MWAIS 2022 Proceedings

Midwest (MWAIS)

5-5-2022

Smart-Contract Enabled Blockchains for the Control of Supply Chain Order Variance

Corban Allenbrand
University of Kansas, callenbrand@ku.edu

Smart-Contract Enabled Consortium Blockchains for the Control of Supply Chain Information Distortion

Corban Allenbrand
University of Kansas, School of Business
callenbrand@ku.du

ABSTRACT

Conflicts between supply chain members emerge because individually strategic actions may not be jointly optimal. Efforts to forecast consumer demand represents a source of conflict. Coordination of forecasts requires a powerful incentive alignment approach. This work proposes a smart-contract equipped consortium blockchain system that creates an incentive structure which makes coordination with respect to forecasts economically appealing. Distortions of demand information due to uncoordinated forecasting is captured by a bullwhip measure which factors both forecast error and variance. Cooperation under the system is shown to help minimize this bullwhip measure thus generating new outcomes to the participants that allow for a higher reward. Under a fixed payout structure, the system achieves credibility of continued cooperation thus promoting an optimal coordinated equilibrium between retailer and supplier. Blockchain technology represents a novel information system and consensus formation mechanism which can intermediate the behavior of a supply chain network.

Keywords

Blockchain; blockchain applications; smart contract; bullwhip effect; supply chain coordination

INTRODUCTION AND BACKGROUND

A supply chain has been defined as a set of entities directly involved in the upstream and downstream flows and processing of products, services, finance, and/or information (Mentzer et al., 2001). If the supply chain is to achieve some sense of optimality, actions must be coordinated and knowable (Flynn et al., 2010). Conflict plays a prominent role in supply network optimization. Mitigation of the conflict, however, is non-trivial even if the entire network can be regarded as sharing some clear global objective. At both an abstract and practical level, the supply chain coordination problem is a multi-participant joint group decision problem in which participants base their decisions on different information, different assessments of random quantities, different decision possibilities, but motivated by the common goal. Numerous actions are embedded within this group decision problem - what product to sell, how to replenish inventory, what transportation routes are to be taken, etc. - but this paper focuses on one, the forecasting of future demand. Demand forecasting is firmly established for the simple fact that a business can be easily out competed by a competitor who acquires knowledge, albeit imperfect, of the future through the efforts of forecasting (Aviv, 2002). Forecasting future demand is also known to engender problems in the supply chain - demand variance amplification and information distortion (Lee, 1997). This distortion of demand information, referred to as the bullwhip effect, has been characterized and examined with several arguments for its cause (Chen et al., 2000; Bray and Mendelson, 2012). A question remains is if there is an arrangement that would permit demand forecasting without compromising attempts at coordination. This arrangement must accomplish the alignment of individual motivations with the system's objective, improvement in how information is obtained and shared, offer tools to verify actions conducted by participants so trust can be enhanced, and the rules of the arrangement must be managed. Existence of some information system would alleviate the coordination burden. One such system that can introduce coordination during demand forecasting is a blockchain.

Blockchain technology garners attention in the public because of its many unique technological characteristics. It is, by design, a multi-user system capable of continuous, non-centrally governed interactions. Core to its capabilities is its support for the creation and management of autonomous, collaborative, and interoperable services by every user of the system (Risius and Spohrer, 2017). Blockchain systems are decomposed into several layers. One such layer provides a platform to deploy autonomous control programs that automatically execute actions. These programs are known as smart contracts and run on top of the blockchain architecture (Glaser, 2017). Blockchain networks may be public, private, or consortium. Public blockchains are permissionless in that any user can transact on the network. Many cryptocurrencies rely upon this architecture (Kroll et al., 2013). Private and consortium blockchains introduce permissions where particular users are granted capabilities over network operations (Casino et al., 2019). Consortium blockchains impart a greater degree of trust and stability which can allow improved transaction speeds and integrity (Polge et al., 2020). Additional attractive features are that all users are identifiable, trusted, and ownership of the data is joint. The consortium would need to reach consensus on rules such as the details on future demand forecasting, how participation is compensated, and how non-participation is penalized. Although agreeing to participate in the consortium, each member cannot be assumed to be devoid of any self-interested motivations. It is the fundamental purpose of the blockchain system to induce the self-interested actors to behave as a coordinated group. Game theoretical modeling provides analysis tools, in the form of established game patterns and theory, that can discover predictable patterns that participants in a blockchain supply network may display

This paper formulates a smart-contract enabled blockchain system which targets the resolution of demand information distortion induced by demand signal processing by a retailer and supplier. At the heart of the problem is the conflict experienced between the supplier and retailer regarding their short-term objectives and the need to present incentives to both parties to cooperate as would a team with a single objective. Non-cooperative dynamic game theory was employed to analytically show how a blockchain system can constrain supplier and retailer to commit to the group-level objective. This paper is the first, to the knowledge of the author, to propose a blockchain system for dealing with the problem of demand signal processing induced order variance. The rest of the paper is organized as follows: a review of past literature pertaining to the streams of research called on in this paper is conducted, a description of the supply chain model and demand process is given, an overview of the blockchain architecture is provided, a formulation of the multi-level game executed by the retailer and supplier during blockchain running is presented, and a final conclusion is delivered.

