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Using Blockchain to Share Demand Forecasts in a Supply Chain

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Abstract

In this study, I explore the dynamics of a Cournot competition model involving two retailers and one manufacturer, focusing on the impact of blockchain technology on demand fore casting and profit sharing. By integrating blockchain for sharing demand forecasts among the participants, I investigate how this technology influences their profitability. My findings reveal that retailers opt to join the blockchain if the costs of participation are outweighed by the benefits of improved information access, leading to unconditional profit increases. Conversely, the manufacturer's benefits from blockchain participation depend on two main factors: the level of uncertainty in aggregate demand and the intensity of competition in the retail market. Specifically, the manufacturer gains more when demand uncertainty is high and retail competition is low. This is because a less competitive retail market leads to higher aggregate orders from the retailers, compensating for the reduced volatility in demand. My study highlights the conditional benefits of blockchain technology in a Cournot competition setting, offering insights into strategic decision-making for manufacturers and retailers considering such technological investments.

Keywords: *Information Sharing; Blockchain Technology; Cournot Competition; Supplychain.*

INTRODUCTION

Blockchain technology, heralded for its transformative potential in the financial sector, also holds promising applications beyond cryptocurrencies, such as enhancing transparency and trust in supply chains. Despite widespread interest, the integration of blockchain into supply chain management, especially in the context of Cournot competition, remains largely underexplored. This study investigates whether the adoption of blockchain for sharing demand forecasts among two retailers and one manufacturer can improve profitability within this competitive framework. By addressing the nuanced incentives for information sharing, this research sheds light on the strategic implications of blockchain in supply chains. Specifically, it examines how blockchain's attributes—decentralization, immutability, and transparency—can mitigate traditional barriers to information sharing, ultimately influencing the profit mar gins of both retailers and manufacturers under varying conditions of demand uncertainty and market competition.

In a nutshell "A blockchain is new type of database that enables multiple parties to share the database and to be able to modify that in a safe and secure way even if they don't trust each other." (Giden Greenspan. CoinScience (Multichain) CEO Hileman & Rauchs (2017)). Identical copies of the ledger are maintained and validated collectively by the members of the network, with approved trans actions added in blocks in a chronological chain of previously validated blocks, using a cryptographic signature (hash). Each new block is marked chronologically and contains information that refers to the block that preceded it, ensuring that any attempt to alter the blockchain would require the alteration of each block previously created, something almost impossible given the decentralized nature of the technology (Vitalik (2014)). Decentralization is one of the main feature of blockchain, which occurs be cause the records are stored at different nodes instead of at a single location; they are accessible to every authorized participant, and they are immutable.

In accounting, blockchains could potentially improve the quality of information reaching investors by making the accounting information more trustworthy, and by making the information more timely. If firms were to keep their financial records on blockchains, the opportunities for accounting-related manipulation and fraud could drop dramatically. Since blockchain-based book keeping would make

each transaction in a firm's ledger instantaneously available, real-time updating of accounting information would be possible. Moreover, this information would be made immediately available not only to insiders within the firm but to (chosen) outsiders like regulators (Yermack (2017)). Consumers of financial statement information would not need to rely on the judgment of auditors and the integrity of managers. Instead, they could trust with certainty the data on

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the blockchain and impose their own accounting judgment to make their own accrual adjustments such as depreciation or inventory assessments.

The use of the blockchain technology goes beyond the management of financial assets (e.g. bit coin); any type of digital asset can be tracked and traded through a blockchain. Information about the provenance of any goods, credentials, individuals' identity, digital rights can all be stored in a distributed ledger. The increase pressure from consumers to know where and how their products are made, make the use of blockchain technology in a supply chain an appealing solution.

The crucial question impacting the adoption of blockchain technology is whether the technology provides substantial benefits compared to alternative digital solutions. The major benefits of blockchain relates to the ability to share data among multiple parties with full transparency and trust without the need to rely on a central authority to manage and validate data and transactions. Blockchains are also tamper-proof; the data are replicated across thousands (or more) machines, as such, fraudulent activities to tamper the date are doomed to fail.

The vast majority of today's supply chain are sequential and siloed. Large amount of data are copied and passed up and down the chain via batch processing. Data takes a long time to propagate throughout the supply chain slowing down operations and causing supply-demand mismatches, excess (or shortage) inventory, and higher logistical costs. Blockchain technology could enable close to "real time" data sharing with a single version of the truth that removes lags, speeds up the supply chain and reduces operating costs.

In this study, I explore the impact of blockchain-enabled information sharing within a Cournot competition framework, involving two retailers and one manufacturer. Specifically, I examine whether the integration of a blockchain, facilitating the exchange of demand forecasts between retailers and the manufacturer, enhances the profitability of all parties involved. While the advantages of information sharing are well-established, the primary challenge lies in aligning incentives. Revealing sensitive demand information to an upstream manufacturer may potentially erode a retailer's leverage in future price negotiations (Lee & Whang (2000)), aligning with economic theories that posit private information as a strategic advantage for the less powerful party (Kreps (1990)). However, should the information sharing incrementally increase supply chain profitability, both manufacturers and retailers stand to gain, thereby pivoting the decision to share information on the net value generated.

The findings indicate that retailers are inclined to adopt blockchain technology provided the marginal benefits of information access outweigh the associated costs. For the manufacturer, the profit implications are contingent upon two factors: the volatility of overall demand and the intensity of retail competition. Specifically, in scenarios of high demand uncertainty, the manufacturer's profits invariably rise. Conversely, in more predictable markets (with less demand volatility), the profitability of information sharing for the manufacturer hinges on the competitive landscape of the retail sector. Reduced competition, by increasing total orders from retailers, can offset lower benefits from blockchain participation, thereby enhancing the manufacturer's sales volume.

Most of the current literature on the use of blockchain technology in supply chains focuses on applications such as product and part traceability (Liu & Li (2020)), sustainability initiatives (Venkatesh et al. (2020)), risk management and operations (Min (2019)), and the integration of the Internet of Things (IoT) and big data (Mazzei et al. (2020)). Studies specifically addressing information sharing are comparatively sparse and tend to be confined to particular industries or contexts, which limits the generalizability of their findings[1].

This study contributes to the literature by demonstrating that improving the reliability of information shared in a supply chain does not necessarily enhance the welfare of its participants. The benefits derived from truthful information sharing in supply chains are not monotonic. Simply improving the reliability of shared information does not guarantee increased participant profits. Instead, the dynamics of demand uncertainty and retail market competition are decisive.

The remainder of this paper is structured as follows: the subsequent section develops a model in the absence of information sharing, the third section examines the dynamics with blockchain-enabled information sharing, and the final section offers concluding remarks.

