The rationale behind this strategy is that lower volatility (ε) leads to an increased demand or maximise revenue for the Ethereum-based retailer's products. By lowering P_j^{ER}, the retailer can attract more customers, thereby enhancing its market share and maintaining stable pricing strategy. This approach not only helps in sustaining demand but also maximises competitiveness against the Bitcoin-based retailer, which might not need to adjust prices as aggressively in response to fluctuations in volatility.

Additionally, the retail price in the Bitcoin platform (p_{BR}^j) tends to drop due to competition with *ER* and its market demand increment. When analyzing the first two game models including Nash and Bitcoin leader game, the price reduction trend (p_i^{NE} and p_i^{Bl}, respectively) is minor compared to the Ethereum leader game.

Additionally, the impact of an increase in the wholesale price (w) on the prices set by retailers (p_i^j) varies depending on the volatility level (ε). For instance, when ε is low, an uptick in w results in a decline in retail

Table 5. Achieved values of p_i^j in terms of ε *and* w in the various game models.

Achieved values of p_i^j in various game models			j	w Low (0.4)	Medium (0.7)	High (1.0)
ε	Low (0.4)	p_{ER}^j	NE	3.874	3.843	3.821
			BL	5.516	5.335	5.154
			EL	7.669	7.369	7.070
		p_{BR}^j	NE	5.150	5.058	4.967
			BL	5.843	5.688	5.530
			EL	5.652	5.479	5.306
	Medium (0.7)	p_{ER}^j	NE	2.273	2.390	2.508
			BL	2.517	2.611	2.705
			EL	2.275	2.394	2.513
		p_{BR}^j	NE	2.001	2.147	2.292
			BL	2.049	2.190	2.331
			EL	2.678	2.757	2.836
	High (1.0)	p_{ER}^j	NE	1.916	2.094	2.272
			BL	1.961	2.136	2.310
			EL	1.513	1.682	1.850
		p_{BR}^j	NE	1.426	1.604	1.783
			BL	1.433	1.612	1.790
			EL	2.248	2.387	2.526

prices (p_i^j). This occurs at lower values of ε, when there is greater demand for Ethereum-based retailer (D_{ER}^j), causing a smaller shift in demand from *ER* to *BR*. As a result, Bitcoin reduces its price (p_{BR}^j) to offset the decreased demand. Conversely, when *ER* suffers from higher ε, the dynamic is reversed, in a way that an increase in w leads to higher p_i^j. In this scenario, the surge in w reduces the demand for *ER*, shifting more demand towards its competitor, the Bitcoin-based retailer. Thus, an increase in w drives up *BR*'s price (p_{BR}^j) as it seeks to maximise its profit (π_{BR}^j), ultimately causing the price of the rival (p_{ER}^j), Ethereum, to increase.

When comparing various games in this study, both retailers in the *Nash* game perform better in terms of attracting customers compared to the other game models leaving the Ethereum leader game as the worst. This discrepancy can be attributed to the fact that prices offered in the *Nash* game (p_i^{NE}) are lower for both retailers, in contrast to the Ethereum leader game (p_i^{El}). This finding is caused by the classic problem of Double Marginalisation.

This interpretation aligns with the study by Roozbehani, Dahleh, and Mitter (2012), which emphasises the critical impact of volatility on market dynamics, pricing strategies, and stability. In power grids at their study, real-time pricing and elasticity influence market volatility, necessitating adaptive control mechanisms. Similarly, in our research, volatility impacts retailer pricing and demand, with game theory offering strategic insights. Effective information management and strategic responses are essential in both fields to mitigate volatility and ensure market stability. On the other hand, while the remarked paper emphasised real-time pricing for mitigating volatility, our study reveals that advertising investments, cybersecurity, and subsidies are equally critical in cryptocurrency-based supply chains. Moreover, our findings show how leadership roles (e.g. Stackelberg games) create unique asymmetries in profitability and volatility management, diverging from traditional models.

These analyses show that there is an area in which volatility is still relatively unproblematic in terms of market outcomes. Here, the Ethereum-based retailer still has so much demand that it can target it with a price reduction and thus compensate for the higher wholesale price. For volatility values higher than this critical threshold, demand shifts significantly from *ER* to *BR*, which increases *BR*'s market power. From this point onwards, a price increase is the remaining option for *ER* to compensate for the loss of sales. *BR* can then also increase its price due to lack of competitive pressure. For a cryptocurrency-based retailer, it is therefore crucial to know this critical threshold in advance and take additional measures to contain volatility, e.g. by financial hedging.

5.3. Advertisement vs. return policy: effects of ε and λ on profit gain/loss

The main goal of this section is to explore the effects of changes in Ethereum crypto volatility (ε) and in the subsidy by the manufacturer (λ) on demand. Note that demand is attracted through advertisement and a demand loss should be prevented by the refund policy of the *ER* as presented in Equation (23).

$$M = (p_E^j - w)(1-\varepsilon)A^j - r(\theta + \varphi r - \lambda A^j)\varepsilon \qquad (23)$$

The initial component of equation (23) represents the revenue gained by the *ER* through advertising, which is influenced by ε. The second component reflects the cost associated with returned products due to ε, which includes the manufacturer's subsidy as part of revenue.

Considering the combined influence of ε and λ, as illustrated in Figure 5, it becomes apparent that in all game models, as ε rises the two components in Equation (23) tend to converge toward similar values, their differences ultimately approaching zero. Additionally, with an increase in λ, the accrued profit of *ER* experiences a boost, since it compensates the part of the return cost across all three game models. Hence, given a low level of ε, an increase in λ results in higher profit value. This happens because along with the rise in λ as a profit source for the *ER*, the lower level of ε attracts a larger number of customers through advertising, who are less willing to return products.

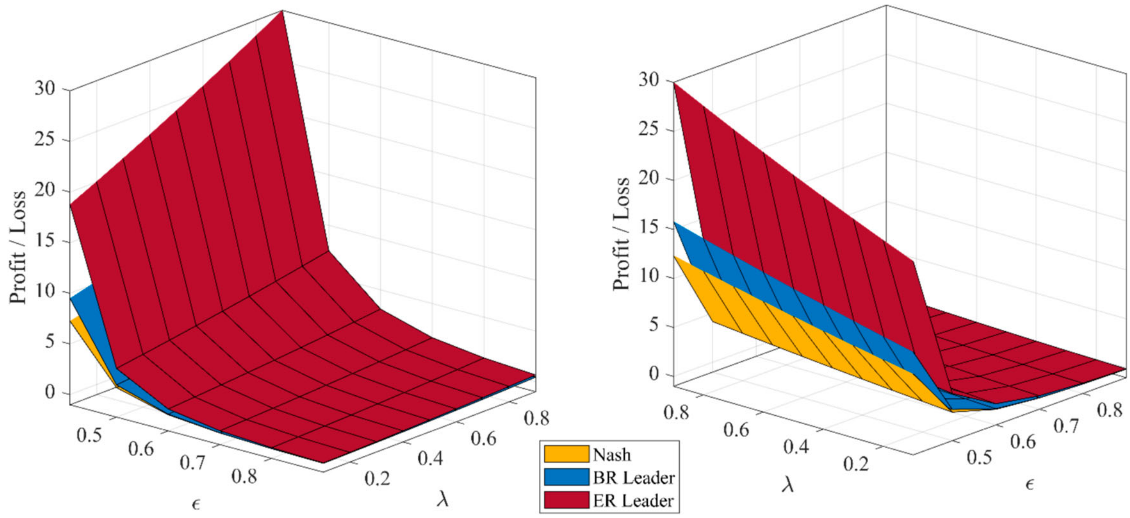

Figure 5. The effects of changes in volatility and manufacturer's subsidy on the gained profit by ER in three game models.

The achieved profit reaches the peak when the *ER* has the leadership role. However, this profit is lower compared to the other Stackelberg-variant, with the *BR* in the leadership position. In the *Nash* game model, these differences are minimal. Furthermore, at higher values of ε and, increasing λ, the value of M (Equation (23)) increases similarly but slightly, due to higher return amount, as shown in the figure above. Across various game models, no significant variations are observed within the given value ranges in the mentioned equation.

It can be understood that in higher values of ε, the *ER* needs more manufacture's support (λ) to hold its profit according to Equation (23), and this is true for all game models since at higher values of ε there is no significant difference between the presented game variants. The important observations are that the manufacturer should take into account that at higher values of ε, it must offer λ at a level larger than 0.4. Lower values drive down the value of M in Equation (23) to almost zero, as depicted in Figure 5.

Tesla's impressive financial growth in 2022, highlighted by increases in net income and revenue, demonstrates the impact of strategic financial management (Tesla, Inc. 2022). Similar strategies are noted in our study, where cryptocurrency retailers must manage volatility (ε) and manufacturer subsidies (λ) s to stay profitable. Both sectors emphasise the importance of cost management, dynamic pricing, and effective advertising to sustain profitability in fluctuating markets. Nevertheless, our study reveals that beyond a certain cryptocurrency volatility threshold (ε), traditional strategies like subsidies and dynamic pricing lose effectiveness, leading to greater demand instability. This contrasts with prior findings that assume these approaches are universally stabilising.

The findings provide important insights for collaboration in the context of cryptocurrency-based SCs. Only when *ER* benefits the most from the return policy (in terms of increasing profits) it can use this policy most effectively. At the same time, however, it is exactly under this constellation that the volatility will execute a rather modest or harmless effect on the price dynamics, which is an important incentive for the manufacturer to enter into this agreement in the first place. The return policy also only becomes a truly effective instrument when volatility is low and the policy coefficient reaches a minimum level. The prerequisites for effective compensation of volatility therefore depend on the level of volatility itself. This illustrates why cryptocurrencies require a minimum level of stability as a precondition to be profitably integrated into supply chains.