LITERATURE REVIEW

Evidence of the impact of inventory decisions by retailers on order variance at suppliers has been well-documented in many industries including in the commercial operations of HP, Proctor & Gamble, and clothing suppliers (Lee et al., 1997). Lee et al. were the first to analytically define and characterize five major forces that contribute to the distortion of order variance moving up a supply chain including the forecasting of future demand. Part of the challenge of quantifying this impact is in the choice of the process generating demand and the equation-based tools to predict its future behavior. Several authors have looked into this problem: Chen et al. (2000) investigate the effect of exponential smoothing and moving average forecasting on the bullwhip when demand follows an autoregressive process , Xu et al. (2001) conducted similar analysis but with a combined exponential smoothing moving average forecast method , the effect of lead time and various forecasting methods on the bullwhip in a simple inventory system was explored by Zhang (2004), Disney et al. (2006) used a control systems approach to quantify the bullwhip under an order-up-to inventory policy and independently and identically distributed autoregressive and moving average demand processes. This paper shows that a blockchain based system of verification and control can ameliorate the repercussions of demand forecasting when demand is assumed to follow a first-order autoregressive AR(1) process.

Supply chain coordination is achievable with several mechanisms including with contracts. Cachon (2003) reviewed many of the contractual methods such as buy-back, revenue sharing, and quantity in the setting of a newsvendor model. This author views the coordination problem as one of a group decision problem under interpersonal conflict. Conflict here is just the presence of certain aspects of the retailer and supplier’s preferences which constrain the joint optimization over the retailer-supplier group system. What is considered acceptable for the group then must accommodate the differences in concern for different dimensions of the problem. The empirical influence of conflict on the quality of the group’s decision making ability was investigated by Bower (1965) where it was shown that conflict plays a dual role in the decision making process, it can stimulate the search and analysis of alternatives but hampers obtaining agreement. Before a coordinative amalgamation of the retailer and supplier’s decision problems can be done, conflict must be properly handled. Bower (1973) argued that a more accurate analysis of group decision making under conflict is accomplished if the behavior of group members is analyzed in terms of the compensation they receive from participating in it. Three properties of a reward-scheme were deemed important: compensation for a member must not be affected by non-optimal behavior of another, optimally and non-optimally performing members must be distinguishable, no single decision maker must be expected to have complete information of the others. This paper uses a unique feature of blockchain technology, automated intermediation through smart contracts, to formulate an incentive structure between retailer and supplier that does not ignore the tension between the members.

A central concern when devising blockchain systems is the attractiveness and robustness of the proposed system. For this paper, this comes down to the question of if the system can attract participation of the retailer and supplier and it will remain intact once the two parties interact. Game theory supplies a rich mathematical toolkit useful to tackle these questions. Applications of game theory to public blockchains, with an intense focus on cryptocurrencies, has been conducted by previous authors. Security issues such as denial-of-service attacks and risk management issues such double-spending have been investigated with game-theoretical models where rich game dynamics, equilibrium strategies, and incentives were discovered (Feng et al., 2018; Johnson et al., 2014). Resource management and cheating issues including optimal-pricing, transaction fees, and network infiltration were found to be amenable to game-theoretical modeling (Xiong et al., 2018; Asgaonkkar and Krishnamachari, 2019; Eyal, 2015). Cooperation enforcement and prevention of exploitation attempts were found with game-theoretical modeling and the use of zero-determinant strategies (Miao and Li, 2017; Zhen et al., 2017). Market stability, participation continuity, and other economic considerations of Bitcoin were modeled with game theory (Easley et al., 2019). This work proposes three levels of game theory analysis to elucidate the advantage a blockchain system provides to the costly problem of order variance disturbance due to demand signal processing.

CONTRIBUTIONS OF THE WORK

A first contribution of this work is to the area of blockchain and its applications. Although recognized by their many fascinating properties, the value and usefulness of blockchains to applied settings is poorly constrained (Casino et al., 2019). This paper is the first to characterize how such an information and technological system can be used to address a fundamental problem in all supply chain networks, distortion of information due to uncoordinated efforts at forecasting customer demand. It does so by establishing a customizable template for a multi-function smart-contract enabled blockchain that is designed to introduce incentives that encourage coordination of forecasting efforts. A second contribution, related to the first, is to the fields of management science and information systems. Information that is poorly managed or employed yields poor outcomes for decision makers (Bower, 1965). From the properties of blockchain systems, this paper is the first to demonstrate with analytical modeling how the structure of a smart-contract enabled blockchain can install the conditions necessary for better use of demand information coming from forecasting activities. To accomplish this, outcomes from the interactions of a retailer and supplier before and after a blockchain system is implemented are compared and it is shown how the new system can introduce more favorable outcomes to both actors. Although attention is dedicated to the supply chain setting, results can be extended to other interaction environments with reasonable modifications.