THE BENCHMARK MODEL WITHOUT BLOCKCHAIN

I consider a supply chain with two retailers, which compete in quantity, and one manufacturer. The inverse consumer demand function for each retailer $i \in \{1, 2\}$ is given by:

$$p_i = a + \theta - \gamma q_j - q_i$$

Where a is the deterministic component of the demand intercept, θ is the stochastic component of the demand (which is normally distributed $\sim N(0, \sigma^2_\theta)$), and γ captures the level of competition in the retail market ($0 < \gamma < 1$), larger γ means higher competition.

Before submitting the orders, each retailer has access to a private signal $Y_i = \theta + \varepsilon_i$, which is an unbiased estimator of θ.[2] Each retailer i has a constant marginal retailing cost normalized to zero. For any wholesale price p_w set by the

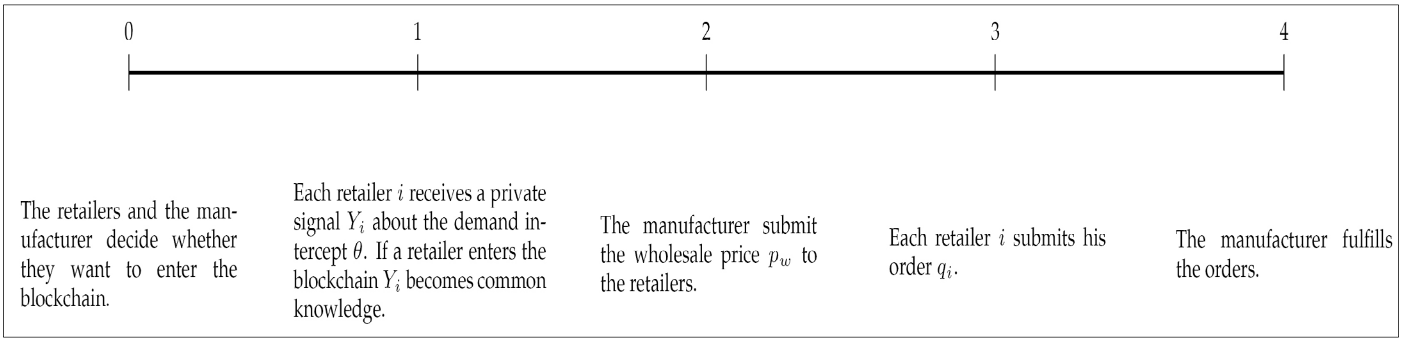
1 See, for example, Allen et al. (2019) for blockchain applications in an international context, Choi & Luo (2019) for the fashion industry, and Lambourdiere & Corbin (2020) for the maritime industry

2 The signals are uncorrelated and $E[Yi|\theta] = \theta$ (with $\varepsilon i \sim N(0, \sigma^2_{\varepsilon i})$

manufacturer, each retailer *i* maximizes his expected profit by choosing the optimal quantity q_i:

$$\max_{q_i}(a + \mathrm{E}[\theta|Y_i] - \gamma E[q_j] - q_i)q_i - p_w q_i \qquad (1)$$

The events unfold according to the following timeline:



I solve the maximization problem backward by first computing the equilibrium wholesale price p_w and then the retail quantities. I then compute the expected payoff for all participants. In this section, I assume that the retailers and the manufacturer do not enter the blockchain; the signals (Y_i and Y_j) are observed by the retailers but not shared among them or with the manufacturer.[3] The first order condition of equation 1, with respect to q_i, delivers the optimal quantity that each retailer *i* orders, for any wholesale price p_w:

$$q_i = \frac{1}{2}\left(a + \mathrm{E}[\theta|Y_i] - \gamma \mathrm{E}[q_j] - p_w\right) \quad \text{with } i \in \{1, 2\} \qquad (2)$$

Anticipating the above quantities, the manufacturer sets the optimal wholesale price p_w to maximizes his expected profit:

$$\max_{p_w}\left(\mathrm{E}[q_i] + \mathrm{E}[q_j]\right)p_w \qquad (3)$$

For simplicity, the cost of producing goods is normalized to zero for the manufacturer.[4] The first order condition of equation 3 delivers the optimal wholesale price p_w:

$$p_w^* = \frac{a}{2} \qquad (4)$$

The wholesale price is independent from q_i; that is, the retailers do not have any incentive to deflate demand information to induce a lower wholesale price (Chu et al. (2017)). For the price p^*_w each retailer *i* submits the following order:

$$q_i^* = \frac{a}{2\gamma + 4} + \frac{\mathrm{E}[\theta|Y_i]}{2} \quad \text{with i} \in \{1, 2\} \qquad (5)$$

For price p^*_w quantities q^*_i and q^*_j, the ex-ante profit of retailer *i* becomes:[5]

$$\Pi_{Ri} = \underbrace{\frac{a^2}{4(\gamma+2)^2}}_{\text{Deterministic Profit}} + \underbrace{\frac{\mathrm{E}[\theta|Y_i](2a + (\gamma+2)\mathrm{E}[\theta|Y_i])}{4(\gamma+2)}}_{\text{Stochastic Profit}} \quad i \in \{1, 2\} \qquad (6)$$

Remark 1:[6] The impacts of signal precision ($\sigma^2_{\epsilon_i}$), market competition (γ), and the volatility of aggregate demand (σ^2_θ) on a retailer's profit are multifaceted. Each factor contributes uniquely to the profit for the retailers.

- **Signal Precision ($\sigma^2_{\epsilon_i}$):** An increase in the precision of the signal, characterized by a decrease in $\sigma^2_{\epsilon_i}$, positively impacts the retailer's profit. Precise signals allow retailers to make more accurate estimations of the stochastic demand component (θ), leading to more informed ordering decisions. Formally, this relationship is captured as $\frac{\delta \Pi_{Ri}}{\delta \sigma^2_{\epsilon_i}} < 0$, indicating that improvements in signal precision enhance profitability by reducing the uncertainty in demand forecasting.

- **Market Competition (γ):** The level of competition in the market inversely affects the retailer's profit. As γ increases, signaling heightened competition, profit margins are squeezed, leading to a decrease in profitability for each retailer. This effect is quantitatively expressed as $\frac{\delta \Pi_{Ri}}{\delta \gamma} < 0$. The competitive dynamics force retailers to adjust their strategies, often resulting in lower profit margins due to the competitive pressures affecting pricing and quantities.

- **Volatility of Aggregate Demand (σ^2_θ):** Interestingly, an increase in the volatility of the aggregate demand can be advantageous for retailers. Higher demand volatility, represented by an increase in σ^2_θ, potentially allows retailers to capitalize on periods of high demand, thereby increasing their profitability. This effect is denoted as $\frac{\delta \Pi_{Ri}}{\delta \sigma^2_\theta} > 0$. The intuition behind this is that with greater demand fluctuations, well-informed retailers can adjust their order quantities to better match de mand peaks, leveraging the stochastic nature of demand to their advantage.