5.4. The impacts of volatility on the rate of partial refunds and cyberattacks on the Ethereum-based retailer

The final goal of this analysis is to investigate how ε impacts the costs of partial refunds and imposed cyber-attacks on the platform of the Ethereum-based retailer as presented in Equation (24).

$$N = \frac{r(\theta + \varphi r - \lambda A^j)\varepsilon}{(p_E^j - w)(1 - Z_i^j) f \mu_E} \tag{24}$$

In the first step, the effect of ε on partial return and cyber-attack cost functions are investigated distinctly as presented in Figure 6. Accordingly, an increase in ε results in a higher cost for a partial refund, as explained in the previous section (5.3), across all three defined game models. Additionally, higher values of ε lead to a

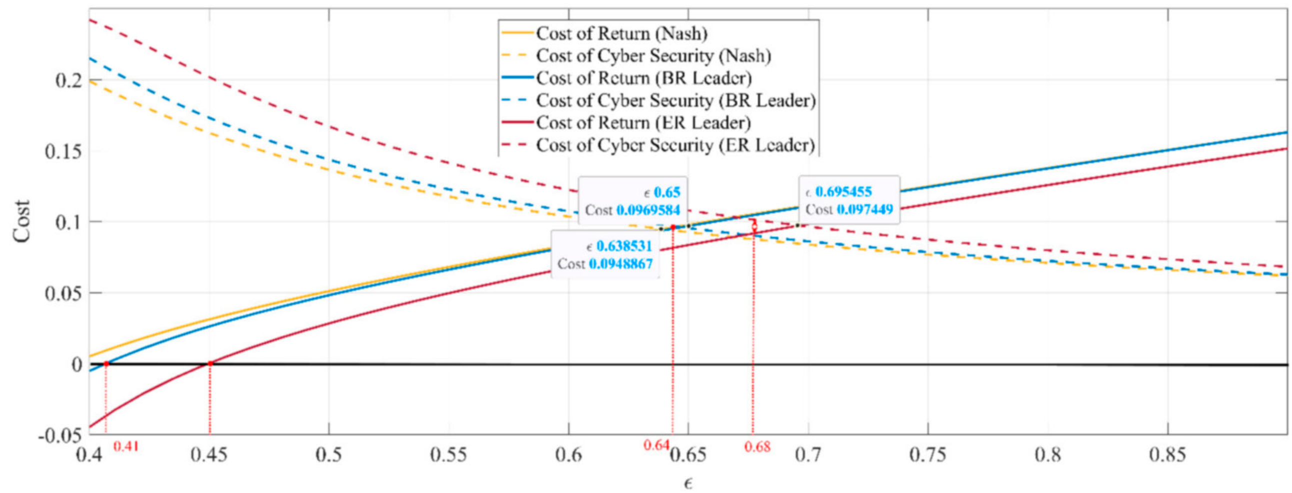

Figure 6. The impact of volatility on costs of return and costs of lost demand due to cyber attacks.

lower cost imposed by successful cyber-attacks, interestingly. Even though an increase in ε raises the probability of cyber-attacks $(1 - Z_E^j)$, it also causes a decrease in prices offered by *ER* (p_{ER}^j). However, the decrease in p_{ER}^j outweighs the increase in the value of $(1-Z_E^j)$ causing $(p_E^j - w)(1 - Z_E^j)f\mu_E$ to decrease, and this function exhibits an upward trend in all three game models.

Additionally, as indicated in Figure 6, both the refund and cyber-attack cost functions in each game model exhibit a peer-to-peer intersecting point, at which the two costs become equal in equilibrium. In the sorted models, these intersection points are $(0.638, 0.094)$, $(0.650, 0.097)$, and $(0.695, 0.097)$, corresponding to the *Nash*, *BR* leader, and *ER* leader game models, respectively. This investigation highlights that when $0.4 < \varepsilon < 0.64$, the minimal difference between the two presented costs makes the *Nash* game as the game variant which balances the two cost components. As long as ε increases and lies within the range $0.64 < \varepsilon < 0.68$, the *BL* leader has the most balancing effect and can withstand larger volatility. As the discrepancies between the two cost measures in the *BL* leader is lower than those in other game models, the intersection occurs at $(0.65, 0.097)$.

Finally, when ε exceeds 0.68, the *EL* leader becomes the balancing strategy by the peak point of $(0.695, 0.097)$, the cross point, with tolerating higher volatility in terms of the disparity between the two aforementioned costs in Equation (24). In conclusion, the most favourable situation for *ER* (in the sense of lowest disparity) emerges in the *EL* leader game in the given range of $\varepsilon > 0.4$.

Figure 7 depicts the costs rate as presented in N (Equation (24)). As ε increases, the cost rate associated with the refund function compared to the cost of lost demand due to cyber-attacks, Equation (24), also increases significantly. Notably, in the Nash game model, within the given specified ε ranges, this upward trend is more pronounced than in the other two game models. This implies that as the level of ε rises, the cost rate becomes higher in the Nash game model compared to others. Conversely, in the Ethereum leader game model, it brings a greater capacity to tolerate differences between the two cost functions.

Moreover, as illustrated in Figure 7, it becomes evident that when Ethereum- and Bitcoin-based retailers play a leadership role within the ε range of $0.4 < \varepsilon < 0.45$ and $0.4 < \varepsilon < 0.41$, respectively, the value of Equation (24) falls to the negative ranges. As also presented in Figure 6, this occurs because the costs of the return function in both of these games turn negative, owing to the higher profits gained from the manufacturer's subsidy (λ) in the *ER*.

This section aligns with the *ESRB*'s systemic risk principles, showing how market volatility and cyber threats destabilise blockchain-based supply chains, similar to financial systems. It underscores the need for robust cyber risk management and resilience strategies to mitigate such impacts. The use of game theory to analyze retailer responses underlines the importance of dynamic pricing and consumer behaviour analysis in addressing systemic risks (Forscey et al. 2022).

The trade-off between the costs of a (partial) refund on the one hand and cyber security on the other illustrates the optimal handling of multiple risks in a supply chain. The cost of cyber security forces the retailer to accept a drop in demand due to increased volatility. In principle, this phenomenon corresponds to the theory of the second best according to Meade (1955) and Lipsey and Lancaster (1956).

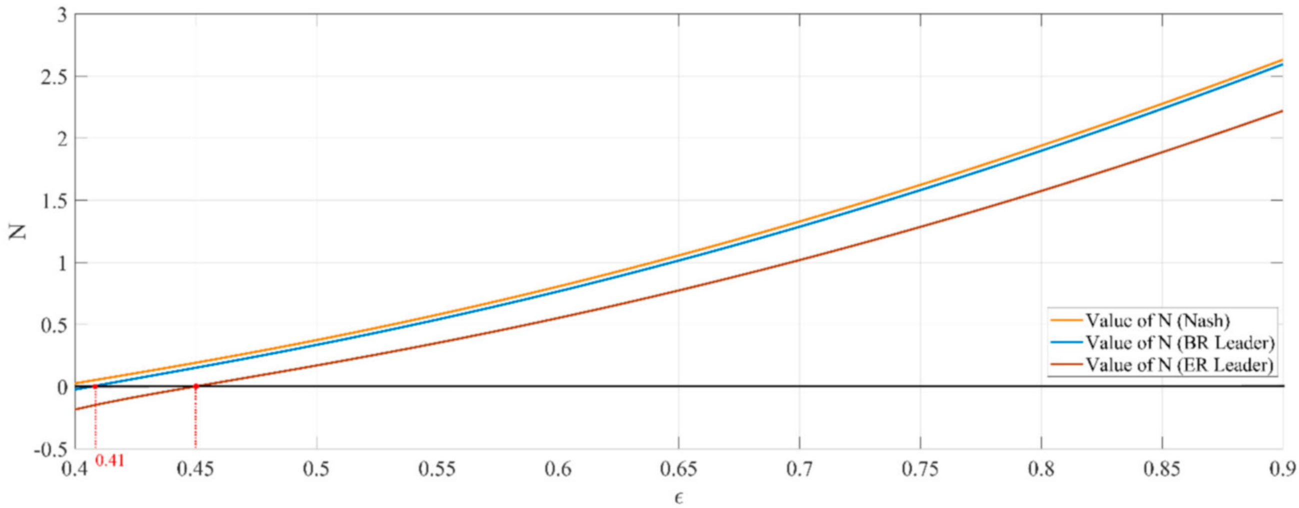

Figure 7. Effects of volatility on the rate of refund cost in terms of cost of cyber attacks.

5.5. Managerial insights

The model developed in this study offers strategic insight into how decision-makers can manage operations under the influence of cryptocurrency volatility and cyber risk. At low levels of volatility, pricing and promotional tools (e.g. return policies or advertising) can effectively stabilise demand. However, as volatility crosses a critical threshold, these mechanisms become insufficient, leading to eroding market share and competitive disadvantage. This highlights a fundamental insight: in blockchain-based supply chains, volatility is not only a consequence of weak market positioning but can also act as a reinforcing cause of instability. Moreover, this helps explain the market structure of cryptocurrency platforms, where smaller players with high volatility are crowded out, and more stable currencies (e.g. Bitcoin, Ethereum) tend to dominate over time. From a dynamic market perspective, only cryptocurrencies with moderate volatility are likely to sustain co-existence in competitive digital environments.

For cryptocurrencies, short-term speculative bets predominate, with the risk of contagious correlation due to interdependencies and volatility co-movements (Palamalai and Maity 2019). However, this is not true for the considered case of Bitcoin and Ethereum since these two currencies belong to different correlation networks (Yongjing et al. 2020). This finding encourages diversified strategies for firms transacting in crypto. Specifically, retailers could hedge financial risk by balancing exposure between Bitcoin and Ethereum – a strategy captured in our model's dual-retailer structure.