A MODEL OF THE SUPPLY CHAIN AND DEMAND PROCESS

The purpose of this section is to introduce a representations of the decision elements used by supply network agents. Decisions reached by each party are dependent on individually forecasted customer demand. Like many forecasts, these are assumed to be made with non-zero error. It is further supposed that the errors occur with variability so that the errors themselves can be regarded as stochastic. Taken together, forecast errors and their corresponding variances are shown to contribute to the bullwhip measure which quantifies the extent to which the demand information originating from the customer is distorted as it travels from retailer to supplier. Results and expressions from this section are then carried over into the subsequent sections.

Supply Chain Model

In this work, the supply chain is structured as a two-stage system with one retailer and one supplier. This choice is general and was made in order to provide a more tractable view of supply network dynamics. It is assumed that the retailer follows an order-up-to (OUT) level replenishment policy with a fixed order lead time (L). Timing of events is as follows: retailer receives order ordered made L periods in past, demand (d_t) is realized for the current period, inventory is reviewed, and then an order quantity (q_t) is placed with the supplier. According to the replenishment policy, the OUT level at time t, S_t is given by

$$S_t = S_{t-1} - d_t + q_t \tag{1}$$

Which can be rearranged to give the order quantity requested to the supplier

$$q_t = S_t - S_{t-1} + d_t \tag{2}$$

A retailer's task is to determine the optimal S_t. In this paper, it is assumed the retailer determines S_t by a linear combination of its prediction of future demand realization over L periods and dispersion of the demand forecast error as,

$$S_t = \widehat{D}_t^L + z\sigma_t^L \tag{3}$$

where $\widehat{D}_t^L$ is the prediction of demand accrued over L periods $D_t^L = \sum_{i=0}^{L} d_{t+i}$, z denotes the normal z-score determined based on the retailer's desired service level, and σ_t^L is the sample standard deviation of the demand forecast error $D_t^L - \widehat{D}_t^L$. Thus, ordering is influenced by the prediction of the actual demand process, its errors, and the spread of the error. If we combine (2) and (3) the order quantity retailer transmits to the supplier at end of period t is,

$$q_t = \widehat{D}_t^L - \widehat{D}_t^{L-1} + z(\hat{\sigma}_t^L - \hat{\sigma}_t^{L-1}) + d_t \tag{4}$$

Observe that if the variance of demand forecast error did not depend on the time index, the third term of (4) becomes zero. We are assuming process is stationary and so factors causing prediction error would not depend explicitly on time, just the length of time between time of prediction and time of realization. Thus, for fixed L, $\hat{\sigma}_t^L - \hat{\sigma}_t^{L-1}$ is set to zero.

The supplier's decision is simplified down to a one-dimensional problem, that of selecting production capacity. This simplification is made in order to focus on the mechanism through which a blockchain can modify the cost structure. A capacity cost function is introduced to guide the supplier's decision,

$$c(x) = c_0 + c_k x \tag{5}$$

where x denotes the quantity to be manufactured in a period, c_0 is fixed costs associated with capacity investment, and c_k is the marginal cost for additional capacity investment. It is assumed in this work that the supplier does not hold a finished goods inventory. This is consistent with just-in-time production which aims at improving system response time. The supplier in this model actively attempts to predict future demand for the retailer to level out its production. The supplier may implement two types of strategies: a flexible strategy which invests in excess capacity so all fluctuations in the retailer's orders are processed or an inflexible strategy that delays production of excess fluctuations of orders until the next period. The first strategy is beneficial for the retailer who gets its orders fulfilled but introduces costs to the supplier when production is idle or capacity investment is high. The second strategy introduces shortages on the retailer thus harming customer service level. Avoidance of running out of capacity is the retailer's preference whereas avoidance of excess or deficient capacity is the supplier's preference. It is assumed that bringing additional capacity online is exorbitantly costly and is avoided. Both retailer and supplier would prefer a supplier's capacity investment to perfectly correlate with the order quantity of the retailer, this way, risks to both parties are controlled. If a retailer's orders fluctuate wildly, however, it is not practical to expect the supplier to accurately predict this behavior. Instead, what is desired is a smooth order pattern submitted by the retailer which improves the predictability of optimal capacity.