In essence, Remark 1 elucidates the critical role played by information accuracy, competitive intensity, and demand volatility in shaping retailer profits. Enhanced signal precision and demand volatility present opportunities for profit maximization, whereas increased competition poses challenges, necessitating strategic adjustments to maintain profitability.

I now turn to the manufacturer, his ex-ante profit is:

$$\Pi_{M_e} = \underbrace{\frac{a^2}{2\gamma + 4}}_{\text{Deterministic Profit}} \qquad (7)$$

The realized profit for the manufacturer (Π_{Mp}), given the quantity q^*_I and the wholesale price of p^*_w, is:

3 I will release this assumption in the next section.

4 The results still holds under the assumption that the manufacturer's cost of producing q units is given by $\frac{1}{2}c\,(E[q_i] + E[q_j])^2$. With a constant marginal cost c > 0.

5 Under the normality assumptions: E[θ|Yi] = $\frac{Y_i\sigma^2_\theta}{\sigma^2_\theta + \sigma^2_{\epsilon_i}}$. with i ∈ {1, 2}

6 See Appendix

$$\Pi_{M_p} = \underbrace{\frac{a^2}{2\gamma+4}}_{Deterministic\ Profit} + \underbrace{\frac{1}{4}a(\mathrm{E}[\theta|Y_i] + \mathrm{E}[\theta|Y_j])}_{Stochastic\ Profit} \quad (8)$$

Remark 2:[7] The indirect impact of market competition (γ) and signal precision ($\sigma^2_{\epsilon_i}$) on the manufacturer's profit warrants nuanced consideration. While the manufacturer's profit, particularly its deterministic component, is primarily a function of the wholesale price p^*_w and the total quantity ordered by the retailers, the underlying dynamics introduced by γ and $\sigma^2_{\epsilon_i}$ play a pivotal role.

• **Market Competition (γ):** The effect of increased competition on the manufacturer's profit is indirect. Higher γ values might lead retailers to order less due to the intensified competitive pressure, potentially reducing the manufacturer's total sales volume. This relationship suggests that while γ does not directly alter the manufacturer's profit formula, its influence through retailers' behavior is critical. Increased competition can indirectly lower the manufacturer's profits by affecting the retailers' order quantities (q^*_i), which are sensitive to the competitive dynamics of the market.

• **Precision of the Signals ($\sigma^2_{\epsilon_i}$):** The precision of the demand signals significantly impacts the manufacturer's profits through its effect on retailers' orders. More accurate signals enable retailers to better estimate demand, potentially leading to increased orders for the manufacturer as retailers make more informed decisions. Thus, an improvement in signal precision indirectly benefits the manufacturer by enhancing the quantity and reliability of the orders placed, underscoring the value of accurate information in the supply chain.

In summary, both γ and $\sigma^2_{\epsilon_i}$ have consequential but indirect effects on the manufacturer's profit. These factors underscore the complex interplay between market competition, information precision, and supply chain dynamics, emphasizing the indirect pathways through which the manufacturer's outcomes are influenced. In the next section, I assume that the retailers and the manufacturer enter a blockchain agreement by which they share the early signal Y_i each retailer receives.

THE MODEL WITH INFORMATION SHARING

In this section I assume that the participants enter a private blockchain which serves as a secure and immutable ledger, enabling transparent and real-time sharing of information among the retailers and the manufacturer. This blockchain is accessible only to verified participants within the supply chain, ensuring confidentiality and trust in the shared data. Retailers upload their early readings of the stochastic component of aggregate demand to the blockchain. This action is cryptographically secured, ensuring that once data is uploaded, it cannot be altered, providing a tamper-proof record of demand signals. The manufacturer, having access to these signals, can update production and pricing strategies in real-time, optimizing the supply chain's responsiveness to demand fluctuations. This setup reduces the traditional communication barriers and information asymmetries that often lead to inefficiencies such as overproduction or stockouts. Moreover, by utilizing smart contracts, the blockchain can automatically execute transactions based on predefined rules, such as adjusting orders or payments when certain conditions are met, further enhancing operational efficiency and trust among the supply chain partners. The implementation of a private blockchain architecture is pivotal in this model, as it offers the dual benefits of transparency in information sharing and protection of sensitive business data, fostering a collaborative yet secure environment for optimizing supply chain operations

Without information sharing the manufacturer benefits, indirectly, from a more precise signal through the increase in the quantity ordered by the retailers (even though the wholesale price is in dependent from the quantity ordered). Under the blockchain agreement each retailer shares his signal with the other retailer and the manufacturer, so the objective function for retailer i becomes:[8]

max(a + E[θ|Y_i, Y_j] − γE[qj |Yi, Yj] − qi)qi − pwqi − bqi with $i \in \{1, 2\}$ (9)

Where $b > 0$ represents the cost of entering the blockchain. By assumption the cost b is always smaller than a ($b << a$). Blockchain provides all parties within the supply chain with access to the same information, potentially reducing communication or transfer data errors. For any wholesale price p_w, each retailer orders:

$$q_i = \frac{1}{2}(a - b + \mathrm{E}[\theta|Y_i, Y_j] - \gamma \mathrm{E}[q_j|Y_i, Y_j] - p_w) \quad \text{with } i \in \{1, 2\} \quad (10)$$

With access to both signals, the manufacturer maximizes:

$$\max\ (\mathrm{E}[q_i/Y_i, Y_j]+\mathrm{E}[q_j/Y_i, Y_j])\, p_w-(\mathrm{E}[q_i/Y_i, Y_j]+\mathrm{E}[q_j/Y_i, Y_j])\, b \quad (11)$$

The first order condition of equation 11 with respect to p_w delivers the optimal wholesale price p^*_w:[9]

$$p^*_w = \frac{a}{2} + \frac{\mathrm{E}[\theta|Y_i, Y_j]}{2} \quad \text{with } i \in \{1, 2\} \quad (12)$$

By substituting equation 12 into equation 10 one obtains the optimal quantity ordered by retailer i:

$$q^*_i = \frac{a-2b}{2\gamma+4} + \frac{\mathrm{E}[\theta|Y_i, Y_j]}{2\gamma+4} \quad \text{with } i \in \{1, 2\} \quad (13)$$

Under the blockchain agrement with wholesale price p^*_w and quantity q^*_I the ex-ante profit for retailer i becomes

$$\Pi_{RB_i} = \underbrace{\frac{(a-2b)^2}{4(\gamma+2)^2}}_{\text{Deterministic Profit}} + \underbrace{\frac{\mathrm{E}[\theta|Y_i, Y_j](2a - 4b + \mathrm{E}[\theta|Y_i, Y_j])}{4(\gamma+2)^2}}_{\text{Stochastic Profit}} \quad \text{with } i \in \{1, 2\} \quad (14)$$

The manufacturer profit is given by:

$$\Pi_{MB} = \underbrace{\frac{(a-2b)^2}{2(\gamma+2)}}_{\text{Deterministic Profit}} + \underbrace{\frac{\mathrm{E}[\theta|Y_i, Y_j](2a - 4b + \mathrm{E}[\theta|Y_i, Y_j])}{2(\gamma+2)}}_{StochasticProfit}$$

with $i \in \{1, 2\}$ (15)

7 See Appendix

8 Each retailer i has now access to both signals, that explains the conditional expectations E[θ|Yi, Yj] and E[qj |Yi, Yj].