The proposed model offers actionable guidance for decision-makers in real-world blockchain-integrated production and logistics systems. For retailers, the model highlights when to adopt aggressive advertising and dynamic pricing strategies to sustain demand in the face of cryptocurrency volatility. For example, firms operating in digital retail (e.g. Overstock, Newegg) can use the model to determine optimal price reductions or advertising investments when dealing with Ethereum's higher volatility compared to Bitcoin. Manufacturers can apply the model to set threshold-based subsidy schemes – supporting retailers only when volatility exceeds critical levels – to stabilise sales and maintain channel resilience. Additionally, the inclusion of cybersecurity investment allows both manufacturers and retailers to model trade-offs between system trust and risk of disruption, which is increasingly relevant as cyber threats to supply chains grow. From a portfolio management perspective, the model also suggests that using a mix of cryptocurrencies (e.g. Bitcoin and Ethereum) can help mitigate risk exposure, making it particularly applicable for omnichannel or multi-region retail platforms. Altogether, the framework provides a decision-aid system that supports pricing, coordination, and risk mitigation in digitally enabled supply chains operating under volatile and decentralised transaction environments. Accordingly, the real-world applications of the proposed model include:

- Retailers (e.g. Overstock, Newegg): Adjust pricing and advertising strategies dynamically in response to crypto market shifts.
- Manufacturers: Design conditional subsidy schemes to stabilise retailer operations when volatility exceeds target levels.
- Supply Chain Managers: Optimise cybersecurity investment to reduce operational risk and avoid platform shutdowns.

- Digital Commerce Platforms: Decide on leadership roles (leader vs. follower) using game-theoretic insights under information asymmetry.
- Omnichannel Firms: Diversify crypto transaction exposure by balancing use between Bitcoin and Ethereum to mitigate volatility shocks.
- Blockchain-Integrated Logistics Networks: Use model simulations to preemptively manage volatility-driven demand instability.

In the future, however, we can expect both the frequency of cyber attacks and the associated volatility to increase. However, this applies to cryptocurrencies in general, as investors are firstly aware of these risks (Caporale et al. 2020), and secondly will only be able to differentiate between the use of different currencies to a limited extent.

6. Conclusion

This study offers insights into the intricate dynamics of blockchain-based supply chains, with a particular focus on the profound impact of cryptocurrency volatility. It investigates the dynamics of pricing, return policies, advertising, and cybersecurity in a supply chain comprised of a manufacturer and two cryptocurrency-based retailers (Ethereum and Bitcoin). The study utilises game theory models to analyze decision-making strategies under different volatility scenarios. The game model structure, comprising three central models, namely Nash game, Bitcoin leader, and Ethereum leader Stackelberg games, provides a nuanced understanding of the dynamic interplay between an Ethereum-based retailer (*ER*), and a Bitcoin-based retailer (*BR*).

The research's findings and related insights, obtained through a rigorous solving approach grounded in game theory and a thorough analysis of decision variables, illuminate critical aspects of this dynamic ecosystem as follows:

- The analysis demonstrates the intricate relationship between changes in the wholesale price (w) and retailer pricing strategies. The impact of w increase varies based on the level of Ethereum's volatility (ε). When ε is low, an increase in the wholesale price leads to lower retail prices due to increased demand in *ER*. In contrast, when Ethereum's volatility is high, a wholesale price increase leads to higher retail prices as demand shifts towards *BR*. This finding highlights the importance of dynamic pricing strategies that factor in multiple variables, including cryptocurrency market dynamics and wholesale costs. Retailers should closely monitor these factors and be prepared to adjust pricing strategies accordingly. By doing so, they can optimise their competitiveness and profitability in a rapidly changing blockchain-based supply chain environment. Overstock.com, which became one of the first major retailers to accept Bitcoin as payment, is recognised as an empirical evidence. Initially, they experienced a significant increase in orders paid with Bitcoin, highlighting the potential benefits of adopting cryptocurrency payments. However, over time, the impact of Bitcoin's volatility led to a decrease in transactions. This fluctuation demonstrates how cryptocurrency volatility can influence retailer pricing and sales strategies, emphasising the need for businesses to adapt their pricing approaches to maintain profitability and remain competitive in a dynamic market.
- The results indicate a key threshold for the subsidy level (λ) provided by the manufacturer. In circumstances with significant volatility, the manufacturer has to provide a subsidy level larger than 0.4 to retain a profit for the Ethereum-based retailer. Otherwise, it may lead a considerable reduction in *ER*'s willingness to spend on advertisement, as a result of demand increment due to the drop in *ER*'s profit level. This research underscores the manufacturer's involvement in minimising the unfavourable impacts of volatility on the Ethereum-based retailer's profitability.
- The findings identify specific thresholds for the optimal strategies of Ethereum Retailer within different volatility ranges, wherein at lower ranges, the Nash game emerges as the cost-balancing strategy. However, as volatility increases and falls within the mid-range, the Bitcoin Retailer leader strategy becomes the preferred choice. The analysis highlights that, in scenarios of higher volatility levels, the Ethereum retailer leader strategy becomes the most favourable choice, in which it brings flexibility in the face of increased volatility, offering the highest profitability and demand resilience. It underscores the importance of leadership roles in managing the challenges posed by cryptocurrency volatility and its impact on customer behaviours, refund policies, and cyberattacks. These thresholds provide clear guidance for blockchain-based retailers to adapt their strategies based on the prevailing volatility conditions.

Future research in blockchain-based supply chains and cryptocurrency dynamics could consider multi-platform competition, dynamic volatility models, regulatory impacts, and customer behaviour. Moreover, also competition between private (e.g. Ethereum) and public (e.g. Bitcoin) cryptocurrencies is shaped by their volatilities. With higher volatility, private cryptocurrencies need aggressive strategies like extensive advertising and return policies to compete. Public cryptocurrencies, with lower volatility, provide a more stable environment for pricing and marketing. On the other hand, the design of public digital currencies (as digital central bank money) has been a challenging topic for monetary policy authorities for almost ten years (Bech and Garratt 2017). For example, the ECB is developing a concept for the digital euro, which raises questions such as the allocation to the money supply, the transaction possibilities of private households and the possible usability of the currency in the event of a crisis. The volatility of an introduced digital public currency is expected to be systematically lower than that of commercial currencies due to the lower risk (central bank as lender of last resort). Most of the results of this paper then apply to the volatility difference between Ethereum (or any other private cryptocurrency) and public crypto currency. Accordingly, further research could also explore how private cryptocurrencies can manage volatility through financial tools and strategic partnerships to stay competitive. Furtheremore, it is essential to study the resilience of blockchain-based supply chains against cyberattacks and evaluate security measures. Keeping up with blockchain technology advancements and their impact on supply chain operations is crucial. Additionally, it is of great value if researchers assess the environmental sustainability of blockchain-based supply chains and conduct real-world case studies across various industries to gain practical insights. To sum up, the findings of this study provide a foundation for several promising research directions that may further enhance the practical and theoretical contributions of blockchain-based supply chain models:

- Dynamic Modelling: Extending the current game-theoretic framework into a dynamic or multi-period setting would allow for modelling the evolution of volatility, adaptive decision-making, and long-term strategic adjustments in decentralised environments.
- Multi-Tier Supply Chains: Incorporating additional layers such as wholesalers, logistics service providers, or third-party platforms would enrich the analysis of coordination and risk-sharing across the full supply network.
- Regulatory and Monetary Impacts: Examining how public digital currencies (e.g. CBDCs), transaction regulations, or tax policies influence operational decisions in blockchain-integrated systems would align this research with ongoing financial digitisation trends.
- Behavioural and Strategic Extensions: Introducing bounded rationality, risk aversion, or reputation-based dynamics into the decision-making process may capture more realistic responses to uncertainty and volatility.
- Empirical Validation and Case Applications: Applying the model to specific sectors (e.g. digital retail, high-tech manufacturing, or food logistics) using real data would allow testing of theoretical insights and increase the model's managerial value.
- Sustainability and ESG Alignment: Investigating how cryptocurrency-enabled systems interact with environmental performance, carbon tracing, or circular economy practices can bridge digitalisation with sustainability goals in supply chain management.

These perspectives offer a roadmap for further enriching both the academic exploration and the real-world applicability of decision models in blockchain-enabled production and logistics systems. These areas collectively enhance our understanding of this evolving field.

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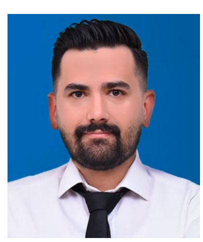

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Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article.

References

"REEDS Jewelers: Bitcoin Currency: Buy Jewelry, Diamonds & Watches With Bitcoin |." 2023. Accessed 7 November 2023. https://www.reeds.com/bitcoin.html.

Agarwal, Udit, Vinay Rishiwal, Sudeep Tanwar, Rashmi Chaudhary, Gulshan Sharma, Pitshou N. Bokoro, and Ravi Sharma. 2022. "Blockchain Technology for Secure Supply Chain Management: A Comprehensive Review." *IEEE Access* 10: 85493–85517.

Alizadeh, Sassan, Michael W. Brandt, and Francis X. Diebold. 2002. "Range-Based Estimation of Stochastic Volatility Models." *The Journal of Finance* 57 (3): 1047–1091. https://doi.org/10.1111/1540-6261.00454.

Anisiuba, Chika A., Obiamaka P. Egbo, Felix C. Alio, Chuka Ifediora, Ebele C. Igwemeka, C. O. Odidi, and Hillary C. Ezeaku. 2021. "Analysis of Cryptocurrency Dynamics in the Emerging Market Economies: Does Reinforcement or Substitution Effect Prevail?" *SAGE Open* 11 (1): 21582440211002516. https://doi.org/10.1177/21582440211002516.

Apergis, Nicholas. 2022. "COVID-19 and Cryptocurrency Volatility: Evidence from Asymmetric Modelling." *Finance Research Letters* 47:102659. https://doi.org/10.1016/j.frl.2021.102659.

