BLOCKCHAIN ENABLED DEMAND INFORMATION SHARING TO MITIGATE THE BULLWHIP EFFECT: AN AGENT-BASED MODELING AND SIMULATION

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Abstract - Supply chain inefficiencies often stem from distorted information when shared across supply chain echelons, resulting in amplified order quantities as one moves up the supply chain. This phenomenon is called the bullwhip effect which causes several challenges in the supply chain such as excessive inventory levels, exacerbated costs, and poor customer service. In this paper, we investigate how block chain technology characteristics could enhances transparent, secure, and immutable customer demand information sharing, thus mitigate the bullwhip effect. For this purpose, agent-based simulation approach is used to model a serial supply chain: customer, retailer, wholesaler, producer, and a supplier with heterogeneous lead times, safety stocks, and exponential smoothing factors. The proposed decentralized model reforms the sequential information sharing process in traditional supply chains and reduces information distortion through enabling full visibility of the same customer demand information by upstream echelons. The inherited features of block chain: decentralization, cryptography, smart contracts and information immutability shows the potential to mitigates the bullwhip effect and serves as an enabler in reshaping supply chain dynamics as the findings show.

Keywords – Block chain, Supply Chain, Information Sharing, Bullwhip Effect, Agent-Based Modeling, Decentralization, Inter-organizational Coordination, Simulation.

I. INTRODUCTION

Supply chain management (SCM) has gained more interest since the mid-1990s in both academia and industry. A supply chain includes different organizations that attempt to achieve the highest level of customer service at the lowest costs (Chopra et al. 2016). The traditional supply chain (TSC), first coined by Keith Olive (1982), typically operates in a sequential manner where each echelon works independently (David, 2009). Therefore, lack of coordination, sharing distorted demand information, uncertainty and duplication of demand forecasting, emphasizing the individual optimization are the main challenges of TSC. The bullwhip effect (BWE) is a well-known inefficient consequence of such challenges in which small fluctuations in customer demand result in larger variations in orders placed further up the supply chain. Excessive inventory levels, poor customer service, challenges in production planning and scheduling, increased costs in production, transportation, and inventory carrying are some of the negative consequences caused by the BWE (Lee et al. 1997; Costantino et al. 2015). As stated by Lee et al. (1997), the BWE can be attributed to four operational causes: demand signal processing, rationing game, order batching, and price fluctuations.

Researchers have come up with several ways to overcome the BWE, including supply chain contracts (Pagnozzi and Saral 2021) joint decision making (Gualandris et al. 2021), and information sharing (IS) (Wang et al. 2021; and Ma et al. 2021).Apparently, IS was found to be the most significant coordination mechanism to mitigate the BWE (Wang and Disney 2016). Additionally, the advancement of information technology (IT) is crucial to facilitate inter-organizational coordination among supply chain echelons to stay competitive in the marketplace (Sahay and Ranjan 2008). Disruptive technologies such as artificial intelligence (AI), the Internet of Things (IoT), big data, and blockchain (BC) are the main technologies that are reforming Industry 4.0. Recently, blockchain technology (BCT) gained intensive attention after the new peer-to-peer financial trading system of the cryptocurrency, Bitcoin, which was introduced by Satoshi Nakamoto in 2008. Furthermore, BCT has the potential to be a remedy for trust and visibility issues among supply chain echelons due to several inherited features such as decentralization, data validation, immutability, and transparent IS (Omar et al. 2021). Therefore, BCT is considered as a source reality, truth, and real-time information detection (Xu et al. 2019; Chen et al. 2020). In this regard, this paper aims to investigate the impact of demand IS-viaBTC on the mitigation of the BWE with respect to IS structure and coordinated operations planning. In the following, a brief literature review is introduced of agent-based modeling in supply chainmanagement and BC in supply chain management. Section 3 represents the agent-based simulation model. Section 4 shows the simulation results. Section 5 discusses the implications and further research, followed by the conclusion section.