9 Where $\mathrm{E}[\theta|Y_i, Y_j] = \frac{\sigma^2_\theta\left(Y_j\sigma^2_{\epsilon i} + Y_i\sigma^2_{\epsilon j}\right)}{\sigma^2_{\epsilon i}\left(\sigma^2_\theta + \sigma^2_{\epsilon j}\right) + \sigma^2_\theta\sigma^2_{\epsilon j}}$, See Appendix

Remark 3: The incorporation of blockchain technology significantly enhances the efficiency of wholesale pricing strategies by facilitating the real-time sharing of accurate demand signals among retailers and the manufacturer. This mechanism allows for a wholesale price that more closely aligns with actual market demand, in contrast to scenarios lacking such transparent information sharing.[10] The resultant pricing efficiency not only optimizes supply chain operations but also contributes to greater resilience against market volatilities. The wholesale price under the blockchain agreement is more efficient than the wholesale price without information sharing.

Equation 16 captures the change between the wholesale price without blockchain (equation 4) and the price under the blockchain agreement (equation 12). The equation shows that the manufacturer is able to incorporate the updated expectation into the price. The manufacturer sees the signals on the blockchain and updates the wholesale price to reflect the change in his expectations about θ. More specifically:

$$\Delta p_w^* = \frac{a}{2} + \frac{\mathrm{E}[\theta|Y_i, Y_j]}{2} - \frac{a}{2} = \frac{\mathrm{E}[\theta|Y_i, Y_j]}{2} \quad \text{with } i \in \{1, 2\} \qquad (16)$$

Remark 4:[11] This analysis unveils the intricate dynamics between signal precision, variance, and the level of competition γ, within a blockchain-enabled supply chain. The interplay of these factors significantly influences retailer profits in a competitive market. The effect of an increase in the variance of a retailer's signal $\sigma^2_{\epsilon_i}$ on their profit (Π_{RBi}) is not uniform but critically depends on the comparative precision of the signals shared through the blockchain. When a retailer's signal (Y_i) is more accurate than that of another retailer (Y_j), an increase in the variance of Y_i tends to diminish the retailer's profit $\left(\frac{\delta \Pi_{RB_i}}{\delta \sigma^2_{\epsilon i}} < 0\right)$. Conversely, should Y_i be less precise, a higher signal variance could benefit the retailer by decreasing overreliance on their own less accurate signal, potentially boosting profit margins $\left(\frac{\delta \Pi_{RB_i}}{\delta \sigma^2_{\epsilon i}} > 0\right)$.

Moreover, the level of competition γ exacerbates the sensitivity of profits to signal precision and variance, with a higher γ generally reducing retailer profits $\left(\frac{\delta \Pi_{RB_i}}{\delta \gamma} < 0\right)$. This highlights the critical role of competitive dynamics in shaping the strategic value of information within blockchain networks. Retailers must navigate this complex landscape, weighing the benefits of sharing against the backdrop of competitive pressures and the inherent variability of information accuracy.

Similarly, the manufacturer's profit (Π_{MB}) is influenced by the aggregate precision and variance of the signals shared by retailers. The manufacturer's ability to adjust production and pricing strategies in real-time, based on more accurate demand forecasts, exemplifies the potential efficiency gains from blockchain technology. However, the manufacturer's profit also faces sensitivity to the level of competition and the quality of information shared, highlighting the broader implications of blockchain adoption for supply chain optimization and competitive strategy.

These insights necessitate a sophisticated approach to blockchain implementation, where both the benefits of enhanced information sharing and the strategic considerations of competition are carefully balanced. For companies, understanding these dynamics is crucial for strategizing their participation in blockchain networks, aiming to leverage transparency and collaboration without undermining competitive advantages. Furthermore, this analysis prompts additional research into blockchain architectures that can optimally manage the trade-offs between collective efficiency improvements and the preservation of competitive differentiation across diverse market scenarios.

To gauge the impact of the blockchain on the participants' profit, I compute the change in the profit under the two regimes (with and without information sharing). For that purpose, I define:

$$\Delta_{Ri} = \Pi_{Ri} - \Pi_{RBi} \quad \text{with } i \in \{1, 2\} \qquad (17)$$

$$\Delta_M = \Pi_{Mp} - \Pi_{MB} \qquad (18)$$

Where Δ_{Ri} is the surplus for retailer i and Δ_M is the surplus for the manufacturer. The surplus for retailer i is equal to:

$$\Delta_{R_i} = -\frac{(2b + (\gamma+2)\mathrm{E}[\theta|Y_i] - \mathrm{E}[\theta|Y_i, Y_j])(2a - 2b + (\gamma+2)\mathrm{E}[\theta|Y_i] + \mathrm{E}[\theta|Y_i, Y_j])}{4(\gamma+2)^2}$$

with $i \in \{1, 2\}$ (19)

A sufficient condition for equation 19 to be positive is for the cost b to be smaller than a threshold b^*, lemma 1 precisely defines b^*.

Lemma 1. *Retailer i enters the blockchain, through which he shares his signal Y_i and reads the signal Y_j, only if the marginal cost of entering the blockchain is smaller than* $b < \frac{1}{2}(E[\theta/Y_i, Y_j] - (\gamma + 2)E[\theta/Y_i]) = b^*$

Lemma 1 provides a crucial insight into the decision-making process of retailers considering joining a blockchain for information sharing within a supply chain context. It establishes a condition under which the marginal cost (b) of blockchain participation is justified by the incremental benefit derived from accessing a more comprehensive set of information.

The lemma articulates that for a retailer to find value in joining the blockchain, the cost b must be less than a calculated threshold b^*. This threshold represents the net benefit of acquiring additional information through blockchain technology. Specifically, b^* is determined by the difference in the expected value of the stochastic component of demand (θ) when considering both signals (Y_i and Y_j), versus re lying solely on one's own signal (Y_i). This difference is adjusted for the level of market competition (γ), highlighting how competitive pressures influence the value derived from additional information.

10 If we assume that both signals Yi and Yj are positive, the wholesale price under blockchain is higher compared to the setting without information sharing.