Assarzadegan, Parisa, Seyed R. Hejazi, and Morteza Rasti-Barzoki. 2023. "A Stackelberg Differential Game Theoretic Approach for Analyzing Coordination Strategies in a Supply Chain with Retailer's Premium Store Brand." *Annals of Operations Research* 336: 1519–1549.

Bai, Chunguang, and Joseph and Sarkis. 2020. "A Supply Chain Transparency and Sustainability Technology Appraisal Model for Blockchain Technology." *International Journal of Production Research* 58 (7): 2142–2162. https://doi.org/10.1080/00207543.2019.1708989.

Baur, Dirk G., and Thomas Dimpfl. 2018. "Asymmetric Volatility in Cryptocurrencies." *Economics Letters* 173:148–151.

Bebeshko, Bohdan, Volodimir Malyukov, M. Lakhno, Pavlo Skladannyi, Volodymyr Sokolov, Svitlana Shevchenko, and M. Zhumadilova. 2022. "Application of Game Theory, Fuzzy Logic and Neural Networks for Assessing Risks and Forecasting Rates of Digital Currency." *Journal of Theoretical and Applied Information Technology* 100:7390–7404.

Bech, Morten, and Rodney Garratt. 2017. "Central Bank Cryptocurrencies." *BIS Quarterly Review*. https://EconPapers.repec.org/RePEc:bis:bisqtr:1709f

Biais, Bruno, Christophe Bisière, Matthieu Bouvard, and Catherine Casamatta. 2021. "Strategic Interactions in Block chain: A Survey of Game-Theoretic Approaches." In *Principles of Blockchain Systems*, edited by Antonio F. Anta, Chryssis Georgiou, Maurice Herlihy, and Maria Potop-Butucaru, 155–174. Cham: Springer International Publishing.

Biswas, Debajyoti, Hamed Jalali, Amir H. Ansaripoor, and Pietro de Giovanni. 2023. "Traceability vs. Sustainability in Supply Chains: The Implications of Blockchain." *European Journal of Operational Research* 305 (1): 128–147. https://doi.org/10.1016/j.ejor.2022.05.034.

Bradbury, Danny. 2014. "Overstock.com Becomes First Major Retailer to Accept Bitcoins." CoinDesk, January 9. Accessed May 31, 2024.

Buterin, Vitalik. 2013. "Ethereum White Paper." *GitHub Repository* 1:22–23.

Cachon, Gerard P., and Serguei Netessine. 2006. "Game Theory in Supply Chain Analysis." In *Models, Methods, and Applications for Innovative Decision Making*, edited by David Simchi-Levi, S. David Wu, and Zuo-Jun (Max) Shen, 200–233. Catonsville: INFORMS.

Caporale, Guglielmo M., Woo-Young Kang, Fabio Spagnolo, and Nicola Spagnolo. 2020. "Cyber-Attacks and Cryptocurrencies."

Casino, Fran, Venetis Kanakaris, Thomas K. Dasaklis, Socrates Moschuris, Spiros Stachtiaris, Maria Pagoni, and Nikolaos P. Rachaniotis. 2021. "Blockchain-Based Food Supply Chain Traceability: A Case Study in the Dairy Sector." *International Journal of Production Research* 59 (19): 5758–5770. https://doi.org/10.1080/00207543.2020.1789238.

Centobelli, Piera, Roberto Cerchione, Pasquale Del Vecchio, Eugenio Oropallo, and Giustina Secundo. 2022. "Blockchain Technology for Bridging Trust, Traceability and Transparency in Circular Supply Chain." *Information & Management* 59 (7): 103508.

Chan, Stephen, Jeffrey Chu, Yuanyuan Zhang, and Saralees Nadarajah. 2020. "Blockchain and Cryptocurrencies." *Journal of Risk and Financial Management* 13:10. https://doi.org/10.3390/jrfm13100227.

Chang, Shuchih E., and Yichian Chen. 2020. "When Blockchain Meets Supply Chain: A Systematic Literature Review on Current Development and Potential Applications." *IEEE Access* 8:62478–62494. https://doi.org/10.1109/ACCESS.2020.2983601.

Chiu, Iris H.-Y. 2021. *Regulating the Crypto Economy. Hart Studies in Commercial and Financial Law*. London: Hart Publishing. http://digital.casalini.it/9781509935758.

Choi, Tsan-Ming. 2021. "Creating All-Win by Blockchain Technology in Supply Chains: Impacts of Agents' Risk Attitudes Towards Cryptocurrency." *Journal of the Operational Research Society* 72 (11): 2580–2595. https://doi.org/10.1080/01605682.2020.1800419.

Choi, Tsan-Ming, Ata A. Taleizadeh, and Xiaohang and Yue. 2020. "Game Theory Applications in Production Research in the Sharing and Circular Economy Era." *International Journal of Production Research* 58 (1): 118–127. https://doi.org/10.1080/00207543.2019.1681137.

coindesk. 2024. "coindesk." Top Cryptocurrency Prices and Market Cap. Accessed 2 June 2024. https://www.coindesk.com/price.

CoinGecko. 2024. "Crypto Market Cap Charts | CoinGecko." Accessed 2 June 2024. https://www.coingecko.com/en/global-charts.

CoinMarketCap. 2023. "Cryptocurrency Prices, Charts and Market Capitalizations | CoinMarketCap." Accessed 23 November 2023. https://coinmarketcap.com/.

CoinMarketCap. 2024. "Cryptocurrency Prices, Charts and Market Capitalizations | CoinMarketCap." Accessed 2 June 2024. https://coinmarketcap.com/.

Corbet, Shaen, Brian Lucey, Andrew Urquhart, and Larisa Yarovaya. 2019. “Cryptocurrencies as a Financial Asset: A Systematic Analysis.” *International Review of Financial Analysis* 62:182–199.

D’Amato, Valeria, Susanna Levantesi, and Gabriella Piscopo. 2022. “Deep Learning in Predicting Cryptocurrency Volatility.” *Physica A: Statistical Mechanics and Its Applications* 596:127158. https://doi.org/10.1016/j.physa.2022.127158.

Ding, Shusheng, Tianxiang Cui, Xiangling Wu, and Min Du. 2022. “Supply Chain Management Based on Volatility Clustering: The Effect of CBDC Volatility.” *Research in International Business and Finance* 62:101690. https://doi.org/10.1016/j.ribaf.2022.101690.

Doumenis, Yianni, Javad Izadi, Pradeep Dhamdhere, Epameinondas Katsikas, and Dimitrios Koufopoulos. 2021. “A Critical Analysis of Volatility Surprise in Bitcoin Cryptocurrency and Other Financial Assets.” *Risks* 9:11. https://doi.org/10.3390/risks9110207.

Eltoukhy, Abdelrahman E., Mohamed Hussein, Min Xu, and T. Felix. 2023. “Data-Driven Game-Theoretic Model Based on Blockchain for Managing Resource Allocation and Vehicle Routing in Modular Integrated Construction.” *International Journal of Production Research* 61 (13): 4472–4502. https://doi.org/10.1080/00207543.2022.2154406.

Forscey, David, Jon Bateman, Nick Beecroft, and Beau Woods. 2022. *Systemic Cyber Risk: A Primer*. Washington: Carnegie Endowment for International Peace.

Gao, Jianbin, Bonsu Adjei-Arthur, Emmanuel B. Sifah, Hu Xia, and Qi Xia. 2022. “Supply Chain Equilibrium on a Game Theory-Incentivized Blockchain Network.” *Journal of Industrial Information Integration* 26:100288. https://doi.org/10.1016/j.jii.2021.100288.

Gerrit, Köchling, Philipp Schmidtke, and Peter N. Posch. 2020. “Volatility Forecasting Accuracy for Bitcoin.” *Economics Letters* 191:108836. https://doi.org/10.1016/j.econlet.2019.108836.

Giovanni, Pietro. 2020. “Blockchain and Smart Contracts in Supply Chain Management: A Game Theoretic Model.” *International Journal of Production Economics* 228:107855. https://doi.org/10.1016/j.ijpe.2020.107855.

Hamledari, Hesam, and Martin Fischer. 2021. “The Application of Blockchain-Based Crypto Assets for Integrating the Physical and Financial Supply Chains in the Construction & Engineering Industry.” *Automation in Construction* 127:103711. https://doi.org/10.1016/j.autcon.2021.103711.

Harikumar, Pallathadka, Korakod Tongkachok, Prashant Subhash Arbune, and Samrat Ray. 2022. “Cryptocurrency and Bitcoin: Future Works, Opportunities, and Challenges.” *ECS Transactions* 107 (1): 16313. https://doi.org/10.1149/10701.16313ecst.

Hayes, Adam. 2015. “What Factors Give Cryptocurrencies Their Value: An Empirical Analysis.” SSRN 2579445.

Heydaryan, Hossein, and Ata A. Taleizadeh. 2017. “Pricing Strategy, Return Policy and Coordination in a Two-Stage Supply Chain.” *International Journal of Systems Science: Operations & Logistics* 4 (4): 384–391.

IvyPanda. 2024. “Overstock.com Inc. Case Study – 1001 Words | Presentation Example.” Accessed 31 May 2024.

Jamali, Mohammad-Bagher, and Morteza Rasti-Barzoki. 2018. “A Game Theoretic Approach for Green and Non-Green Product Pricing in Chain-to-Chain Competitive Sustainable and Regular Dual-Channel Supply Chains.” *Journal of Cleaner Production* 170:1029–1043.

Jernej, Drofenik, and R. Kovačič Batista. 2018. “Approaches to Crypto Assets Valuation.” Master’s Thesis University of Ljubljana. Ljubljana, Slovenia, Faculty of … .

John, Geanakoplos. 2021. “Game Theory Without Partitions, and Applications to Speculation and Consensus.” *The B.E. Journal of Theoretical Economics* 21 (2): 361–394. https://doi.org/10.1515/bejte-2019-0010.