Demand Process Model

If a retailer assumes external demand is independently generated and stationary, linear processes can be used for reasons of simplicity. Assume the retailer chooses an autoregression process, AR(1), model for the demand process. Autoregressive demand means current demand depends on past demand in a linear way, a common assumption. This choice is made by a retailer that is constrained insofar as it cannot invest sufficient resources in using a more complex model. If demand does not follow an AR(1) model then the retailer experiences a misspecifcation error. Part of the appeal of the blockchain system is that the risk of misspecification could be alleviated by exploiting distributed calculations. Actual demand at time t is then

$$d_t = \mu_d + \varphi d_{t-1} + \epsilon_t \tag{6}$$

where μ_d is the mean demand for the process, φ is the AR(1) parameter, and $\epsilon_t \sim IID(0, \sigma^2)$ are random disturbances which are uncorrelated with any future demand. The assumption of stationarity requires $|\ \varphi\ | < 1$. Up to time t, the sequence of historically realized and observed demands p periods in the past is the history of demand $\{h_{t-1}\} = \{d_{t-p}, \cdots,\ d_{t-1}\}$. It can be shown that, unconditionally,

$$E[d_t] = \frac{\mu_d}{1-\varphi} \tag{7}$$

$$Var(d_t) = \frac{\sigma^2}{1-\varphi} \tag{8}$$

and conditionally on the history of demand,

$$E[d_t \mid \{h_{t-1}] = \mu_d + \varphi d_{t-1} \tag{9}$$

$$Var(d_t \mid \{h_{t-1}\}) = \sigma^2. \tag{10}$$

Specific techniques are used to determine $\hat{d}_t$ with a generic method of forecasting denoted by $f(\{h_{t-1}\}, \Theta)$ which returns a prediction of d_t from history and a fixed set of parameters Θ. In reality, the parameters are likely adaptively learned with time but it is assumed that the retailers are limited by technical abilities and only update parameters when major business operations are changed. For an AR(1) process, the one-step ahead prediction is,

$$\hat{d}_t = \mu_d + \hat{\varphi} d_{t-1} \tag{11}$$

and the L-step ahead prediction can be derived using the recursive definition of AR(1) as,

$$\hat{d}_{t+L} = \hat{\varphi}^L \mu_d + \hat{\varphi}^L d_{t-1}. \tag{12}$$

Forecast error for (12) is then

$$\hat{e} = \epsilon_{t+L} + \hat{\varphi}\epsilon_{t+L-1} + \cdots + \hat{\varphi}^{L-1}\epsilon_{t+1} \tag{13}$$

with variance,

$$Var(\hat{e}) = \sigma^3 \frac{1-\hat{\varphi}^{2L}}{1-\hat{\varphi}^2} \tag{14}$$

It was shown in (4) how the order quantity submitted by retailer at time t depends on the difference between two L-step ahead predictions of accrued demand. The forecast error of this the true accrued demand difference $D_t^L - \widehat{D}_t^{L-1}$ is simply,

$$\hat{e}^L = (D_t^L - \widehat{D}_t^L) + (D_t^{L-1} - \widehat{D}_t^{L-1}) \tag{15}$$

by the triangle inequality,

$$|\hat{e}^L| \le \left|D_t^L - \widehat{D}_t^L\right| + \left|D_t^{L-1} - \widehat{D}_t^{L-1}\right| \tag{16}$$

and thus the error in prediction is going to be bounded above by the departures of predicted accrued demand for the two L-step ahead predictions. Assume an optimal order quantity q_t^*, where optimality is defined in the sense that the coordinate supply chain maximizes its objective at this order quantity, so that the magnitude of $|\hat{e}^L|$ represents the distance q_t is expected to be from q_t^* . Moreover, the variance of $|\hat{e}^L|$ is also a representation of the variance of the distance q_t is expected to be from q_t^*. Even when the retailer commits a non-zero prediction error,$|\hat{e}^L| \neq 0$, variance of the error would be small for stable errors. It is primarily the size of the variance of the error which is regarded as injurious to the supply chain in this work.

Bullwhip Measure

This paper introduces a modified version of a standard measure of the bullwhip $B(\cdot)$, the ratio of the variance of submitted orders to variance of demand of the process, given by a ratio that factors in forecast errors $|\hat{e}^L|$ or forecast error variance $Var(|\hat{e}^L|)$

$$B(q_t, d_t) = \frac{Var(|\hat{e}^L|)}{Var(d_t)} = \frac{(1-\varphi)|\hat{e}^L|}{\sigma^2}. \tag{17}$$

In practice, the AR coefficient φ would need to be estimated with $\hat{\varphi}$ using knowledge of $\{h_{t-1}\}$. Although separate sources of bias are not explicitly enumerated, (17) suggests how a bad estimator or φ would contribute positively to B. Any decisions made or not made by the retailer or supplier that result in increases in $|\hat{e}^L|$. The next section presents a consortium blockchain architecture whose automated intermediation is designed to decrease $|\hat{e}^L|$ and $Var(|\hat{e}^L|)$ which consequently decreases B.

CONSORTIUM BLOCKCHAIN MODEL

One useful functionality of blockchain systems is the smart contract. Smart contracts execute independently and automatically on every node in the blockchain. These executables can manage data-driven interactions between the retailer and supplier. In a way, a smart contract behaves as an autonomous actor whose behavior is entirely deterministic and predictable. Further, the retailer and supplier get to inspect the code of the contracts to know of its outcome before engaging with it. Tamper-proof qualities of smart contracts mean more confidence on the execution of the contract exists and all interactions are verifiable through the use of digital signatures.

