The Effects of Signaling Blockchain-based Track and Trace on Consumer Purchases: Insights from a Quasi-natural Experiment

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Abstract: Blockchain-based track and trace (BCT) is increasingly adopted in the retail supply chain. However, there is little rigorous empirical evidence quantifying the effects of BCT on consumer purchases or examining the heterogeneity of these effects with varying product-related characteristics. Employing transactional data from a leading global e-retailer that contains 540 SKUs, we design a quasi-natural experiment spanning 80 weeks to estimate the signaling effect of BCT (i.e., disclosure of the BCT to consumers) on consumer purchases. Drawing on the signaling theory, we propose that BCT can serve as an effective and reliable signal of the product quality and trustworthiness of the retailer. Our research uncovers significant positive effects of BCT on the average purchase quantity per buyer, the total number of buyers, the number of new buyers, and the number of unique visitors to the traced products. We also find nuanced moderation effects for two product-related characteristics – namely, consumer review inconsistency and product origins – on the influence of BCT on consumer purchases. Specifically, the signal effectiveness of BCT is stronger for products with more inconsistent customer reviews that indicate greater information asymmetry. The effect of BCT for products sourced globally is magnified because of the high BCT signal reliability attributed to the unique properties of the blockchain. The heterogeneous effects of BCT by varying product-related characteristics can inform managers in selecting the right products to implement BCT.

Key words: blockchain-based track and trace; supply chain transparency; consumer purchase behavior; signaling theory; consumer reviews

1. Introduction

Modern retailers source products globally through a supply network that connects multi-tiered, geographically disjointed entities. As the global supply network becomes increasingly complex, supply chain transparency – communications to stakeholders about supply chain operations and products sold to consumers (Sodhi and Tang 2019) – has become a key concern for managers (Birkey et al. 2018, Chen et al. 2019, Swift et al. 2019). Recently, blockchains have been touted as having the potential to substantially increase supply chain transparency and reduce supply chain risk (Hastig and Sodhi 2020). A blockchain can record data on product provenance, logistics processes, production environments, and other quality-related back-end supply chain information (Lansiti and Lakhani 2017). As a distributed ledger system, blockchain can encrypt information into blocks, incorporate those blocks into a chronological chain, and synchronize the chain among all participating agents via a consensus mechanism (Bahga and Madisetti 2016). Since blockchain records are dispersedly stored on linked blocks and all involved parties are accountable for the integrity of the data, they are traceable and therefore difficult to maliciously alter. As a result, supply chain track and trace information based on blockchain (blockchain-based track and trace, or BCT hereafter) tends to be more reliable than information that is reliant on a centralized data repository. For this reason, consumer trust in products and retailers may increase when the quality-related back-end supply chain information captured by the blockchain is disclosed to consumers at an appropriate level.

In recent years, an increasing number of firms have begun to implement blockchain technologies within their supply chains. For example, Walmart and IBM pioneered blockchain track and trace to address longstanding problems related to food safety and traceability (McKenzie 2018). A number of leading online retailers (e.g., Alibaba and JD.com) have also started to use blockchain to collect and share data regarding product movements throughout the supply chain (Xiao 2017). Although the popular press has showcased the success stories of BCT within a supply chain, the real impacts of BCT have not yet been adequately demonstrated. Previous research has focused on the effects of BCT on the upstream supply chain, such as streamlining supply chain processes, improving data integrity (Hastig and Sodhi 2020), and precisely targeting product failures to enhance supply chain responsiveness (Dong et al. 2022). However, the literature provides little empirical evidence about the benefits of BCT-enabled supply chain transparency to the downstream supply chain using real world data, i.e., the impacts on consumer purchase behavior (e.g., page visits, number of buyers, and purchase quantity). Further, the related literature provides limited yet mixed evidence on the effects of increasing supply chain transparency on consumer purchase behavior through means other than BCT (Kline 2017, Sodhi and Tang 2019).

Given the complexity of the global supply chain, there are significant costs associated with BCT implementation. To promote the adoption of BCT, firms require rigorous evidence of the benefits of BCT to alleviate concerns about uncertain returns on BCT investments. While the benefits of BCT to the upstream supply chain with respect to reducing operational costs are arguably difficult to quantify directly, the effects of BCT on the downstream supply chain, specifically on consumer purchases as a result of BCT implementation, are likely quantifiable if researchers can isolate the beneficial effects on consumer purchases attributable to BCT. The objectives of our research, therefore, are to examine whether and under what circumstances retailers' implementation of BCT and its associated supply chain information disclosure can affect consumer purchases.