Khan, Ruby, and Tahani A. Hakami. 2022. “Cryptocurrency: Usability Perspective Versus Volatility Threat.” *Journal of Money and Business* 2 (1): 16–28.

Kitamura, Yukinobu. 2022. “Can we Stabilize the Price of a Cryptocurrency? Understanding the Design of Bitcoin and its Potential to Compete with Central Bank Money.” In *Quest for Good Money: Past, Present and Future*, edited by Yukinobu Kitamura, 103–123. Singapore: Springer Nature Singapore.

Kumar, Milan, Preetam Basu, and Balram Avittathur. 2018. “Pricing and Sourcing Strategies for Competing Retailers in Supply Chains Under Disruption Risk.” *European Journal of Operational Research* 265 (2): 533–543. https://doi.org/10.1016/j.ejor.2017.08.019.

Li, Xin, and Chong A. Wang. 2017. “The Technology and Economic Determinants of Cryptocurrency Exchange Rates: The Case of Bitcoin.” *Decision Support Systems* 95:49–60. https://doi.org/10.1016/j.dss.2016.12.001.

Lipsey, Richard G., and Kelvin Lancaster. 1956. “The General Theory of Second Best.” *The Review of Economic Studies* 24 (1): 11–32.

Lo, Stephanie, and J. C. Wang. 2014. “Bitcoin as Money?”.

Mamoudan, Mobina M., Zahra Mohammadnazari, Ali Ostadi, and Ali Esfahbodi. 2024. “Food Products Pricing Theory with Application of Machine Learning and Game Theory Approach.” *International Journal of Production Research* 62 (15): 5489–5509. https://doi.org/10.1080/00207543.2022.2128921.

Mathivathanan, Deepak, K. Mathiyazhagan, Nripendra P. Rana, Sangeeta Khorana, and Yogesh K. Dwivedi. 2021. “Barriers to the Adoption of Blockchain Technology in Business Supply Chains: A Total Interpretive Structural Modelling (TISM) Approach.” *International Journal of Production Research* 59 (11): 3338–3359. https://doi.org/10.1080/00207543.2020.1868597.

Meade, J. E. 1955. *Trade and Welfare Bd. 2*. Oxford: Oxford University Press. https://books.google.de/books?id=7nNswgEACAAJ.

Moretto, Antonella, and Laura Macchion. 2022. “Drivers, Barriers and Supply Chain Variables Influencing the Adoption of the Blockchain to Support Traceability Along Fashion Supply Chains.” *Operations Management Research* 15 (3-4): 1470–1489.

Nakamoto, Satoshi. 2008. “Bitcoin: A Peer-to-Peer Electronic Cash System.”

Newegg Knowledge Base. 2023. “Using Crypto on Newegg – Newegg Knowledge Base.” Accessed 11 July 2023. https://kb.newegg.com/knowledge-base/using-crypto-on-newegg/.

Oliver, Huse, Erica Reeve, Colin Bell, Gary Sacks, Phillip Baker, Benjamin Wood, and Kathryn Backholer. 2022.

"Strategies Used by the Soft Drink Industry to Grow and Sustain Sales: A Case-Study of the Coca-Cola Company in East Asia." *BMJ Global Health* 7 (12): e010386. https://doi.org/10.1136/bmjgh-2022-010386.

Osagwu, Anthony, and Ekwunife Okafor. 2022. "Understanding the Nexus Between Advertising and Purchase Intention of Cryptocurrency Among Young Adults in Nigeria." *European Journal of Business and Innovation Research* 10:34–70. https://doi.org/10.37745/ejbir.2013/vo10.n6pp3470.

OSTK-2015. "OSTK-2015.12.31-10K." https://www.annualreports.com/HostedData/AnnualReportArchive/o/NASDAQ_OSTK_2015.pdf. Accessed 31 May 2024.

Overstock.com. 2024. "Overstock.com – AnnualReports.com." Accessed 31 May 2024.

Palamalai, Srinivasan, and Bipasha Maity. 2019. "Return and Volatility Spillover Effects in Leading Cryptocurrencies." *Global Economy Journal* 19 (03): 1950017. https://doi.org/10.1142/S2194565919500179.

Panagiotidis, Theodore, Georgios Papapanagiotou, and Thanasis Stengos. 2022. "On the Volatility of Cryptocurrencies." *Research in International Business and Finance* 62:101724.

Phillip, Andrew, Jennifer S. K. Chan, and Shelton Peiris. 2018. "A New Look at Cryptocurrencies." *Economics Letters* 163:6–9.

Rajabzadeh, Hamed, and Reza Babazadeh. 2022. "A Game-Theoretic Approach for Power Pricing in a Resilient Supply Chain Considering a Dual Channel Biorefining Structure and the Hybrid Power Plant." *Renewable Energy* 198:1082–1094.

Roozbehani, Mardavij, Munther A. Dahleh, and Sanjoy K. Mitter. 2012. "Volatility of Power Grids Under Real-Time Pricing." *IEEE Transactions on Power Systems* 27 (4): 1926–1940.

Sabry, Farida, Wadha Labda, Aiman Erbad, and Qutaibah Malluhi. 2020. "Cryptocurrencies and Artificial Intelligence: Challenges and Opportunities." *IEEE Access* 8:175840–58.

Sakas, Damianos P., Nikolaos T. Giannakopoulos, Dimitrios K. Nasiopoulos, Nikos Kanellos, and Giannis T. Tsoulfas. 2023. "Assessing the Efficacy of Cryptocurrency Applications Affiliate Marketing Process on Supply Chain Firms' Website Visibility." *Sustainability* 15 (9): 7326.

SeyedEsfahani, Mir M., Maryam Biazaran, and Mohsen Gharakhani. 2011. "A Game Theoretic Approach to Coordinate Pricing and Vertical Co-Op Advertising in Manufacturer–Retailer Supply Chains." *European Journal of Operational Research* 211 (2): 263–273.

Shittu, Hassan. 2024. "Visa Partners with Transak To Enable Direct Crypto-to-Fiat Transactions." January 30. Accessed 10 June 2024. https://cryptonews.com/news/visa-partners-with-transak-to-enable-direct-crypto-to-fiat-transactions.htm.

Song, Luona, Yiqing Luo, Zixi Chang, Chunhua Jin, and Merveille Nicolas. 2022. "Blockchain Adoption in Agricultural Supply Chain for Better Sustainability: A Game Theory Perspective." *Sustainability* 14:3. https://doi.org/10.3390/su14031470.

Taleizadeh, Ata A., Vahid R. Soleymanfar, and Tsan-Ming Choi. 2017. "Optimal Pricing and Alliance Strategy in a Retailer-Led Supply Chain with the Return Policy: A Game-Theoretic Analysis." *Information Sciences* 420:466–489. https://doi.org/10.1016/j.ins.2017.08.054.

Tao, Feng, Yao-Yu Wang, and Shi-Hu Zhu. 2023. "Impact of Blockchain Technology on the Optimal Pricing and Quality Decisions of Platform Supply Chains." *International Journal of Production Research* 61 (11): 3670–3684. https://doi.org/10.1080/00207543.2022.2050828.

Tesla, Inc. 2022. "2022 Annual Report."

Vatankhah Barenji, Ali, Zhi Li, W. M. Wang, George Q. Huang, and David A. Guerra-Zubiaga. 2020. "Blockchain-Based Ubiquitous Manufacturing: A Secure and Reliable Cyber-Physical System." *International Journal of Production Research* 58 (7): 2200–2221. https://doi.org/10.1080/00207543.2019.1680899.

Viriyasitavat, Wattana, Danupol Hoonsopon, and Zhuming Bi. 2021. "Augmenting Cryptocurrency in Smart Supply Chain." *Journal of Industrial Information Integration* 21:100188. https://doi.org/10.1016/j.jii.2020.100188.

Vuteva, Zornitsa. 2024. "Understanding Fiat-to-Crypto Payment Gateways: The Future of Digital Transactions – Coinlabz." Coinlabz, May 15. Accessed 10 June 2024. https://coinlabz.com/what-is-fiat-to-crypto-payment-gateway/.

Wu, Jianghua, and Jiahao Yu. 2023. "Blockchain's Impact on Platform Supply Chains: Transaction Cost and Information Transparency Perspectives." *International Journal of Production Research* 61 (11): 3703–3716. https://doi.org/10.1080/00207543.2022.2027037.

Yang, Liu, Yaodong Ni, and Chi-To Ng. 2023a. "Blockchain-Enabled Traceability and Producer's Incentive to Outsource Delivery." *International Journal of Production Research* 61 (11): 3811–3828. https://doi.org/10.1080/00207543.2022.2072785.

Yang, Dennis, and Qiang Zhang. 2000. "Drift-Independent Volatility Estimation Based on High, Low, Open, and Close Prices." *The Journal of Business* 73 (3): 477–492.

Yang, Wu, Wang Ziyang, Zhou Xiaohao, and Yao Jianming. 2023b. "The Optimisation Research of Blockchain Application in the Financial Institution-Dominated Supply Chain Finance System." *International Journal of Production Research* 61 (11): 3735–3755. https://doi.org/10.1080/00207543.2022.2087567.

Yongjing, Shi, Aviral Kumar Tiwari, Giray Gozgor, and Zhou Lu. 2020. "Correlations Among Cryptocurrencies: Evidence from Multivariate Factor Stochastic Volatility Model." *Research in International Business and Finance* 53:101231. https://doi.org/10.1016/j.ribaf.2020.101231.

Yu, Yugang, George Q. Huang, and Liang Liang. 2009. "Stackelberg Game-Theoretic Model for Optimizing Advertising, Pricing and Inventory Policies in Vendor Managed Inventory (VMI) Production Supply Chains." *Computers & Industrial Engineering* 57 (1): 368–382.