The surplus for the manufacturer is defined by:

$$\Delta_M = -\frac{2a^2 - 2(a - 2b + \mathrm{E}[\theta|Y_i, Y_j])^2 + a(\gamma + 2)(\mathrm{E}[\theta|Y_i] + \mathrm{E}[\theta|Y_j])}{4(\gamma + 2)} \quad (20)$$

Under the assumption that the marginal cost of entering the blockchain is small enough ($b < b^*$), equation 20 is positive if $a < a^*$; lemma 2 defines the threshold a^*.

Lemma 2. *When the marginal cost b is small enough ($b < b^*$), the manufacturer surplus is positive if the deterministic component of the aggregate demand is smaller than* $a < \frac{2(E[\theta|Y_i,Y_j]-2b)^2}{8b+(\gamma+2)E[\theta|Y_i]-4E[\theta|Y_i,Y_j]+(\gamma+2)E[\theta|Y_j]} = a^*$. *If the deterministic component of the aggregate demand is bigger than the threshold $a > a^*$, the surplus is positive if the level of competition in the market is smaller than* $0 < \gamma < -\frac{2(2b-E[\theta|Y_i,Y_j)])(2a-2b+E[\theta|Y_i,Y_j])}{a(E[\theta|Y_i]+E[\theta|Y_j])} - 2 = \gamma^*$

The lemma elucidates the conditions under which blockchain adoption proves economically viable for a manufacturer within a supply chain. At its core, it navigates the intricate balance between the costs of adopting blockchain technology and the tangible benefits derived from enhanced information sharing. This balance is critically influenced by the deterministic component of demand (a), the market's competitive intensity (γ), and the inherent cost (b) associated with blockchain participation.

Enhanced Demand Forecast Accuracy: The primary benefit of blockchain for a manufacturer lies in obtaining a clearer picture of aggregate demand. By accessing a broader dataset, including signals from all retailers (Y_i and Y_j), the manufacturer can achieve a more accurate forecast of demand. This lemma underscores that when the aggregate demand's deterministic component is relatively low, implying a market driven by volatile demand patterns, the value of precise information significantly increases. The precision enables a manufacturer to tailor its production and pricing strategies more closely to actual market needs, thereby optimizing their operations and potentially increasing their surplus.

The Role of Market Competition (γ): As competition within the market tightens, the marginal utility of additional information obtained through blockchain diminishes. In highly competitive environments, the ability to act on this information may be constrained by other factors, such as aggressive pricing strategies or rapid changes in consumer preferences. Thus, the incentive for a manufacturer to invest in blockchain technology reduces as the competition level escalates.

Volatility of Aggregate Demand: A volatile demand environment magnifies the blockchain's value. In such scenarios, the stochastic component of demand becomes a critical factor in decision making. Blockchain's capacity to enhance demand forecast accuracy through shared information becomes particularly valuable, making the technology an attractive proposition for a manufacturer operating in an uncertain markets.

Cost-Benefit Analysis for Blockchain Participation: The lemma assesses the cost of blockchain participation against its benefits. For a manufacturer, the decision hinges on whether the cost (b) is outweighed by the improved operational efficiency and potential surplus gains facilitated by access to enriched demand data. This analysis is encapsulated in the thresholds a^* and γ^*, which delineate the conditions under which blockchain adoption is economically justified.

The strategic implications and broader economic considerations of blockchain adoption within supply chains, as delineated through my analysis, underscore a pivotal transition towards more trans parent, efficient, and collaborative operations. The identified cost and benefit thresholds for the retailers and the manufacturer not only highlight the conditions under which blockchain technology becomes economically viable but also illuminate the potential for blockchain to redefine competitive dynamics within industries. By facilitating real-time, secure information sharing, blockchain can significantly re duce informational asymmetries, leading to more accurate demand forecasting, optimized inventory management, and enhanced operational efficiency.

These improvements could foster a more resilient supply chain capable of responding agilely to market fluctuations, thereby enhancing consumer welfare through more stable prices and consistent product availability. Furthermore, the model suggests that the strategic adoption of blockchain could catalyze a shift towards cooperative competition—or "coopetition"—whereby companies share critical data to mutual benefit while still maintaining competitive advantages in other areas. This evolution to wards a more integrated and cooperative marketplace could drive broader economic benefits, including increased innovation, sustainability through reduced waste, and more equitable distribution of profits along the supply chain. As such, the decision to implement blockchain technology extends beyond im mediate financial calculations to encompass strategic positioning within the future economic landscape.

CONCLUSION

This study ventures into the dynamics of information sharing within a supply chain, employing a blockchain framework to analyze interactions between two retailers and one manufacturer. It dissects the multifaceted impact of blockchain-based information sharing on the welfare of supply chain participants, underscored by the interplay of demand volatility, market competition, and the economic thresholds of blockchain adoption.

The investigation reveals that the benefits of blockchain engagement are subtle and contingent upon several critical factors. Retailers are inclined to participate in the blockchain when the value de rived from accessing additional forecast data surpasses the incurred costs. For the manufacturer, the allure of blockchain participation intensifies with increasing demand volatility, highlighting the technology's potential in mitigating uncertainty. However, this advantage narrows as the deterministic component of demand becomes more predominant, with the manufacturer's gains from blockchain engagement hinging on the level of market competition.

A pivotal insight from this research is the differential motivation across supply chain actors towards blockchain-enabled information sharing. Notably, the manufacturer's threshold for deriving benefits from this collaborative approach is more restrictive compared to that of the retailers, suggesting a complex calculus underpinning the decision to adopt blockchain technology in supply chains.

This study enriches the academic discourse on blockchain in supply chain management and offers some insights for practitioners considering blockchain for enhanced operational efficiency. The strategic implications suggest that both retailers and manufacturers must evaluate the cost-benefit dynamics of blockchain participation, considering their unique positions within the supply chain and the prevailing market conditions.

Future research could explore diverse competitive settings, such as price-based competition, or by expanding the scope to include multiple retailers with varied levels of blockchain engagement. Additionally, investigating the role of different blockchain architectures and the impact of trust among supply chain participants could offer deeper insights into the technology's operational and strategic implications.

In conclusion, while blockchain technology harbors the potential to revolutionize supply chain operations, its adoption is intricately tied to economic, strategic, and market-specific factors. Understanding these differences is crucial for harnessing blockchain's full potential in enhancing supply chain resilience, efficiency, and sustainability.