II. LITERATURE REVIEW

Agent based modeling and SCM

Agent-based modeling (ABM) is an intelligent approach used to simulate and investigate complex

systems by modeling individual interactions in a given environment (Tang and Pan 2014; Pour et al. 2018). An agent represents an autonomous entity capable of making decisions and interacting with different entities based on predefined behaviors (North and Macal 2007). ABM has been used in different supply chain areas, such as inventory management, procurement, scheduling, and production (Caridi and Cavalieri 2004). Additionally, ABM provides a bottom-up perspective, i.e., it enables the investigation of system behavior resulting from individual interactions (Gilbert and Troitzsch 2005). Several papers use ABM to address various challenges in supply chain management. Particularly, Fu and Xing (2021) proposed a model combining an evolutionary algorithm and ABM to resolve resource conflicts in a project-driven supply chain under decentralized decision-making and information asymmetry. Min and Bjornsson (2008) investigated the importance of real-time IS in the construction supply chain using ABM. Hsu et al. (2016) introduce a new negotiation model using autonomous and interactive agents and fuzzy preference functions to achieve a mutually beneficial agreement. Fu-ren et al. (2002) employed ABM to simulate the information-sharing correlation between a buyer and a seller. The results show that IS increases order fulfillment rates and reduces order cycle time and demand uncertainty. Moreover, Zhu (2008) used ABM to study the impact of horizontal and vertical IS among customers and among suppliers.

Blockchain technology and SCM

BTC is a distributed and decentralized database that securely stores and transfers data through blocks that are chained together with cryptographic technology (Zachariadis et al. 2019). The transactions are recorded in the blocks after being validated by the network nodes through a consensus algorithm that prevents any change or alteration of the recorded data. The main idea of BTC is allowing the nodes to transact information in a peer-to-peer network that stores the information in a distributed manner (Ølnes et al. 2017). BTC consists of three main technologies: consensus algorithms, smart contracts, and cryptography. Consensus algorithms such as proof of work (POW) and proof of stake (POS) are responsible for transaction validity and ownership proof of all nodes (Feng et al. 2020). On the other hand, smart contracts are self-executing contracts written in codes that are responsible for transaction execution when specific terms and conditions are met without the need for a central authority (Tanwar et al. 2020). While cryptography plays a crucial role in terms of creating encrypted public keys and hash functions (Wang et al. 2019), The public key, an asymmetrical encryption method, verifies the identities of participants within the BC network (Lopez and Farooq 2020). While the hash function converts incoming data into a compact output of fixed length, which supports the consistency, authenticity, and unchangeable nature of the distributed data ledger (Maesa and Mori 2020).

As stated by Gourisetti et al. (2020), BTC has three main types: public, private, and consortium blockchains. Public blockchains allow anyone to participate in the network and allow for decentralized transactions (Nakamoto 2008). On the other hand, private blockchains are exclusive and only accessible to authorized participants (Wüst and Gervais 2017). While consortium blockchains are a combination of public and private blockchains where certain users have permission to participate in the network in certain areas (Qiao et al. 2018). Several research studies have investigated the implementation of BTC in the supply chain field. Pardis and Yoon's (2020) examined how BTC fosters a trust-enhanced environment within the construction supply chain. They emphasize the distributed trust capabilities of BTC, which promise substantial benefits to the sector. Their findings underscore the potential for enhanced transparency and reliability in supply chain processes. Treiblmaier's (2018) introduces a comprehensive framework based on established economic theories like agent theory, transaction cost analysis, resource-based view, and network theory. This framework serves as a foundational guide for exploring the impact of BTC on supply chain management practices. Pour et al. (2018) examined the application of BCT in governing sand supply. Their focus lies in developing a governance framework that utilizes BTC to regulate sand extraction and trade. Longo et al. (2019) demonstrate that adopting BTC technology to share accurate information with suppliers can result in significant economic and operational benefits while minimizing the negative consequences of information asymmetry.

III. RESEARCH DESIGN

This study proposes an ABM approach to investigate the impact of demand IS-based BTC on the mitigation of the BWE. Two IS scenarios are considered, i.e., no IS (NIS) and customer demand ISvia BTC (CDIS-BTC). The purpose of BTC adoption is to redesign the process of sharing information as a new remedy to mitigate the BWE effect and enhance trust and visibility related issues among supply chain echelons. The BWE is the main performance metric that is calculated by the order variance ratio (OVR) which represents the variance of orders placed by echelon to its provider divided by the variance of echelon i customer demand. To perform the mathematical modeling, we adopted the assumptions that have been used in the literature (Sterman1989; Dejonchheere et al. 2004; Ciancimino et al. 2012; Costantino et al. 2015; Jeong and Hong 2019). NetLogo 6.3.0 software is used for modeling and simulation (Wilensky1999).