Zhang, Xuemei, Haoran Chen, Jiawei Hu, Chenhao Ma, Wei Shi, and Ya Jia. 2021. "Optimal Showroom Service Strategy and Power Structure for Retailers considering Consumer Return." *Discrete Dynamics in Nature and Society* 2021:4598341. https://doi.org/10.1155/2021/4598341.

Zhang, Shiyuan, Xiao-Xue Zheng, Fu Jia, and Zhi and Liu. 2024. "Pricing Strategy and Blockchain Technology Investment Under Hybrid Carbon Trading Schemes: A Biform Game Analysis." *International Journal of Production Research*: 1–22. https://doi.org/10.1080/00207543.2024.2398582.

Zhu, Qingyun, Chunguang Bai, and Joseph Sarkis. 2022. “Blockchain Technology and Supply Chains: The Paradox of the Atheoretical Research Discourse.” *Transportation Research Part e: Logistics and Transportation Review* 164:102824.

Appendix

Equilibrium values of decision variables in the Nash game

Lemma A.1: *The profit function of ER exhibits concavity in* A^{NE}, Z^{NE}_{ER}, p^{NE}_{ER}.

Proof: The profit function of $ER's$ hessian in A^{NE}, Z^{NE}_{ER}, p^{NE}_{ER} is as follows:

$$H_{\pi^{NE}_{ER}(A^{NE},Z^{NE}_{ER},p^{NE}_{ER})} = \begin{bmatrix} -2\beta & 1-\varepsilon & \mu_E f \\ 1-\varepsilon & -1 & 0 \\ \mu_E f & 0 & -1 \end{bmatrix} \tag{A1}$$

Since $|-2\beta| < 0$, $\begin{vmatrix} -2\beta & 1-\varepsilon \\ 1-\varepsilon & -1 \end{vmatrix} = 2\beta - (1-\varepsilon)^2 > 0$, the only condition for profit function of $ER's$ hessian to be concave is: $\begin{vmatrix} -2\beta & 1-\varepsilon & \mu_E f \\ 1-\varepsilon & -1 & 0 \\ \mu_E f & 0 & -1 \end{vmatrix} = {\mu_E}^2 f^2 + \varepsilon^2 - 2\beta - 2\varepsilon + 1 < 0$.

Lemma A.2: *The profit function of BR shows concavity in* Z^{NE}_{BR}, p^{NE}_{BR}.

Proof: The profit function of $BR's$ hessian in Z^{NE}_{BR}, p^{NE}_{BR} is as follows:

$$H_{\pi^{NE}_{BR}(Z^{NE}_{BR},p^{NE}_{BR})} = \begin{bmatrix} -2\beta & \mu_B f \\ \mu_B f & -1 \end{bmatrix} \tag{A2}$$

Since $|-2\beta| < 0$, the only condition for profit function of $BR's$ hessian to be concave is: $\begin{vmatrix} -2\beta & \mu_B f \\ \mu_B f & -1 \end{vmatrix} = -{\mu_B}^2 f^2 + 2\beta > 0$.

Proposition A.1: *The optimal outcomes for the decision variables of both retailers in the Nash equilibrium game are as follows.*

Proof: getting the first derivatives of profit functions regarding the decision variables we got:

$$\frac{\partial \pi^{NE}_{ER}}{\partial A^{NE}} = (p^{NE}_{ER} - w)(1-\varepsilon) + r\varepsilon\lambda - A^{NE} \tag{A3}$$

$$\frac{\partial \pi^{NE}_{ER}}{\partial Z^{NE}_{ER}} = (p^{NE}_{ER} - w)\mu_E f + fK_E - Z^{NE}_{ER} \tag{A4}$$

$$\begin{aligned} \frac{\partial \pi^{NE}_{ER}}{\partial p^{NE}_{ER}} &= ((1-\varepsilon)\alpha + \sigma - \beta p^{NE}_{ER} + \gamma p^{NE}_{BR} + (1-\varepsilon)A^{NE} \\ &\quad - (1 - Z^{NE}_{ER}) f\mu_E - (p^{NE}_{ER} - w)\beta) \end{aligned} \tag{A5}$$

$$\frac{\partial \pi^{NE}_{BR}}{\partial Z^{NE}_{BR}} = (p^{NE}_{BR} - w)\mu_B f + fK_B - Z^{NE}_{BR} \tag{A6}$$

$$\begin{aligned} \frac{\partial \pi^{NE}_{BR}}{\partial p^{NE}_{BR}} &= (\varepsilon\alpha + 1 - \sigma - \beta p^{NE}_{BR} + \gamma p^{NE}_{ER} + \varepsilon A^{NE} \\ &\quad - (1 - Z^{NE}_{BR}) f\mu_B) - (p^{NE}_{BR} - w)\beta \end{aligned} \tag{A7}$$

When we solve the 5 Equations (A3–A7), we get the values as Equations (8–12).

$$\begin{aligned} N_1 &= f^4\mu_B^2\mu_E^2 + f^2\mu_B^2\varepsilon^2 - 2\beta f^2\mu_B^2 - 2\beta f^2\mu_E^2 - 2f^2\varepsilon\mu_B^2 \\ &\quad + f^2\mu_B^2 - 2\beta\varepsilon^2 + \gamma\varepsilon^2 + 4\beta^2 + 4\beta\varepsilon - \gamma^2 - \gamma\varepsilon - 2\beta \end{aligned}$$

$$\begin{aligned} N2 = (&-\alpha f^2\varepsilon^2\mu_B^2 - \beta f^2 w\mu_B^2 - f^3\varepsilon\mu_B^2\mu_E + f^2\gamma w\varepsilon\mu_B^2 \\ &+ 2\alpha f^2\varepsilon\mu_B^2 + \beta f^2 w\mu_B^2 + 2\beta f^2 k_E\mu_E + f^3\mu_B^2\mu_E \\ &- f^2\gamma w\mu_B^2 - f^2\gamma\varepsilon k_B\mu_B + f^2\sigma\varepsilon\mu_B^2 + \alpha f^2\mu_B^2 - 4\beta^2\gamma\varepsilon r \\ &+ 2\beta f^2 k_E\mu_E + f^2\gamma k_B\mu_B - f^2\sigma\mu_B^2 - \gamma^2\lambda\varepsilon r \\ &+ 2\alpha\beta\varepsilon^2 - \alpha\gamma\varepsilon^2 + 2\beta^2 w\varepsilon + 2\beta f\varepsilon\mu_E - \beta\gamma w\varepsilon \\ &+ f\gamma\varepsilon\mu_B - \gamma^2 w\varepsilon - 4\alpha\beta\varepsilon + \alpha\gamma\varepsilon - 2\beta^2 w \\ &- 2\beta f\mu_E - 2\beta f\mu_E + \beta\gamma w - 2\beta\varepsilon\sigma - f\gamma\mu_B + \gamma^2 w \\ &+ \gamma\sigma\varepsilon + 2\alpha\beta + 2\beta\sigma - \gamma\sigma - \gamma\varepsilon + \gamma) \end{aligned}$$

$$\begin{aligned} N3 = (&f^3\mu_B^2\mu_E^2 - f^2\gamma w\mu_E\mu_B^2 - f^2\varepsilon^2 k_E{\mu_B}^2 - \alpha f^2\mu_B^2\mu_E \\ &- 2\beta f^2 k_E\mu_B^2 - 2\beta\lambda\varepsilon^2\mu_E r + f^2\gamma k_B\mu_E\mu_B - f^2\sigma\mu_E\mu_B^2 \\ &- 2f^2\varepsilon k_E{\mu_B}^2 + \gamma\lambda\varepsilon^2\mu_E r + 2\beta\lambda\varepsilon\mu_E r + f^2 k_E\mu_E^2 \\ &- 2\alpha\beta\varepsilon\mu_E + \alpha\gamma\varepsilon\mu_E - 2\beta^2 w\mu_E - 2\beta f\mu_E^2 + \beta\gamma w\mu_E \\ &- 2\beta\varepsilon^2 k_E - f\gamma\mu_B\mu_E + \gamma^2 w\mu_E + \gamma\varepsilon^2 k_E + 2\alpha\beta\mu_E\mu_B \\ &+ 4\beta^2 k_E + 2\sigma\beta\mu_E + 4\beta\varepsilon k_E - \gamma^2 k_E - \gamma\sigma\mu_E - \gamma\varepsilon k_E \\ &- 2\beta k_E + \gamma\mu_E \end{aligned}$$

$$\begin{aligned} N4 = (&-f^2\gamma w\mu_B\mu_E^2 - f^2\varepsilon^2 k_E\mu_E\mu_B - 2\beta f^2 k_E\mu_E^2 \\ &+ 2\beta\gamma\varepsilon^2\mu_B r + f^2\gamma k_E\mu_E\mu_B + f^2\sigma\mu_B\mu_E^2 + f^2\varepsilon k_E\mu_E\mu_B \\ &- \gamma\lambda\varepsilon^2\mu_B r + 2\beta w\varepsilon^2\mu_B - f^2\mu_B\mu_E^2 + f\varepsilon^2\mu_B^2 \\ &+ f\varepsilon^2\mu_B\mu_E + \gamma\lambda\varepsilon\mu_B r - 2\gamma w\varepsilon^2\mu_B + 2\alpha\beta\varepsilon\mu_B \\ &- \alpha\gamma\varepsilon\mu_B - 2\beta^2 w\mu_B - 2\beta f\mu_B^2 + 3\beta w\varepsilon\mu_B - 2\beta\varepsilon^2 k_B \\ &- f\gamma\mu_B\mu_E - 2f\varepsilon\mu_B^2 - f\varepsilon\mu_B\mu_E + \gamma^2 w\mu_B + 3\gamma w\varepsilon\mu_B + \\ &+ \gamma\varepsilon^2 k_B + \alpha\gamma\mu_B + 4\beta^2 k_B - 2\beta\sigma\mu_B + 4\beta\varepsilon k_B + f\mu_B^2 \\ &- \gamma^2 k_B + \gamma\sigma\mu_B - \gamma w\mu_B - \gamma\varepsilon k_B - \sigma\varepsilon\mu_B - \varepsilon^2\mu_B \\ &- 2\beta k_B + 2\beta\mu_B + \sigma\mu_B + 2\varepsilon\mu_B - \mu_B) \end{aligned}$$