Consider a simple smart contract that will serve as an automatic intermediary between the retailer and supplier. Authorship of the smart contract is assumed to reside with the supplier but joint development between retailer and supplier is also possible. Full code inspection is permitted and so a retailer's participation in the network indicates its acceptance of the routines. A supplier is not required to submit a prediction of the retailer's order quantity for contract execution but is required to submit its chosen capacity. The following is an abstract description of the smart contract's functionality:

• ***Function 1****:* Retailer deposits order quantity, forecasted demand, and data used to reach the forecast

• ***Function 2:*** Supplier deposits forecasted demand, data used to reach forecast, and chosen capacity

• ***Function 3:*** Dynamic estimation of the model for demand process, given all demand history stored over the blockchain

• ***Function 4:*** Forecast future demand through a combination of forecast techniques or the use of more sophisticated technique

• ***Function 5:*** Check retailer submitted order and supplier submitted order to that forecasted by blockchain

• ***Function 6:*** Construct distribution of prediction error for retailer and supplier

• ***Function 7:*** Compensate retailer and supplier inversely proportional to prediction error and prediction error variance

Functions 1 and *2* are input operations and are regarded as trigger events for the smart contract, once received the sequence of operations from *Function 3* onward is initiated. *Function 3* is designed to improve model specification of the demand process for the retailer. *Function 4* is designed to compensate for simplifications made by both the retailer and supplier when computing forecasts. This compensation derives from the assumption that the retailer and supplier are not experts in forecasting. Since the computations are off-loaded to the chain, no party is burdened with the computational effort. *Function 5* performs validation of consensus with respect to the blockchain system's operations. *Function 6* builds a representation of the retailer's forecast error variance. This is done so that the retailer can be compensated for good faith attempts at controlling order variance. *Function 7* is an output operation that incentivizes the retailer to commit to reducing B and the supplier to commit to capacity c_t that follows demand process more closely. Although the automated execution environment would seem to achieve the necessary incentivization of the retailer and supplier, analytical proof of this is required. Expanded benefits may attend participation in the blockchain, but both retailer and supplier may not find the existing arrangement satisfactory after factoring in the switching costs.

BLOCKCHAIN GAME FORMULATION AND ANALYSIS

An analytical representation of the interactions between the retailer and supplier would be an essential element to persuade either party to initially commit to the blockchain system. Recall, the attractiveness of a blockchain system is crucial for the first step of persuading participants to join. Without a characterization of strategic interactions, it is surmised that neither retailer nor supplier will experience an adequate persuasion effect to adopt the technology. Game theory provides just the tools to perform a principled analysis of strategic interactions. The idea of a game is just a formal structure of the decisions available to a set of participants and the outcomes from those decisions. Repeated interactions between retailer and supplier invite the use of a dynamic repeated game of complete but imperfect information. Complete information means that knowledge of the retailer and supplier payoff functions is shared between both parties. Completeness is more realistically obtained under the blockchain system since transparency of transactions is one of its design principles. Information is imperfect because at each decision, the retailer and supplier simultaneously decide and do not have the ability to know what either party decided.

Consider a single stage of what would be a repeated game between the retailer and supplier without the blockchain system. In order to focus the analysis on the interaction dynamics between the two agents, payouts are kept in symbolic form. Four distinct payouts are presented:

• ***T*:** temptation payout obtained by the retailer or supplier when the other agent commits to blockchain requirements, but it does not. It may be beneficial to have the other party conform to requirements without making the initial investment to initiate participation in the system. It is assumed that a technological investment or other expenditure would be required to first join the system.

• ***R*:** reward payout obtained when cooperation within the blockchain system is adopted by both agents. This reward payout would originate from improvements to the supply chain efficiency due to reductions in $|\hat{e}^L|$, $Var(|\hat{e}^L|)$, and B.

• ***P*:** penalty payout obtained when both retailer and supplier both decide not to participate in the blockchain and act according to self-directed motivations. This would correspond to the payout achieved where either retailer or supplier uses individualized forecasting efforts to make order decisions. A penalty here should be understood to represent a payout inferior to the superior alternative of participation in the blockchain.

• ***S*:** sucker payout obtained by either retailer or supplier when it commits to blockchain requirements, but the other agent does not.

Payouts are exogenously ordered according to $T > R > P > S$ and the order would be established by the design features of the system. Four outcomes, sub-optimal coordination (P, P), optimal coordination (R, R), and dominated non-coordination (T, S) or (S, T), occur in a single-stage of the larger repeated game.

		Supplier	
		q	q'
Retailer	q	(P, P)	(T, S)
	q'	(S, T)	(R, R)

Table 1. Game matrix for the single-stage demand forecasting game between retailer and supplier.