In this model, we considered a serial supply chain structure consisting of a customer (i=0), a retailer (i=1), a wholesaler (i=2), a producer (i=3) and a supplier (i=4). For investigating the BWE mitigation, the model assumes a single product which is commonly used in supply chain analysis. The customer demand is normally distributed. The supply chain echelons use an order-up-to policy (OUT) to manage their inventory. Exponential smoothing is used by all supply chain echelons for demand forecasting. Heterogeneity is considered for all echelons with different safety stock factor (ε), delivery lead time (Ld) and smoothing factor (α). The unfulfilled orders at any echelon are not lost but they become backlogs. Finally, the supply chain echelons have unconstrained capacity, while a nonnegative condition for order quantity is assumed, i.e., the products delivered to downstream echelons can't be returned to the supplier.

Following the supply chain model presented in (Sterman 1989; Chatfield et al. 2004; Ciancimino et al. 2012), each echelon i in any period$t$receives shipment (SR_t^i) from one step upstream echelon ($i+1$)which is calculated as the minimum value of demand considering the backlogs and the on-hand inventory after upstream delivery of the product as shown in Eq. (1).Then,echelon $i$fulfills the incoming orders from its on-hand-inventory (I_t^i) which is calculatedby adding the initial on-hand inventory to the orders quantity that is released from upstream echelon, ($SR_{t-Ld_i}^{i+1}$), and subtracts the orders quantity that is delivered to downstream echelon, (SR_t^i), shown in Eq. (2). Theunfulfilled order is backlogged (B_t^i)which is presented as the initial backlog plus the orders or demand form downstream echelon(O_t^i) and the shipment received from upstream echelon(SR_t^i)as in Eq. (3). After that, the echelon$i$update its work-in-progress inventory (WiP_t^i)which is calculated by the initial work-in-progress plus the shipments sent by upstream echelonattime $t(SR_t^{i+1})$ minus the shipments sent by upstream echelon($SR_{t-Ld_i}^{i+1}$) attime$t-Ld$, as shown in Eq. (4).Then, echelon $i$forecast the demand($\widehat{D}_t^i$)in which the demand received by retailer $(i=1)$in period t is the actual customer demand(D_t) as shown in Eq. (5). However, the demand received by upstream echelons $(i>1)$ is the order quantity placed one stage downstream (O_t^{i-1}), shown in Eq. (6). Eq. (7) and (8), define the target ($TWiP_t^i$) which considers the lead time (Ld_i)and demand forecast ($\widehat{D}_t^i$),and the target inventory level (TI_t^i)which considers the safety stock factor (ε_i)and demand forecast ($\widehat{D}_t^i$). Accordingly, echelon $i$places an order (O_t^i) to echelon $(i+1)$with an order interval of (R =1)at the end of each review periodwhich is calculated by the forecasted demand plus the difference between the target work-in-progress and the current work-in-progress and the difference between target inventory level and the current inventory level as in Eq (9).

$$SR_t^i = min\left\{O_t^i + B_{t-1}^i;\ I_{t-1}^i + SR_{t-Ld_i}^{i+1}\right\} \quad (1)$$

$$I_t^i = I_{t-1}^i + SR_{t-Ld_i}^{i+1} - SR_t^i \quad (2)$$

$$B_t^i = B_{t-1}^i + O_t^i - SR_t^i \quad (3)$$

$$WiP_t^i = WiP_{t-1}^i + SR_t^{i+1} - SR_{t-Ld_i}^{i+1} \quad (4)$$

Eq. (10) and Eq. (11) represent thenon-negative constrain for orders and the unlimited raw materials for supplier, respectively. Finally,Eq. (12) introduce the calculation of the BWE which is the variance of orders placed by echelon$i$to its provider ($\sigma_{O_i}^2$)relative to the variance of echelon i customer demand (σ_D^2) (Chen et al. 2000).

$$\widehat{D}_t^{i=1} = \alpha\, D_t + (1-a)\widehat{D}_{t-1}^{i=1}, \text{for}(i=1) \quad (5)$$

$$\widehat{D}_t^i = \alpha\, O_t^{i-1} + (1-\alpha)\widehat{D}_{t-1}^i, \text{ for } (i>1) \quad (6)$$

$$TWiP_t^i = Ld_i\widehat{D}_t^i \quad (7)$$

$$TI_t^i = \varepsilon_i\widehat{D}_t^i \quad (8)$$

$$O_t^i = \widehat{D}_t^i + \left(TWiP_t^i - WiP_t^i\right) + \left(TI_t^i - I_t^i\right) \quad (9)$$