$$\begin{aligned} N_5 = (&-\alpha f^2{\mu_B}^2 - 2\beta f^2 w\mu_E^2 - \beta f^2 w\mu_B^2 + f^3\mu_E\mu_B^2 \\ &- f^2\gamma w\mu_B^2 - 2f^2 w\varepsilon\mu_B^2 - \alpha f^2\mu_B^2 + 2\beta f^2 k_E\mu_E - 2\beta\lambda\varepsilon^2 r \\ &- f^2\sigma\mu_B^2 + f^2 w\mu_B^2 - \gamma\lambda r\varepsilon^2 + 2\beta\lambda\varepsilon r + 2\beta W\varepsilon^2 \\ &+ \gamma w\varepsilon^2 - 2\alpha\beta\varepsilon + \alpha\gamma\varepsilon + 2\beta^2 w - 2\beta f\mu_E + \beta\gamma w \\ &+ 4\beta w\varepsilon - f\gamma\mu_B - \gamma w\varepsilon + 2\beta\alpha + 2\beta\sigma + 2\beta w \\ &- \gamma\sigma + \gamma) \end{aligned}$$

$$N_6 = ((-\alpha f^2 {\mu_E}^2 - 2\beta f^2 w \mu_B^2 - \beta f^2 w \mu_E^2 + f^3 \mu_B \mu_E^2 - f^2 \gamma w \mu_E^2 - 2f^2 w\varepsilon \mu_E^2 - f^2 k_B \mu_B \varepsilon^2 - f^2 k_E \mu_E \varepsilon^2 + 2\beta f^2 k_B \mu_B + 2\beta\lambda\varepsilon^2 r + f^2 \gamma k_E \mu_E + f^2 \sigma \mu_E^2 + f^2 w \mu_B^2 + 2f^2 \varepsilon k_B \mu_B + 2f^2 \varepsilon k_E \mu_E - \gamma \lambda r \varepsilon^2 - f^2 k_B \mu_B - f^2 \mu_E^2 + f\varepsilon^2 \mu_B + f\varepsilon^2 \mu_E + \gamma \lambda r \varepsilon - \gamma w\varepsilon^2 + 2\alpha\beta\varepsilon - \alpha\gamma\varepsilon + 2\beta^2 w - 2\beta f \mu_B + \beta\gamma w + \beta w\varepsilon - f\gamma \mu_E - 2f\varepsilon\mu_B - f\varepsilon\mu_E + 2\gamma w\varepsilon + \alpha\gamma - 2\beta\sigma - \beta w + f\mu_B + \gamma\sigma - \gamma w - \sigma\varepsilon - \varepsilon^2 + 2\beta + \sigma + 2\varepsilon - 1)$$

Equilibrium values of decision variables in the Stackelberg game with BR leadership

First of all, considering ER as the follower, the concavity condition of its profit value is investigated.

Lemma A.3: *The profit function of ER exhibits concavity in A^{BL}, Z_{ER}^{BL}, p_{ER}^{BL}.*

Proof: The profit function of $ER's$ hessian in A^{NE}, Z_{ER}^{NE}, p_{ER}^{NE} is as follows:

$$H_{\pi_{ER}^{BL}(A^{BL}, Z_{ER}^{BL}, p_{ER}^{BL})} = \begin{bmatrix} -2\beta & 1-\varepsilon & \mu_E f \\ 1-\varepsilon & -1 & 0 \\ \mu_E f & 0 & -1 \end{bmatrix} \quad \text{(A8)}$$

Since $|-2\beta| < 0$, $\begin{vmatrix} -2\beta & 1-\varepsilon \\ 1-\varepsilon & -1 \end{vmatrix} = 2\beta - (1-\varepsilon)^2 > 0$, the only condition for profit function of $ER's$ hessian to be concave is: $\begin{vmatrix} -2\beta & 1-\varepsilon & \mu_E f \\ 1-\varepsilon & -1 & 0 \\ \mu_E f & 0 & -1 \end{vmatrix} = {\mu_E}^2 f^2 + \varepsilon^2 - 2\beta - 2\varepsilon + 1 < 0$

Proposition A.2: *The optimal solutions for the decision variables of ER in the second scenario are as Equations (13–15).*

***Proof*:** getting the first derivatives of $ER's$ profit function regarding the A^{BL}, Z_{ER}^{BL}, p_{ER}^{BL} we got:

$$\frac{\partial \pi_{ER}^{BL}}{\partial A^{BL}} = (p_{ER}^{BL} - w)(1-\varepsilon) + r\varepsilon\lambda - A^{BL} \quad \text{(A9)}$$

$$\frac{\partial \pi_{ER}^{BL}}{\partial Z_{ER}^{BL}} = (p_{ER}^{BL} - w)\mu_E f + fK_E - Z_{ER}^{BL} \quad \text{(A10)}$$

$$\frac{\partial \pi_{ER}^{BL}}{\partial p_{ER}^{BL}} = ((1-\varepsilon)\alpha + \sigma - \beta p_{ER}^{BL} + \gamma p_{BR}^{BL} + (1-\varepsilon)A^{BL} - (1 - Z_{ER}^{BL}) f \mu_E - (p_{ER}^{BL} - w)\beta) \quad \text{(A11)}$$

Solving Equations (A9–A11) we got optimal values as Equations (13,14,15).

Lemma A.4: *The profit function of BR exhibits concavity in Z_{BR}^{BL}, p_{BR}^{BL}.*

By substituting the optimal values as Equations (13–15) in BR's profit function as leader the Hessian gained as below:

$$H_{\pi_{BR}^{BL}(Z_{BR}^{BL}, p_{BR}^{BL})} = \begin{bmatrix} -2\beta + \dfrac{2\gamma^2}{-f^2\mu_E^2 - \varepsilon^2 + 2\beta + 2\varepsilon - 1} - \dfrac{2\varepsilon(\gamma\varepsilon - \gamma)}{-f^2\mu_E^2 - \varepsilon^2 + 2\beta + 2\varepsilon - 1} & \mu_B f \\ \mu_B f & -1 \end{bmatrix} \quad \text{(A12)}$$

Since $\left|-2\beta + \frac{2\gamma^2}{-f^2\mu_E^2 - \varepsilon^2 + 2\beta + 2\varepsilon - 1} - \frac{2\varepsilon(\gamma\varepsilon - \gamma)}{-f^2\mu_E^2 - \varepsilon^2 + 2\beta + 2\varepsilon - 1}\right| < 0$, the only condition for profit function of $BR's$ hessian to be concave is: $\begin{vmatrix} -2\beta + \frac{2\gamma^2}{-f^2\mu_E^2 - \varepsilon^2 + 2\beta + 2\varepsilon - 1} - \frac{2\varepsilon(\gamma\varepsilon - \gamma)}{-f^2\mu_E^2 - \varepsilon^2 + 2\beta + 2\varepsilon - 1} & \mu_B f \\ \mu_B f & -1 \end{vmatrix}$

$$= \frac{f^4\mu_E^2\mu_B^2 + f^2\varepsilon^2\mu_B^2 - 2\beta f^2\mu_B^2 - 2\beta f^2\mu_E^2 - 2f^2\varepsilon\mu_B^2 + f^2\mu_B^2 - 2\beta\varepsilon^2 + 2\gamma\varepsilon^2 + 4\beta^2 + 4\beta\varepsilon - 2\gamma^2 - 2\gamma\varepsilon - 2\beta}{{\mu_E}^2 f^2 + \varepsilon^2 - 2\beta - 2\varepsilon + 1} > 0$$

Proposition A.3: *The optimal, profit-maximising choice of both retailers in the second scenario are derived as follows.*

***Proof*:** getting the first derivatives of $BR's$ profit function regarding the Z_{BR}^{BL}, p_{BR}^{BL} we got:

$$\frac{\partial \pi_{BR}^{BL}}{\partial Z_{BR}^{BL}} = (p_{BR}^{BL} - w)\mu_B f - Z_{BR}^{BL} + fk_B \quad \text{(A13)}$$

$$\frac{\partial \pi_{BR}^{BL}}{\partial p_{BR}^{BL}} = \varepsilon\alpha - \beta p_{BR}^{BL} - \sigma + 1 + \frac{\begin{gathered}\gamma(f^2 w\mu_E^2 - f^2 k_E\mu_E + \lambda\varepsilon^2 r - \lambda\varepsilon r + w\varepsilon^2 + \alpha\varepsilon_{\beta w} + f\mu_E - \gamma p_{BR}^{BL} - 2w\varepsilon - \alpha - \sigma + w) \\ + \varepsilon(f^2\lambda\varepsilon r\mu_E^2 + f^2\varepsilon k_E\mu_E - 2\beta\lambda\varepsilon r - f^2 k_E\mu_E - \alpha\varepsilon^2 w\beta\varepsilon - f\varepsilon\mu_E + \gamma\varepsilon p_{BR}^{BL} - 2\varepsilon\alpha - w\beta + \mu_E f - \gamma p_{BR}^{BL} + \sigma\varepsilon - \alpha - \sigma)\end{gathered}}{{\mu_E}^2 f^2 + \varepsilon^2 - 2\beta - 2\varepsilon + 1} \times \mu_B(1 - Z_{BR}^{BL}) f + (p_{BR}^{BL} - w) \times \left(-\beta + \frac{-\gamma^2 + \varepsilon(\gamma\varepsilon - \gamma)}{{\mu_E}^2 f^2 + \varepsilon^2 - 2\beta - 2\varepsilon + 1}\right. \quad \text{(A14)}$$

Solving the equations (A13–14) regarding Z_{BR}^{BL}, p_{BR}^{BL}, the optimal values gained as Equations (16–17).