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APPENDIX

The Model without Blockchain

The inverse consumer demand function for each retailer $i \in \{1,2\}$ is given by:

$$p_i = a + \theta - \gamma q_j - q_i$$

For any wholesale price p_w set by the manufacturer, each retailer i maximizes his expected profit by choosing the optimal quantity q_i:

$$\max_{q_i}(a + \mathrm{E}[\theta|Y_i] - \gamma E[q_j] - q_i)q_i - p_w q_i \tag{A1}$$

The first order condition of equation A1, with respect to q_i, delivers the optimal quantity that each retailer i orders, for any wholesale price p_w:

$$q_i = \frac{1}{2}\left(a + \mathrm{E}[\theta|Y_i] - \gamma \mathrm{E}[q_j] - p_w\right) \quad \text{with } i \in \{1,2\} \tag{A2}$$

Anticipating the above quantities, the manufacturer sets the optimal wholesale price p_w to maximizes his expected profit:

$$\max_{p_w}\left(\mathrm{E}[q_1] + \mathrm{E}[q_2]\right) p_w \tag{A3}$$

For simplicity, the cost of producing goods is normalized to zero for the manufacturer(See footnote 4). The first order condition of equation 3 delivers the optimal wholesale price p_w:

$$p_w^* = \frac{a}{2} \tag{A4}$$

Notice that the wholesale price is independent from q_i.
For the price p_w^* each retailer submits the following order:

$$q_i^* = \frac{a}{2\gamma + 4} + \frac{\mathrm{E}[\theta|Y_i]}{2} \quad \text{with } i \in \{1,2\} \tag{A5}$$

For price p_w^* quantities q_1^* and q_2^* the ex-ante profit of retailer i becomes:

$$\Pi_{Ri} = \underbrace{\frac{a^2}{4(\gamma+2)^2}}_{\textit{Deterministic Profit}} + \underbrace{\frac{\mathrm{E}[\theta|Y_i](2a + (\gamma+2)\mathrm{E}[\theta|Y_i])}{4(\gamma+2)}}_{\textit{Stochastic Profit}} \quad \text{with } i \in \{1,2\} \tag{A6}$$

Where: $\mathrm{E}[\theta|Y_i] = \frac{Y_i\sigma_\theta^2}{\sigma_\theta^2 + \sigma_{\epsilon_i}^2}$. With $i \in \{1,2\}$.
The realized profit for the manufacturer (Π_{M_p}), given the quantity q_i^* and the wholesale price of p_w^*, is:

$$\Pi_{M_p} = \underbrace{\frac{a^2}{2\gamma+4}}_{\textit{Deterministic Profit}} + \underbrace{\frac{1}{4}a(\mathrm{E}[\theta|Y_i] + \mathrm{E}[\theta|Y_j])}_{\textit{Stochastic Profit}} \tag{A7}$$

Proof or Remark 1
The partial derivative of equation A6 with respect to γ is:

$$\frac{\delta\Pi_{Ri}}{\delta\gamma} = -\frac{a(a+(\gamma+2)\mathrm{E}[\theta|Y_i])}{2(\gamma+2)^3} = \frac{a\left(-a-\frac{(\gamma+2)Y_i\sigma_\theta^2}{\sigma_\theta^2+\sigma_{\epsilon_i}^2}\right)}{2(\gamma+2)^3} < 0$$

Under the assumption that the signal Y_i is positive, the derivative is always negative. An increase in the competition reduces the retailer's profit.
The partial derivative of equation A6 with respect to $\sigma_{\epsilon_i}^2$ is:

$$\frac{\delta\Pi_{R_i}}{\delta\sigma_{\epsilon_i}^2} = -\frac{Y_i\sigma_\theta^2\left(\sigma_\theta^2(a+(\gamma+2)Y_i)+a\sigma_{\epsilon_i}^2\right)}{2(\gamma+2)\left(\sigma_\theta^2+\sigma_{\epsilon_i}^2\right)^3} < 0$$

Under the assumption that the signal Y_i is positive, the derivative is always negative. An increase in the variance of the signal reduces the retailer's profit.
The partial derivative of equation A6 with respect to σ_θ^2 is:

$\frac{\delta \Pi_{R_i}}{\delta \sigma_\theta^2} = \frac{Y_i \sigma_{\epsilon 1}^2 \left(\sigma_\theta^2 (a+(\gamma+2)Y_i)+a\sigma_{\epsilon_i}^2\right)}{2(\gamma+2)\left(\sigma_\theta^2+\sigma_{\epsilon_i}^2\right)^3} > 0$

Under the assumption that the signal Y_i is positive, the derivative is always positive. An increase in the volatility in the aggregate demand increases the retailer's profit.

Proof or Remark 2

The partial derivative of equation A7 with respect to γ is:

$\frac{\delta \Pi_{Mp}}{\delta \gamma} = -\frac{a^2}{2(\gamma+2)^2} < 0$

An increase in the competition in the market reduces the manufacturer's profit.

The partial derivative of equation A7 with respect to $\sigma_{\epsilon_i}^2$ is:

$\frac{\delta \Pi_M}{\delta \sigma_{\epsilon_i}^2} = -\frac{aY_i\sigma_\theta^2}{4\left(\sigma_\theta^2+\sigma_{\epsilon_i}^2\right)^2}$

Under the assumption that the signal Y_i is positive, the derivative is always negative. An increase in the variance of the signal reduces the manufacturer's profit.

The Model with Blockchain

When the retailers and the manufacturer share information on the blockchain, the objective function for retailer i becomes:

$$\max(a + \mathrm{E}[\theta|Y_i, Y_j] - \gamma E[q_j|Y_i, Y_j] - q_i)q_i - p_w q_i - bq_i \qquad \text{with } i \in \{1,2\} \quad \text{(A8)}$$

Where $b > 0$ represents the marginal cost of entering the blockchain. By assumption the marginal cost of entering the blockchain is always smaller than the deterministic component of the aggregate demand a ($b << a$). For any wholesale price p_w, each retailer orders:

$$q_i = \frac{1}{2}\left(a - b + \mathrm{E}[\theta|Y_i, Y_j] - \gamma \mathrm{E}[q_j|Y_i, Y_j] - p_w\right) \qquad \text{with } i \in \{1,2\} \quad \text{(A9)}$$

With access to both signals, the manufacturer maximizes:

$$\max\left(\mathrm{E}[q_1|Y_1, Y_2] + \mathrm{E}[q_2|Y_1, Y_2]\right) p_w - \left(\mathrm{E}[q_1|Y_1, Y_2] + \mathrm{E}[q_2|Y_1, Y_2]\right) b \qquad \text{(A10)}$$

The first order condition of equation A10 with respect to p_w delivers the optimal wholesale price p_w^*:

$$p_w^* = \frac{a}{2} + \frac{\mathrm{E}[\theta|Y_i, Y_j]}{2} \qquad \text{with } i \in \{1,2\} \quad \text{(A11)}$$

By substituting equation A11 into equation A9 one obtains the optimal quantity ordered by retailer i:

$$q_i^* = \frac{a - 2b}{2\gamma + 4} + \frac{\mathrm{E}[\theta|Y_i, Y_j]}{2\gamma + 4} \qquad \text{with } i \in \{1,2\} \quad \text{(A12)}$$

Where $\mathrm{E}[\theta|Y_i, Y_j] = \frac{\sigma_\theta^2\left(Y_j\sigma_{\epsilon 1}^2 + Y_i\sigma_{\epsilon j}^2\right)}{\sigma_{\epsilon i}^2\left(\sigma_\theta^2+\sigma_{\epsilon j}^2\right)+\sigma_\theta^2\sigma_{\epsilon j}^2}$.