$$O_t^i \geq 0 \quad (10)$$

$$SR_t^i = O_t^i, \text{ for } (i=4) \quad (11)$$

$$OVR_i = \frac{\sigma_{O_i}^2}{\sigma_D^2} \quad (12)$$

IV. SIMULATION RESULTS

We carried out simulation under two scenarios: 1) NIS2) customer demand IS via BTC(CDIS-BTC). The order policy follows equation (1) through (9), with different smoothing factor (α), lead time(Ld) and safety stock(ε) for eachechelon which have been generated randomly using R programming language(see table I).The model assumes that the decisions are made weekly, and lead-time is measured in weeks (Streman, 1989). We ran each simulation 500 weeks to represent the supply chain operation in a 10-year period. Each scenario is based ten repeated runs with random initialization seeds.

Parameters	Retailer	Wholesale	Producer	Supplier
Smoothing factor (α)	0.742	0.47	0.291	-
Lead time (Ld)	3	4	1	3
Safety stock factor (ε)	1	4	4	-

Table I. Simulation Parameters for each echelon

1) No Information Sharing - Traditional supply chain

In a traditional SC each echelon has its own ledger, and the information flow follows a sequential, linear manner among supply chain echelons (see Figure 1).

As Figure 1 shows, each echelon typically shares orders information directly with the immediate next entity in the supply chain. This sequential sharing is often centralized, relies on trust between parties, and can lead to information silos or limited visibility into the overall supply chain. Therefore, in this case, the retailer is the only echelon who has access to the customer demand information (see Eq. (5)). On the other hand, the upstream echelons don't have full access and visibility to the end customer's demand. As a result, they rely on the order received from the downstream echelon to forecast the demand (see Eq. (6)) and manage their inventory. Particularly, in each period t, the retailer ($i = 1$) receives customers demand (D_t) and fulfils it from its on-hand-inventory and then issues an order (O_t^i) to the respective wholesaler ($i = 2$)at the beginning of period t according to its current inventory level. The producer($i = 3$) then gets an order from the wholesaler. The producer's places an order to the supplier($i = 4$) which is later received aftera lead time (Ld).

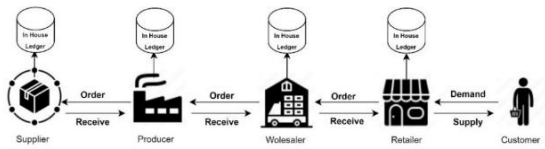


Figure 1.Information flow in traditional supply chain

In order to investigate the BWE occurrence in the first scenario, we calculated the order variance ratio for the retailer, wholesaler, and producer(see Figure 2).

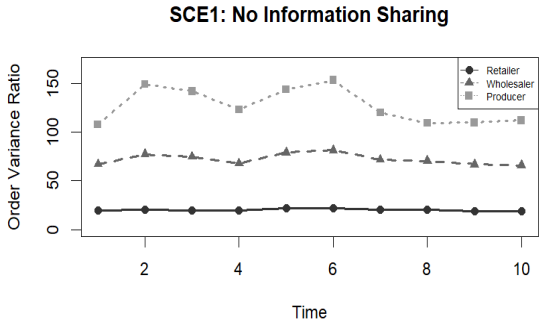


Figure. 2. The order variance ration for SC echelons with NIS

Figure 2 shows the order variance ratios of the retailer, wholesaler and the producer with NIS. As can be seen, the order variance ratio amplifies as one moves from retailer upstream to wholesaler and producer with time. Particularly, the retailer order variance ratio is relatively stable. On the other hand, wholesaler and producer order variances realize greater fluctuations. Therefore, a strong BWE effect is present in this supply chain as no information is shared. That's to say, upstream echelons have no excess or full visibility of customer demand information, which results in fluctuations in demand and order quantity that increase substantially.