The goal for the system is to minimize the bullwhip measure *B* given by (17) and occurs when $Var(|\hat{e}^L|)$ and $|\hat{e}^L|$ are minimized. Let q^* denote an optimal quantity for the stage. Optimality is defined here to be the quantity which introduces the smallest $|\hat{e}^L|$ and $Var(|\hat{e}^L|)$. The blockchain system would provide a superior forecasting method so that both error and its variance would be smaller when using it. Action spaces of the retailer and supplier are both q and q' where q is an order quantity that disregards q^* with high forecast error whereas q' approximates the demand process better, that is, it minimizes $Var(|\hat{e}^L|)$ and $|\hat{e}^L|$. When choosing q instead of q', the retailer has based its selection on a forecast that was in error and would increase the magnitude of $|\hat{e}^L|$ and hence *B*. The choice of q is equivalent to the choice of capacity c for the supplier since the supplier rationally selects c based on its own forecast of q. So, when the supplier chooses q instead of q', it has decided on a capacity c that is based on a forecast that was in error and would similarly increase the magnitude of $|\hat{e}^L|$ and hence *B*. Furthermore, in the absence the blockchain control, decisions regarding q or q' are not regulated for variability and must be allowed to contribute to increased $Var(|\hat{e}^L|)$ and hence in *B*. This single stage game has one unique Nash equilibrium, sub-optimal coordination. With no intervention, the sub-optimal coordination would persist.

Proposition *The single stage game has a unique Nash equilibrium, so for any finite number of times played, the repeated game has a unique subgame-perfect outcome which is the Nash equilibrium played in every stage*.

Proof of this proposition follows from the definition of subgame-perfection and the uniqueness of (P, P) as an equilibrium action.

The blockchain system, with its smart contract, provides credibility to future cooperation since the contract confers non-repudiation, that is, the inability to renege on the agreement. A notion of a future reward that develops from current cooperation entails that agents factor the value of this cooperation in their present decisions. A natural mechanism to factor the influence of future reward on current behavior is through discounting. It enables the incorporation of the possible future rewards into blockchain participation decisions but realistically imposes a reduction of the value of payouts for every time increment into the future. To illustrate this formalization, let δ denote the discount a retailer or supplier applies to the present value of a payoff π to be received in the next stage of a repeated game. Given δ and some infinite sequence of payoffs $\{\pi_1, \pi_2, \dots\}$ then the present value of this infinite sequence is,

$$\pi_1 + \delta\pi_2 + \delta^2\pi_3 + \cdots = \sum_{t=1}^{\infty} \delta^{t-1}\pi_t \tag{18}$$

The discount factor δ reflects two aspects of the situations. First, it captures the time-value of a payoff as would be seen in a time-value of money calculation where a payoff later is no more valuable than a payoff now. Second, it reflects the probability that the retailer and supplier relationship could fall apart. To see this, let us specify δ as inversely proportional to some interest rate r a retailer or supplier would require in order for persistence in the blockchain-based supply chain relationship to be economically attractive. Now, suppose both the retailer and supplier think the relationship would fail with probability p, ending the arrangement, and succeed with probability $1 - p$, prompting a move onto the next round of the repeated game. This way, at the current period *t*, the payoff to be received in the next immediate period would be,

$$(1 - p)\frac{\pi_{t+1}}{1 + r} \tag{19}$$

and in subsequent period,

$$(1 - p)^2 \frac{\pi_{t+1}}{(1 + r)^2} \tag{20}$$

If we set $\delta = (1 - p)/(1 + r)$ then the infinitely repeated game is a model of repeated interactions between retailer and supplier where there exists some possibility of the interactions permanently terminating. Provided this interpretation of an infinitely repeated game, let us assume the supplier has committed to the blockchain but will not remain in it if the retailer defects. This commitment is tantamount to a statement by the supplier that they will choose q' , consequently c', at every stage as long as the retailer does the same but will forever shift to q once the retailer does. Credibility of this promise is a concern to the retailer. Reversal of roles, retailer committing and then the supplier playing, yields symmetrical arguments at this level of analysis but we adopt the first interpretation hereinafter. At the first stage, supplier plays q' and the retailer can choose either q' or q. If he chooses q, he attains reward T but then the supplier adopts q thereafter and so the infinite payoff for retailer would be,

$$T + \delta P + \delta^2 P + \cdots = T + \frac{\delta P}{1-\delta} \tag{21}$$

If the retailer had chosen q' instead, then the game would move to the next period, and the retailer would face the same choice. Let us denote V to the value of making the optimal choice at every decision point with,

$$V = \begin{cases} R + \delta V, & q' \ chosen \\ T + \frac{\delta P}{1-\delta}, & q \ chosen \end{cases}$$

And thus playing q' is optimal for the retailer if and only if,

$$\frac{R}{1-\delta} \geq T + \frac{\delta P}{1-\delta} \tag{22}$$

or

$$\delta \leq \frac{R-T}{P-T} \tag{23}$$

Which indicates that both the retailer and supplier have a Nash equilibrium where (23) holds.