For the price p_w^* and the quantities q_1^* and q_2^* the ex-ante profit of retailer i becomes:

$$\Pi_{RB_i} = \underbrace{\frac{(a-2b)^2}{4(\gamma+2)^2}}_{\text{Deterministic Profit}} + \underbrace{\frac{\mathrm{E}[\theta|Y_i, Y_j](2a - 4b + \mathrm{E}[\theta|Y_i, Y_j])}{4(\gamma+2)^2}}_{\text{Stochastic Profit}} \qquad \text{with } i \in \{1,2\} \quad \text{(A13)}$$

The manufacturer profit is given by:

$$\Pi_{MB} = \underbrace{\frac{(a-2b)^2}{2(\gamma+2)}}_{\text{Deterministic Profit}} + \underbrace{\frac{\mathrm{E}[\theta|Y_i, Y_j](2a - 4b + \mathrm{E}[\theta|Y_i, Y_j])}{2(\gamma+2)}}_{StochasticProfit} \qquad \text{with } i \in \{1,2\} \quad \text{(A14)}$$

Proof or Remark 4

The partial derivative of equation A13 with respect to γ is:

$\frac{\delta\Pi_{RB_i}}{\delta\gamma} = -\frac{\left(a-2b+\frac{\sigma_\theta^2\left(Y_j\sigma_{\epsilon 1}^2+Y_i\sigma_{\epsilon j}^2\right)}{\sigma_{\epsilon i}^2\left(\sigma_\theta^2+\sigma_{\epsilon j}^2\right)+\sigma_\theta^2\sigma_{\epsilon j}^2}\right)^2}{2(\gamma+2)^3} < 0$

An increase in the competition in the market reduces the retailer's profit.

The partial derivative of equation A13 with respect to $\sigma_{\epsilon i}^2$ is:

$\frac{\delta\Pi_{RB_i}}{\delta\sigma_{\epsilon i}^2} = -\frac{\sigma_\theta^2\sigma_{\epsilon j}^2\left(\sigma_\theta^2(Y_i-Y_j)+Y_i\sigma_{\epsilon j}^2\right)\left(\sigma_\theta^2\left(\sigma_{\epsilon j}^2(a-2b+Y_i)+\sigma_{\epsilon 1}(a-2b+Y_j)\right)+(a-2b)\sigma_{\epsilon i}^2\sigma_{\epsilon j}^2\right)}{2(\gamma+2)^2\left(\sigma_\theta^2\left(\sigma_{\epsilon i}^2+\sigma_{\epsilon j}^2\right)+\sigma_{\epsilon i}^2\sigma_{\epsilon j}^2\right)^3} \gtreqless 0$

The derivative is negative for $Y_i > Y_j\frac{\sigma_\theta^2}{\sigma_\theta^2+\sigma_{\epsilon j}^2}$: that is, an increase in the variance of the signal received by retailer i will decrease its profit, $\frac{\delta\Pi_{RB_i}}{\delta\sigma_{\epsilon i}^2} < 0$. The derivative is positive for $Y_i < Y_j\frac{\sigma_\theta^2}{\sigma_\theta^2+\sigma_{\epsilon j}^2}$: that is, an increase in the variance of the signal received by retailer i will increase the retailer's profit, $\frac{\delta\Pi_{RB_i}}{\delta\sigma_{\epsilon i}^2} > 0$.

Proof or Lemma 1

The surplus for retailer i is equal to:

$$\begin{aligned}\Delta_{R_i} &= -\frac{(2b+(\gamma+2)\mathrm{E}[\theta|Y_i]-\mathrm{E}[\theta|Y_i,Y_j])(2a-2b+(\gamma+2)\mathrm{E}[\theta|Y_i]+\mathrm{E}[\theta|Y_i,Y_j])}{4(\gamma+2)^2} \\ &= -\frac{\left(2b-\frac{\sigma_\theta^2\left(Y_i\sigma_{\epsilon j}^2+Y_j\sigma_{\epsilon i}^2\right)}{\sigma_{\epsilon i}^2\left(\sigma_\theta^2+\sigma_{\epsilon j}^2\right)+\sigma_\theta^2\sigma_{\epsilon j}^2}+\frac{(\gamma+2)\sigma_\theta^2 Y_i}{\sigma_\theta^2+\sigma_{\epsilon i}^2}\right)\left(2a-2b+\frac{\sigma_\theta^2\left(Y_i\sigma_{\epsilon j}^2+Y_j\sigma_{\epsilon i}^2\right)}{\sigma_{\epsilon i}^2\left(\sigma_\theta^2+\sigma_{\epsilon j}^2\right)+\sigma_\theta^2\sigma_{\epsilon j}^2}+\frac{(\gamma+2)\sigma_\theta^2 Y_i}{\sigma_\theta^2+\sigma_{\epsilon i}^2}\right)}{4(\gamma+2)^2}\end{aligned} \tag{A15}$$

The derivative is always positive for

$b < \frac{1}{2}(\mathrm{E}[\theta|Y_i,Y_j]-(\gamma+2)\mathrm{E}[\theta|Y_i]) = \frac{1}{2}\sigma_\theta^2\left(\frac{Y_j\sigma_{\epsilon i}^2+Y_i\sigma_{\epsilon j}^2}{\sigma_{\epsilon i}^2\left(\sigma_\theta^2+\sigma_{\epsilon j}^2\right)+\sigma_\theta^2\sigma_{\epsilon j}^2}-\frac{(\gamma+2)Y_1}{\sigma_\theta^2+\sigma_{\epsilon i}^2}\right) = b^*$.

Retailer i enters the blockchain if the marginal cost b is smaller than the value of the information received.