Prior research on supply chain transparency/visibility tends to focus on social and environmental responsibilities (Bateman and Bonanni 2019, Davies et al. 2012), and the outcome measures are typically consumers' willingness or intention to purchase. Extending this literature, we examine the effects of BCT and subsequent supply chain information disclosure on consumers' actual purchases. Although BCT is primarily used in enterprise applications, information disclosure to consumers through BCT can be viewed as a "social" aspect of BCT since the technology is used to disclose back-end supply chain information to consumers and enable their follow-up actions to seek additional information regarding product movement through the supply chain. To the best of our knowledge, no study has attempted to quantify the effects of supply chain transparency enabled by BCT on consumer purchase behavior.

Figure 1.1. The Traceability Icon and General Information for Online Consumers

(a) Traceability icon (b) General information for consumers

For blockchain-traced products, implementation information (traceability icon and generic supply chain information after clicking the icon) is displayed on the product page, signaling to consumers that the product they are viewing is tracked and traced by the blockchain (See Figure 1.1). This signal can act as an advertisement to positively affect consumers' perceptions of product quality before purchase. After receiving the particular product, consumers can scan the QR code on the product they have purchased and obtain the supply chain track and trace information specific to that product, such as production environment, manufacturing processes and standards, product batches, warehousing, and transit time. We aim to demonstrate whether BCT is beneficial to retailers with respect to their downstream supply chain, i.e., consumers. Further, exploring the circumstances under which BCT is likely to have greater effects on consumer purchases can inform managerial decisions regarding BCT implementation. Accordingly, we address the following two research questions: i) *What is the impact of BCT implementation on consumer purchases?* ii) *What product-related characteristics can magnify* *the signaling effect of BCT?*

To answer these questions, we employ measures of the weekly number of buyers and average purchase amount per buyer of a product, which collectively provide direct insights on product sales. We also measure the number of new buyers who had no prior experience purchasing the product and the amount of site traffic to the product. We adopt the signaling theory as our primary theoretical lens through which to develop hypotheses on the effects of BCT on consumer purchases. Drawing on the signaling theory, we suggest that BCT serves as an effective signal of product quality, as well as the trustworthiness of the producer and the retailer, which helps to reduce information asymmetry in online transactions and in turn leads to increased consumer purchases. After consumers receive the products, BCT provides reliable signals of supply chain integrity by disclosing information (i.e., information available when consumers scan the QR code) that is safeguarded by the traceability and immutability of blockchain.

Further, based on the signaling theory, when information asymmetry is higher, signal effectiveness becomes stronger, and therefore, signaling and information disclosure via BCT tend to affect consumer purchases to a greater extent. In our setting, consumer review inconsistency is a measure of information asymmetry between the producer/retailer and consumers. Additionally, the reliability or honesty of the signal can also substantially increase consumers' confidence in the product. Consumers tend to value information integrity for products with overseas origins to a greater extent since such products are likely associated with higher risks arising from the long and complex global supply chain. Therefore, we suggest that consumers may react more strongly to BCT signaling for products with a higher degree of consumer review inconsistency or sourced from overseas.

Using proprietary transactional data from a leading global online retailer, we designed a quasi-natural experiment to investigate the impact of BCT on consumer purchases, as well as how two product-related characteristics – namely, consumer rating inconsistency and product origins – may moderate the signaling effect of BCT on consumer purchases. We found that BCT (including its implementation and subsequent information disclosure to consumers) increases consumers' purchases. In addition, the positive effects of BCT on consumer purchases are greater for products with higher consumer review inconsistency, and for products sourced overseas. However, we also observe a negative spillover effect on competitive imported products.

Our research makes several contributions. First, to our knowledge, this study is among the first to uncover the effects of BCT on consumer purchases using real world transactional data. Our findings show that the benefits of BCT can go beyond the upstream supply chain processes (e.g., manufacturing, transportation, and warehousing) and directly boost consumer purchases. Our study also adds to the nascent body of work on blockchain applications in supply chain track and trace and complements the literature on the signaling mechanisms of blockchains (Chod et al. 2020, Pun et al. 2021) by articulating the unique characteristics of BCT signaling. Second, our work contributes to the broader literature on the benefits of increasing supply chain transparency. The bulk of the previous work focuses on supply chain information sharing between business functions, with business partners or with external stakeholders through annual reports, press releases and third-party websites, and surveys (Sodhi and Tang 2019). Yet, few studies have investigated the effects of increasing supply chain transparency using decentralized information systems (e.g., blockchains) on consumers. Our study fills this void. Third, our study deepens the understanding of the relationships between blockchain technologies and other social technologies (e.g., online consumer review systems) and thereby complements the literature on information disclosure technology/strategy in e-commerce, which covers topics such as website quality (Wells et al. 2011), live chat tools (Tan et al. 2019), and online management responses (Kumar et al. 2018). Finally, from a managerial perspective, our results highlight the need for firms to implement BCT, disclose relevant information to consumers, and uncover two product-related characteristics that can enhance the effects of BCT on consumer purchases. These findings can inform online retailers and their supply chain partners in choosing the right product supply chains to implement BCT.