Proposition *The trigger strategy of the retailer's participation in the blockchain is subgame perfect in the infinitely repeated retailer-supplier interaction game.*

Proof of this relies on the fact that, by definition, every subgame of an infinitely repeated game is identical to the game as a whole. It must be shown that following the trigger strategy yields Nash equilibrium at every stage. We can classify all subgames into two classes, (i) those for which all outcomes on previous stages have been (R,R) and (ii) those for which at least one previous outcome differs from (R,R). In (i), if condition (23) is met, it was shown that it is a Nash equilibrium for the retailer to remain in the blockchain at the current stage. As for (ii), we know from the single stage game that (P, P) is the Nash equilibrium to be played once (R,R) is not played. Thus, the strategy of participation in the blockchain with its coordination equilibrium is subgame-perfect.

This result depends crucially on condition (23), using the fact that $\delta = (1-p)/(1+r)$ the result can be equivalently written as,

$$(1-p) \leq (1+r)\frac{R-T}{P-T} \tag{24}$$

From (24), it can be seen that for fixed r, R, T, P stable participation in the blockchain requires the probability of passing to the next stage to be sufficiently high. If instead r, p were fixed, then stable participation occurs only for $(R-T)/(P-T)$ sufficiently large. It was assumed in this system that $T > R > P > S$ and so for distance $|R-T|$ to be sufficiently larger than $|P-T|$, compensation for participation in the blockchain for both retailer and supplier must be greater than the discounted difference between the sub-optimal coordination payout. In other words, the retailer and supplier must receive a payout under participation in the blockchain that would be larger than what they could hope to achieve by not participating in it and simply following the demand forecasting and ordering policy that is assumed to generate error.

INTERPRETATION OF RESULTS

Unconstrained, there is no way to ensure a retailer and supplier would have an incentive to make forecasts of future demand that deliberately minimize forecast error or variance of forecast error if neither are directly related to their bottom-line. Both the magnitude of the forecast error and its variability contribute to the bullwhip measure that signifies how distorted information from the customer becomes when propagating from the retailer to the supplier. A retailer or supplier is subject to limitations regarding its forecasting capabilities needed to reduce the bullwhip measure. To overcome this, both retailer and supplier could participate in a smart-contract enabled blockchain system that would manage demand forecasting in a way that would be technologically more sophisticated, generating less forecast error, variance in error, and information distortion. With logic governed by autonomously executed functions, the system would reward participants when their decisions aligned with its. With payouts properly designed so that the perceived probability of the blockchain system's failure and the extent to which a participant discounts any future reward from participation are taken into account, the smart-contract enabled blockchain system introduces a new situation where both retailer and supplier are better off by participating in it instead of relying on their individual forecasting activities. Thus, it successfully intermediates the conflict that exists between the two parties that results in poor usage and management of demand information.

This work was a first examination of the application of a blockchain system to a well-established and enduring operational problem, the bullwhip, using information system ideas. It provided an illustration of the applicability and general provability of the benefit of a blockchain system to this problem. However, deeper analysis is required that can show how incorporation of specific real-world payouts into the game structure preserves any optimality. The smart contract design feature was presented as a more abstract template and would need to be instantiated with more detail before experimental work could be explored with it. Further work into the architectural design and implementation of this system would need to be performed before testable implications are empirically examined. For instance, what is the form of the compensation rewarded for participation in the system or the initial investment cost to join the system. No exact forecasting algorithm was assigned to the retailer or supplier, but it was assumed its output was less accurate and more variable than that sourced from the blockchain system. An assignment of an exact algorithm could provide forecast error and variance expressions that are more specific and less general. These specific expressions would then be substituted into the bullwhip so that construction of payouts and utilities for retailer and supplier employing the blockchain system. Throughout the paper, several assumptions were made but these would need to be relaxed if implementation of a system was attempted.

CONCLUSION

Exposure of a supply chain to conflict between a retailer and supplier can create conditions conducive to non-coordinated and inefficient behavior of both parties. Inefficiency in this paper focused on the excess error and error variance in a retailer's orders. Non-coordination is a natural state of the interactions without external controls due to the retailer's desire to chase consumer demand and the supplier's desire for orders to be as smooth as possible. Coordination fails because a retailer cannot trust the supplier to consistently decide in its favor and likewise for the supplier. This work introduced a novel mechanism designed to inject a degree of credibility and trust between the two parties to facilitate coordination. Under a simple inventory management and demand process model, it was shown that the retailer and supplier will commit a non-zero forecast error when predicting future accrued demand. This forecast error directly translates into order quantities different from an optimal order quantity. When using a simple forecasting technique, the variance of forecast error is expected to be larger than what is optimal thus contributing to the bullwhip effect, that is, distortion of the demand information. A consortium blockchain with smart contracts was introduced as a novel system to address this problem. Central to this idea was the smart contract which comprised several automated routines that intermediate ordering between retailer and supplier. The design objective was to compensate the retailer for submitting orders consistent with the more accurate and less variable system recommendations and compensate the supplier for choosing a capacity that also came from guidance from the system. A dynamic game of complete and imperfect information was shown to offer to the retailer and supplier a strategy which was a provable Nash equilibrium and sub-game perfect.