Time	OVR.R	OVR.W	OVR.P
1	19.93707	66.90601	107.696
2	20.61015	77.39321	149.0072
3	19.6183	74.59651	141.7656
4	19.47578	67.82925	122.9644
5	21.69258	79.02905	143.5222
6	21.71001	81.40133	153.0394
7	20.45271	71.76943	119.8891
8	20.74564	70.30994	109.2064
9	19.22147	66.7964	109.7791
10	18.59378	65.83941	111.8771
AVG	**20.26575**	**73.187054**	**117.87466**

Table II The Order Variance Ratio with NIS

In Table II, the average order variance ratios (OVR) across the supply chain levels provide insights into the BWE. The calculated averages reveal a progressively increasing trend in variability amplification from the retailer to the wholesaler and further to the producer. With an average OVR of approximately 20.27 at the retailer level, there's a relatively lower degree of variability amplification. However, at the wholesaler level, the average OVR of around 73.19 indicates a notable increase in variability. The producer level displays the highest average OVR at approximately 117.87, indicating a substantial amplification of variability from the wholesaler to the producer, likely caused by information delays and intensifying demand distortions as orders progress upstream in the supply chain. The increasing OVR values from the retailer to the wholesaler and further to the producer suggest that small fluctuations in actual demand at the consumer level are being magnified as they move upstream, leading to larger swings in orders which cause the BWE occurrence.

2) Demand Information sharing -BC-based supply chain

In this scenario, a decentralized IS structure is applied using the distinct features of BTC: distributed ledger, smart contracts, cryptography, and consensus algorithms. The proposed model involves four supply chain echelons that collaborate by sharing customer demand information (CDI). All echelons are assumed to use permissioned BTC and smart contracts for managing orders (Hyperledger 2022). This means, access is only open to echelons authorized as a part of the SC. The advantages of implementingBCT over the traditionalsupply chain is the visibility ofCDI and immutability across supply chain echelons. Additionally, BCT as a shared and public ledger, enables all supply chain echelons to access the same customer demand information and enhances the

transparency, security, efficiency, immutability, and trust among supply chain echelons. Relying on BCT features,CDI become accessible and not subject to any tampering which greatly resolves the problem of information asymmetry as a main cause of the BWE occurrence (see Figure 3).

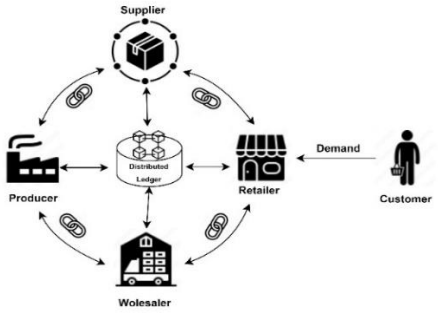


Figure 3. Information flow inBCT-based supply chain

Figure 3 illustrates the flow of information in BTC - based supply chain. In this scenario, the retailer receives the demand from the end customer. He shares the CDI with other upstream echelons in the BC network. Upstream echelons use such information to manage their inventories and forecast the demand, which is made public by using BCT. Comparing with the base scenario (NIS), the same equations (1)-(9) are used except for Eq. (6). In other words, instead of suing Eq. (6), the upstream echelons calculate their order-up-to level and forecast the demand using Eq. (13) relying on the mean and variance of actual customer demand information rather than the mean and variance of retailer orders.Eq. (13)consist of CDI that have been shared by retailer on BTC network and the upstream initial demand forecast. That's to say,the retailer orders are the actual customer demand when uploaded and verified in BC network. To illustrate the process of sharing CDI via blockchain technology, Figure 4 highlights the implementation of BTC features and how they redesign the information flow in traditional supply chain.

$$\hat{d}_t^i = \alpha D_t + (1-\alpha)\widehat{D}_{t-1}^i \, , for \; i > 1 \qquad (13)$$

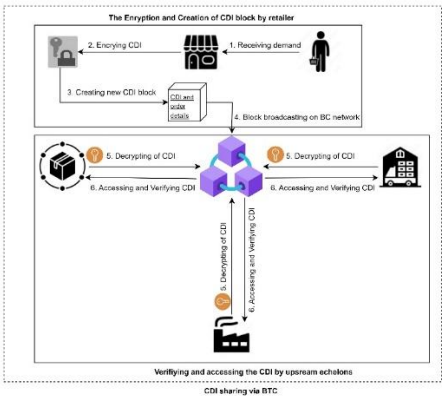


Figure 4.Customer demand information sharing process via BCT.

Figure 4 shows the proposed working process of sharing DIS via BCT which occurred in the seven steps in order to add the new block (transaction) in BTC network as follows

Step 1: The retailer receives the CDI in time t.

Step 2: The retailer encryptsthe CDI using encryption algorithm.

Step 3: Once the CDI encrypted, the retailer creates new transaction as block including CDI and order details.

Step 4: The CDI broadcasted on BC network which can be seen by upstream echelons.