The threshold b^* is decreasing in the level of competition γ. The partial derivative of b^* with respect to γ delivers the result:

$\frac{\delta b^*}{\delta\gamma} = -\frac{Y_i\sigma_\theta^2}{2\left(\sigma_\theta^2+\sigma_{\epsilon i}^2\right)} < 0.$

Proof or Lemma 2

The surplus for manufacturer is equal to:

$$\begin{aligned}\Delta_M &= -\frac{2a^2-2(a-2b+\mathrm{E}[\theta|Y_i,Y_j])^2+a(\gamma+2)(\mathrm{E}[\theta|Y_i]+\mathrm{E}[\theta|Y_j])}{4(\gamma+2)} \\ &= -\frac{2a^2-2\left(a-2b+\frac{\sigma_\theta^2\left(Y_i\sigma_{\epsilon j}^2+Y_j\sigma_{\epsilon i}^2\right)}{\sigma_{\epsilon i}^2\left(\sigma_\theta^2+\sigma_{\epsilon j}^2\right)+\sigma_\theta^2\sigma_{\epsilon j}^2}\right)^2+a(\gamma+2)\sigma_\theta^2\left(\frac{Y_i}{\sigma_\theta^2+\sigma_{\epsilon i}^2}+\frac{Y_j}{\sigma_\theta^2+\sigma_{\epsilon j}^2}\right)}{4(\gamma+2)}\end{aligned} \tag{A16}$$

When the marginal cost b is small enough ($b < b^*$), the manufacturer surplus is positive if the deterministic component of the aggregate demand a is smaller than a^*:

$$\begin{aligned}a &< \frac{2(\mathrm{E}[\theta|Y_i,Y_j]-2b)^2}{8b+(\gamma+2)\mathrm{E}[\theta|Y_i]-4\mathrm{E}[\theta|Y_i,Y_j]+(\gamma+2)\mathrm{E}[\theta|Y_j]} \\ &< \frac{2\left(\frac{\sigma_\theta^2\left(Y_i\sigma_{\epsilon j}^2+Y_j\sigma_{\epsilon i}^2\right)}{\sigma_{\epsilon i}^2\left(\sigma_\theta^2+\sigma_{\epsilon j}^2\right)+\sigma_\theta^2\sigma_{\epsilon j}^2}-2b\right)^2}{8b-\frac{4\sigma_\theta^2\left(Y_i\sigma_{\epsilon j}^2+Y_j\sigma_{\epsilon i}^2\right)}{\sigma_{\epsilon i}^2\left(\sigma_\theta^2+\sigma_{\epsilon j}^2\right)+\sigma_\theta^2\sigma_{\epsilon j}^2}+\frac{(\gamma+2)\sigma_\theta^2 Y_i}{\sigma_\theta^2+\sigma_{\epsilon i}^2}+\frac{(\gamma+2)\sigma_\theta^2 Y_j}{\sigma_\theta^2+\sigma_{\epsilon j}^2}} = a^*\end{aligned} \tag{A17}$$

When $a > a^*$, the surplus for the manufacturer is positive if:

$$\gamma < -\frac{2(2b - \mathrm{E}[\theta|Y_i, Y_j)])(2a - 2b + \mathrm{E}[\theta|Y_i, Y_j])}{a(\mathrm{E}[\theta|Y_i] + \mathrm{E}[\theta|Y_j])} - 2$$

$$< -\frac{2\left(2b - \frac{\sigma_\theta^2\left(Y_i\sigma_{\epsilon j}^2 + Y_j\sigma_{\epsilon i}^2\right)}{\sigma_{\epsilon i}^2\left(\sigma_\theta^2 + \sigma_{\epsilon j}^2\right) + \sigma_\theta^2\sigma_{\epsilon j}^2}\right)\left(2a - 2b + \frac{\sigma_\theta^2\left(Y_i\sigma_{\epsilon j}^2 + Y_j\sigma_{\epsilon i}^2\right)}{\sigma_{\epsilon i}^2\left(\sigma_\theta^2 + \sigma_{\epsilon j}^2\right) + \sigma_\theta^2\sigma_{\epsilon j}^2}\right)}{a\sigma_\theta^2\left(\frac{Y_i}{\sigma_\theta^2 + \sigma_{\epsilon i}^2} + \frac{Y_j}{\sigma_\theta^2 + \sigma_{\epsilon j}^2}\right)} - 2 = \gamma^* \qquad \text{(A18)}$$

The threshold a^* is decreasing in the level of competition in the market, $\frac{\delta a^*}{\delta\gamma} < 0$. The partial derivative of A17 with respect to γ is:

$$\frac{\delta a^*}{\delta\gamma} = -\frac{2\left(\frac{\sigma_\theta^2 Y_i}{\sigma_\theta^2 + \sigma_{\epsilon i}^2} + \frac{\sigma_\theta^2 Y_j}{\sigma_\theta^2 + \sigma_{\epsilon j}^2}\right)\left(\frac{\sigma_\theta^2\left(Y_i\sigma_{\epsilon j}^2 + Y_j\sigma_{\epsilon i}^2\right)}{\sigma_{\epsilon i}^2\left(\sigma_\theta^2 + \sigma_{\epsilon j}^2\right) + \sigma_\theta^2\sigma_{\epsilon j}^2} - 2b\right)^2}{\left(8b - \frac{4\sigma_\theta^2\left(Y_i\sigma_{\epsilon j}^2 + Y_j\sigma_{\epsilon i}^2\right)}{\sigma_{\epsilon i}^2\left(\sigma_\theta^2 + \sigma_{\epsilon j}^2\right) + \sigma_\theta^2\sigma_{\epsilon j}^2} + \frac{(\gamma+2)\sigma_\theta^2 Y_i}{\sigma_\theta^2 + \sigma_{\epsilon i}^2} + \frac{(\gamma+2)\sigma_\theta^2 Y_j}{\sigma_\theta^2 + \sigma_{\epsilon j}^2}\right)^2} < 0$$

The derivative is always negative assuming that the signals Y_i and Y_j are positive.
Form equation A12 the aggregate quantity ordered by the retailers is equal to:

$$q_i^* + q_j^* = \frac{\sigma_{\epsilon i}^2\left(\sigma_\theta^2\left(a - 2b + Y_j\right) + (a - 2b)\sigma_{\epsilon j}^2\right) + \sigma_\theta^2\sigma_{\epsilon j}^2\left(a - 2b + Y_i\right)}{(\gamma + 2)\left(\sigma_{\epsilon i}^2\left(\sigma_\theta^2 + \sigma_{\epsilon j}^2\right) + \sigma_\theta^2\sigma_{\epsilon j}^2\right)} \qquad \text{(A19)}$$

The derivative of equation A19 with respect to γ is:

$$\frac{\delta(q_i^* + q_j^*)}{\delta\gamma} = -\frac{a - 2b + \frac{\sigma_\theta^2\left(Y_i\sigma_{\epsilon j}^2 + Y_j\sigma_{\epsilon i}^2\right)}{\sigma_{\epsilon i}^2\left(\sigma_\theta^2 + \sigma_{\epsilon j}^2\right) + \sigma_\theta^2\sigma_{\epsilon j}^2}}{(\gamma+2)^2}$$

Which is always negative for Y_i and Y_j positive.