REFERENCES

1. Asgaonkkar, A. and Krishnamachari, B. (2019). Solving the buyer and seller's dilemma: A dual-deposit escrow smart contract for provably cheat-proof delivery and payment for a digital good without a trusted mediator. In *2019 IEEE International Confernce on Blockchain and Cryptocurrency*.

2. Aviv, Y. (2002). Gaining benefits from joint forecasting and replenishment processes: The case of autocorrelated demand. *Manufacturing & Service Operations Management*, 4:23–37.

3. Bower, J. (1965). The role of conflict in economic decision-making groups: Some empirical results. *Quarterly Journal of Economics*, 79:263–277.

4. Bower, J. (1973). Incentive in teams. *The Econometrica Society*, 41:617–631.

5. Bray, R. and Mendelson, H. (2012). Information transmission and the bullwhip effect: An empirical investigation. *Management Science*, 58:860–875.

6. Cachon, G. (2003). Supply chain coordination with contracts. *Handbooks in Operations Research and Management Science*, 11:227–339.

7. Casino, F., Dasaklis, T., and Patsakis, C. (2019). A systematic literature review of blockchain-based applications: Current status, classification and open issues. *Telematics and Informatics*, 36:55–81.

8. Chen, F., Dresner, Z., Ryan, J., and Simchi-Levi, D. (2000). Quantifying the bullwhip effect in a simple supply chain: the impact of forecasting, lead times, and information. *Management Science*, 46:436–443.

9. Choi, T. and Cheng, T. (2011). *Supply Chain Coordination under Uncertainty*. Springer, New York.

10. Disney, S., Farasyn, I., Lambrecht, M., and Towill, D. (2006). Taming the bullwhip effect whilst watching customer service in a single supply chain echelon. *European Journal of Operational Research*, 173:151–172.
11. Easley, D., Ohara, M., and Basu, S. (2019). From mining to markets: The evolution of bitcoin transaction fees. *Journal of Financial Economics*, 134:91–109.
12. Eyal, I. (2015). The miner’s dilemma. In *2015 IEEE Symposium on Security and Privacy*.
13. Feng, S., Wang, W., Xiong, Z., Niyato, D., Wang, P., and Wang, S. (2018). On cyber risk management of blockchain networks: A game theoretic approach. *IEEE Transactions on Services Computing*, 1:1–18.
14. Flynn, B., Huo, B., and Zhao, X. (2010). The impact of supply chain integration on performance: A contingency and configuration approach. *Journal of Operations Management*, 28:58–71.
15. Glaser, F. (2017). Pervasive decentralization of digital infrastructures: A framework for blockchain enabled system and use case analysis. In *Proceedings of the 50th Hawaii International Conference on System Sciences*.
16. Johnson, B., Laszka, A., Grossklags, J., and Vasek, M. (2014). The economics of bitcoin mining, or bitcoin in the presence of adversaries. In *International Conference on Financial Cryptography and Data Security*.
17. Kroll, J., Davey, I., and Felten, E. (2013). The economics of bitcoin mining, or bitcoin in the presence of adversaries. In *The Twelth Workship on the Economics of Information Security*.
18. Lee, H., Pdmanabhan, V., and Whang, S. (1997). The bullwhip effect in supply chains. *Sloan Management Review*, 38:93–102.
19. Mentzer, J., DeWitt, W., Keebler, J., Minh, S., Nix, N., and Smith, C. (2001). Defining supply chain management. *Journal of Business Logistics*, 22:2–25.
20. Miao, Y. and Li, X. (2017). Zero-determinant strategy for cooperation enforcement in crowdsourcing. In *2017 IEEE Second International Conference on Data Science in Cyberspace*.
21. Polge, J., Robert, J., and Traon, Y. L. (2020). Permissioned blockchain frameworks in the industry: A comparison. *ICT Express*, 1:1–15.
22. Risius, M. and Spohrer, K. (2017). A blockchain research framework. *Business and Information Systems Engineering*, 59:385–409.
23. Xiong, Z., Feng, S., Niyato, D., Wang, P., and Han, Z. (2018). Optimal pricing-based edge computing resource management in mobile blockchain. In *2018 IEEE International Conference on Communications*.
24. Xu, K., Dong, Y., and Evers, P. (2001). Towards better coordination of the supply chain. *Transportation Research Part E: Logistics and Transportation Review*, 37:35–54.
25. Zhang, X. (2004). The impact of forecasting methods on the bullwhip effect. *International Journal of Production Economics*, 88:15–27.
26. Zhen, Y., Yue, M., Zhone, C., and T. Chang, C. X. (2017). Zero-determinant strategy for the algorithm optimize of blockchain pow consensus. In *Proceedings of the 36th Chinese Control Conference*