Step 5: Upstream echelons use the retailer'sencryption key to decrypt CDI.

Step 6: Once the CDI block decrypted by upstream echelons, they access and verify the authenticity and reliability of CDI.

Step 7: All supply chain echelons have access to the same CDI which is permanent and unchangeable record.

To investigate how BTC via sharing CDI might mitigate the BWE we also caluclaue the order variance ratio for the retailer, wholesaler and producer (see Figure 5).

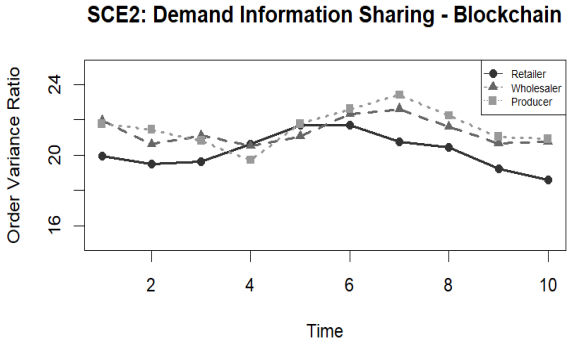


Figure 5. OVR for all echelons in BCT-based CDIS

In Figure 5, we can notice the reduction of order variance ratio for upstream echelons. In other words, the BWE is reduced significantly when the retailer shares CDI with upstream echelons after implementing the BCT. Comparing both scenarios, scenario 1 (NIS), a significant BWE is occurred with considerably higher average OVRs at the wholesaler and producer levels, indicating substantial variability amplification and supply chain inefficiencies. In contrast, Scenario 2, (CDIS-BCT), exhibits lower average OVRs across all levels, suggesting a notable stabilization and potential mitigation of the BWE, particularly evident in reduced variability amplification across upstream echelons.

In other words, the BWE mitigation becomes more pronounced as one moves upstream towards the producer which agrees with previous literature results (Dominguez et al. 2021; Jeong and Hong 2019; Shaban et al. 2020; Cannella et al. 2015).

Time	OVR.R	OVR.W	ORV.P
1	19.93707	21.94821	21.76315
2	19.47578	20.61491	21.43782
3	19.6183	21.08843	20.79927
4	20.61015	20.51726	19.70828
5	21.71001	21.06332	21.76647
6	21.69258	22.3149	22.61195
7	20.74564	22.61329	23.40033
8	20.45271	21.59896	22.23036
9	19.22147	20.6715	21.03533
10	18.59378	20.75632	20.91831
AVG	**20.20574**	**21.31870**	**21.56712**

Table III The Order Variance Ratio With CDIS-BCT

Table III shows the OVR after implementing BCT. After implementing BTC for sharing CDI, the average OVRs across the supply chain levels show a different picture.As shown, the average order variance ratios depict a notable stabilization and potential mitigation of the BWE. At the retailer level, the average OVR remains consistent at around 20.21, indicating sustained minimal variability amplification due to improved Information flow structure. Moreover, the average OVRs of the wholesaler and the producer exhibit a significant reduction of approximate 21,32 and 21,57 respectively. That means, the implementation of BTC appears to have positively influenced the supply chain performance in terms of the BWE mitigation. Additionally, better synchronization and distortion reduction in CDI is appeared resulting in slightly controlled variability amplification, particularly evident at the wholesaler level and the producer. Overall, the adoption of BTC demonstrates promising strides in controlling the BWE.

V. CONCLUSION

An agent-based modeling approach is developed to investigate how CDI-based BCT influence the mitigation of the BWE with the focus on IS visibility and accessibility in the whole supply chain. Two scenarios have been considered: NIS and CDI sharing via BCT. The BWE is measured using the order variance ratio for the retailer, wholesaler, and producer in both scenarios. To improve the IS flow, we adopted a permissioned BC is a serial supply chain configuration. The simulation results show that CDI via BTC has clear advantage on BWE mitigation in comparison with NIS. This attributed to the distinct features of the BTC as an enabler to improve CDI for upstream echelons and improve the overall supply chain performance. Additionally, accessing CDI by upstream echelons reduces the BWE significantlyas the numerical results show with greater order variance ratio reduction for upstream echelons (the wholesaler and the producer). In conclusion, CDIvia BTC has improved in SC which results in BWE reduction. However, this model can be extended to involve different SC configurationother than serial one. In addition, a comparison between bi-lateral and uni-lateralIS and how this could affect the BWE via BTC could be a future research venue as well.

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