2. Literature Review and Hypothesis Development

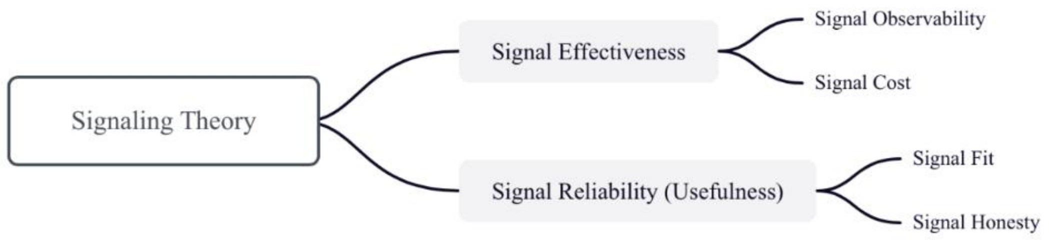
2.1. Literature Review

2.1.1. Signaling Theory. The signaling theory is the primary theoretical lens through which we examine the impact of BCT on consumer purchases. Originally proposed by Spence (1973), the signaling theory describes how certain parties with asymmetric information (the signaler) convey credible information to other parties (the receiver) (Connelly et al. 2011, Kirmani and Rao 2000). In online retailing, asymmetric information on product quality exists between the seller and consumers (Mavlanova et al. 2012, Rao et al. 2018). Consumers observe signals sent by the seller to make inferences about product quality (i.e., separate high- and low-quality products), as well as the trustworthiness of the seller, which subsequently influence their purchase decisions. For example, various studies have shown the signaling effects of return policies (time leniency, restocking fees, and others) on consumer perceptions of product quality and consumer behavior (Abdulla et al. 2019, Bonifield et al. 2010, Patel et al. 2021, Rao et al. 2018). Other signal strategies of sellers that can affect consumer behavior include disclosure of labeling alliance information (Gammoh et al. 2006, Rao et al. 1999), environmental management information (Borin et al. 2011), and supplier monitoring information (Duan et al. 2021).

Effective signals have two primary characteristics, namely, *signal observability* and *signal cost* (Connelly et al. 2011). Signal observability refers to the extent to which the receivers of a signal are able to notice that signal. For example, in retail, the ISO 9000 certification can be printed on the label of a product to signal to consumers that the product is produced following ISO 9000 standards. Consumers are likely to notice this label and may then accordingly perceive the product with that label to be of superior quality (Delmas 2001, Martínez Caro and Martínez García 2009). Signal cost represents "the transaction cost associated with implementing a signal," which is crucial to the validity of the signaling theory (Connelly et al. 2011). Some signalers (senders of a signal), typically those with high-quality products, are in a better position than other signalers, typically those with low-quality products, to absorb the associated costs of signaling. For example, the costs associated with obtaining the ISO 9000 certification for a high-quality manufacturer tend to be lower than the costs for a low-quality manufacturer, as the latter must make considerably greater efforts to meet the ISO 9000 standards (Connelly et al. 2011). This difference allows signalers with high-quality products to take certain actions to signal their product quality, which would be too costly for low-quality signalers to imitate. Therefore, the actions of signalers are differentiated by quality levels, and consumers can infer true quality by observing the different actions of signalers.

Previous research has also defined *signal reliability* (or usefulness), which is a combination of *signal fit* and *signal honesty* (Connelly et al. 2011). Signal fit refers to the extent to which a signal is consistent with the quality of the signaler. For example, Busenitz et al. (2005) demonstrate that a new venture team can signal its investment quality to venture capitalists via the team members' own investment behavior, but such behavior (e.g., portfolio of individual team members' equity holding) in the early stage of the funding process has no long-term correlation with the venture team's investment outcome. This is an example of a low signal fit. Next, signal honesty refers to the extent to which the signaler actually possesses the underlying quality associated with the signal. For example, Westphal and Zajac (2001) describe how firms that signal future stock repurchases do not actually purchase the stock and therefore develop a reputation of being dishonest. Figure 2.1 lists the key terms of the signaling theory articulated above.