Equation substitution:

In Equations 16, 17:

$$X1 = -w\left(-\beta + \frac{\gamma^2}{-{\mu_E}^2 f^2 - \varepsilon^2 + 2\beta + 2\varepsilon - 1} - \frac{\varepsilon(\varepsilon\gamma - \gamma)}{-{\mu_E}^2 f^2 - \varepsilon^2 + 2\beta + 2\varepsilon - 1}\right) + \alpha + \frac{\gamma(-f^2 w\mu_E^2 + f^2\mu_E - \lambda\varepsilon^2 r + r\lambda\varepsilon + w\varepsilon^2 + \beta w - \mu_E f + 2w\varepsilon + \alpha - w)}{-{\mu_E}^2 f^2 - \varepsilon^2 + 2\beta + 2\varepsilon - 1} - \frac{\varepsilon(f^2\lambda\varepsilon r{\mu_E}^2 + f^2\varepsilon k_E\mu_E - \beta w\varepsilon - f\varepsilon\mu_E + \alpha\varepsilon + \beta\varepsilon + \mu_E f - \alpha)}{-{\mu_E}^2 f^2 - \varepsilon^2 + 2\beta + 2\varepsilon - 1}\mu_B f$$

$$X2 = \left(-\beta + \frac{\gamma^2}{-\mu_E{}^2 f^2 - \varepsilon^2 + 2\beta + 2\varepsilon - 1} - \frac{\varepsilon(\varepsilon\gamma - \gamma)}{-\mu_E{}^2 f^2 - \varepsilon^2 + 2\beta + 2\varepsilon - 1}\right)$$

Equilibrium values of decision variables in the Stackelberg game with ER leadership

First of all, considering *BR* as the follower, the concavity condition of its profit value is investigated.

Lemma A.5: *The profit function of the BR shows concavity in* Z^{EL}_{BR}, p^{EL}_{BR}.

Proof: The profit function of $BR's$ hessian in Z^{EL}_{BR}, p^{EL}_{BR} is as follows.

$$H_{\pi^{EL}_{BR}(Z^{EL}_{BR}, p^{EL}_{BR})} = \begin{bmatrix} -2\beta & f\mu_B \\ f\mu_B & -1 \end{bmatrix} \tag{A15}$$

Since $(-2\beta) < 0$, the only condition for profit function of $BR's$ hessian to be concave is: $\begin{vmatrix} -2\beta & f\mu_B \\ f\mu_B & -1 \end{vmatrix} = -f^2\mu_B^2 + 2\beta > 0$

Proposition A.4: *The optimal value for the decision variables of BR in the third scenario are outlined as Equations (17–18).*

Proof**:** getting the first derivatives of $BR's$ profit function regarding the Z^{EL}_{BR}, p^{EL}_{BR} we got:

$$\frac{\partial \pi^{EL}_{BR}}{\partial\, Z^{EL}_{BR}} = (p^{EL}_{BR} - w)\mu_B f + fK_B - Z^{EL}_{BR} \tag{A16}$$

$$\frac{\partial \pi^{EL}_{BR}}{\partial\, p^{EL}_{BR}} = (\varepsilon\alpha + 1 - \sigma - \beta p^{EL}_{BR} + \gamma\, p^{EL}_{ER} + \varepsilon A^{EL} - (1 - Z^{EL}_{BR}) f\mu_B) - (p^{EL}_{BR} - w)\beta \tag{A17}$$

Solving Equations (A16–17) we got optimal values as Equations (18–19).

Lemma A.6: *The profit function of ER exhibits concavity in* A^{EL}, Z^{EL}_{ER}, p^{EL}_{ER}.

By substituting the optimal values as Equations (18–19) in ER's profit function as leader, the Hessian gained as below:

$$H_{\pi^{EL}_{ER}(A^{EL}, Z^{EL}_{ER}, p^{EL}_{ER})} = \begin{bmatrix} -2\beta - \dfrac{2\gamma^2}{f^2\mu_B^2 - 2\beta} & \dfrac{-\gamma\,\varepsilon}{f^2\mu_B^2 - 2\beta} + 1 - \varepsilon & f\mu_E \\ \dfrac{-\gamma\,\varepsilon}{f^2\mu_B^2 - 2\beta} + 1 - \varepsilon & -1 & 0 \\ f\mu_E & 0 & -1 \end{bmatrix} \tag{A18}$$

Since $\left|-2\beta - \frac{2\gamma^2}{f^2\mu_B^2 - 2\beta}\right| < 0$,

$$\begin{vmatrix} -2\beta - \frac{2\gamma^2}{f^2\mu_B^2 - 2\beta} & \frac{-\gamma\,\varepsilon}{f^2\mu_B^2 - 2\beta} + 1 - \varepsilon \\ \frac{-\gamma\,\varepsilon}{f^2\mu_B^2 - 2\beta} + 1 - \varepsilon & -1 \end{vmatrix} = \left(\frac{-\gamma\,\varepsilon}{f^2\mu_B^2 - 2\beta} + 1 - \varepsilon\right)^2$$

$\beta - 2 - \frac{2\gamma^2}{f^2\mu_B^2 - 2\beta} > 0$, the only condition for profit function of $ER's$ hessian to be concave is:

$$\begin{vmatrix} -2\beta - \dfrac{2\gamma^2}{f^2\mu_B^2 - 2\beta} & \dfrac{-\gamma\,\varepsilon}{f^2\mu_B^2 - 2\beta} + 1 - \varepsilon f\mu_E \\ \dfrac{-\gamma\,\varepsilon}{f^2\mu_B^2 - 2\beta} + 1 - \varepsilon & -1 & 0 \\ f\mu_E & 0 & -1 \end{vmatrix}$$

$$\begin{aligned} &= \frac{-1}{f^2\mu_B^2 - 2\beta}(f^6\mu_B^4\mu_E^2 + f^4\varepsilon^2\mu_B^4 - 2\beta f^4\mu_B^4 - 4\beta f^4\mu_B^2\mu_E^2 \\ &\quad - 2f^4\varepsilon\mu_B^4 + f^4\mu_B^4 - 4\beta f^2\mu_B^2\varepsilon^2 \\ &\quad + 2f^2\gamma\,\mu_B^2\varepsilon^2 + 8\beta^2 f^2\mu_B^2 + 4\beta^2 f^2\mu_E^2 + 8\beta f^2\varepsilon\mu_B^2 \\ &\quad - 2f^2\gamma^2\mu_B{}^2 - 2f^2\gamma\,\varepsilon\mu_B{}^2 - 4f^2\mu_B^2 + 4\beta^2\varepsilon^2 \\ &\quad - 4\beta\gamma\,\varepsilon^2 + \gamma^2\varepsilon^2 = 8\beta^3 - 8\beta^2\varepsilon \\ &\quad + 4\beta\gamma^2 + 4\beta\gamma\,\varepsilon + 4\beta^2) < 0. \end{aligned}$$

Proposition A.5: *For the third game variant, the optimal solutions for the decision variables are gained as Equations (19–21).*

Proof**:** getting the first derivatives of $ER's$ profit function regarding the A^{EL}, Z^{EL}_{ER}, p^{EL}_{ER} we got:

$$\frac{\partial \pi^{EL}_{ER}}{\partial A^{EL}} = (p^{EL}_{ER} - w)\left(\frac{-\gamma\,\varepsilon}{f^2\mu_B^2 - 2\beta} + 1 - \varepsilon\right) + r\lambda\varepsilon - A \tag{A19}$$

$$\frac{\partial \pi^{EL}_{ER}}{\partial Z^{EL}_{ER}} = (p^{EL}_{ER} - w)\mu_E f - Z^{EL}_{ER} + fk_E \tag{A20}$$

$$\begin{aligned} \frac{\partial \pi^{EL}_{ER}}{\partial p^{EL}_{ER}} &= (1 - \varepsilon)\alpha + \sigma - \beta p^{EL}_{ER} \\ &\quad + \frac{\gamma\,(f^2 w\mu_B^2 - f^2 k_B\mu_B - A\varepsilon - \varepsilon\alpha - w\beta + f\mu_B - \gamma\, p^{EL}_{ER} + \sigma - 1)}{f^2\mu_B^2 - 2\beta} \\ &\quad + (1 - \varepsilon)A - \mu_E(1 - Z^{EL}_{ER})f \\ &\quad + (p^{EL}_{ER} - w)\left(-\beta - \frac{\gamma^2}{f^2\mu_B^2 - 2\beta}\right) \end{aligned} \tag{A21}$$

Solving the equations (A19–21) regarding A^{EL}, Z^{EL}_{ER}, p^{EL}_{ER}, the optimal values gained as Equations (20, 21, and 22).

In Equations 20, 21, and 22:

$$Y1 = \left(\frac{\gamma\,\varepsilon}{-\mu_E{}^2 f^2 + 2\beta} + 1 - \varepsilon\right)$$

$$Y2 = w\left(\frac{\gamma\,\varepsilon}{-\mu_E{}^2 f^2 + 2\beta} + 1 - \varepsilon\right) + \lambda\varepsilon r$$

$$Y3 = (-w\left(-\beta + \frac{\gamma\,\varepsilon}{-\mu_E{}^2 f^2 + 2\beta}\right) + \alpha + \frac{\gamma\,(-f^2 w\mu_B^2 + f^2 k_B\mu_B + \beta w - f\mu_B + \alpha)}{-\mu_E{}^2 f^2 + 2\beta} - f\mu_E$$

$$Y4 = \left(-\beta + \frac{\gamma^2}{-\mu_E{}^2 f^2 + 2\beta}\right)$$