Figure 2.1. Signaling Theory



Our study contributes to the signaling theory by articulating the theoretical underpinning of effective signaling through BCT and linking signal reliability to the characteristics of the blockchain, such as decentralized storage, immutability, and the traceability of the quality-related back-end supply chain data. We further examine the effectiveness of BCT signaling under the circumstance of higher quality information asymmetry (higher consumer review inconsistency) and study the reliability of BCT signaling with products sourced globally/domestically, which differentiates BCT signaling from traditional quality signaling tools (e.g., ISO quality label).

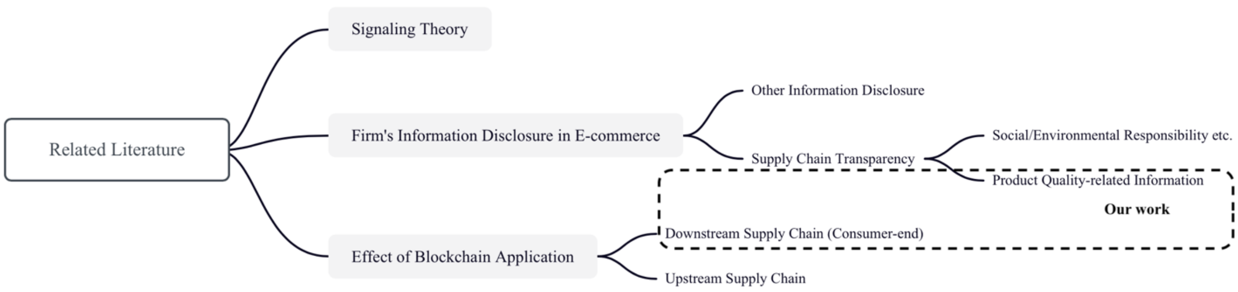
2.1.2. Blockchain Applications in Operations and Supply Chain Management. Blockchain applications are increasingly used in operations and supply chain management (See Babich and Hilary (2020) for a comprehensive review and directions for future research on blockchain-based operations management systems). Existing studies on the application of blockchain within the supply chain are comprised of predominantly conceptual work (Rao et al. 2021, Rejeb et al. 2021), case studies (Casado-Vara et al. 2018), analytical models (Cui et al. 2020, Dong et al. 2022), surveys (Durach et al. 2021, Dutta et al. 2020, Lim et al. 2021), and event studies that estimate the effect of the announcement of blockchain initiatives on stock market returns (Cahill et al. 2020, Xu 2021). In contrast, our work is among the first to use transactional data to rigorously quantify the signaling effects of BCT on consumer purchases.

While other studies have considered the signaling effects of blockchain, our study has a distinctly unique focus. For example, Chod et al. (2020) demonstrate that signaling the operational capabilities of a firm through blockchain-based inventory transactions is more efficient than using loan requests. Pun et al. (2021) compare the counterfeit combating strategies between deploying the blockchain and price signaling. Shen et al. (2022) also study the role of blockchain in combating copycats through the modeling of supply chains with different channel structures. Our study differs from these theoretical and analytical studies by empirically investigating the effectiveness and reliability of BCT signaling in conveying credible product quality information to consumers.

2.1.3. Impacts of Supply Chain Transparency on Consumer Purchase. The disclosure of supply chain and product-related information to consumers plays an important role in influencing consumers' willingness to pay and subsequent product purchases. Through laboratory experiments, Buell and Norton (2011) and Buell et al. (2017) show that consumers value a service more when they can observe the production process. Kraft et al. (2018) reveal that consumers value supply chain visibility and are willing to pay more for a firm's active engagement in improving social responsibilities and the transparency of its supply chain (e.g., ensuring payoff for its workers). Relevant studies typically evaluate consumers' intention to purchase or willingness to pay, which is not always an accurate indicator of their actual purchases (Chandon et al. 2005). Our work instead directly measures consumer purchases by using online retail transactional data from an e-commerce platform. Moreover, other relevant studies have examined the various types of supply chain information disclosed to consumers, including social and environmental sustainability and non-compliance regarding child labor or human rights. Our work complements this stream of literature by uncovering the impact of blockchain-based, quality-related back-end supply chain information disclosure (e.g., provenance, cultivated methods, and processing environments for food items) on actual consumer purchases.

2.1.4. Other Information Disclosure in E-commerce. Besides the disclosure of supply chain information to consumers in e-commerce, online retailers also adopt other online information disclosure strategies and technologies to convey the quality of their products to consumers. For example, online retailers have attempted to enhance website quality to influence consumers' perception of product quality and their purchase intention (Wells et al. 2011). Online retailers have also implemented live chat to enable synchronous conversations with consumers to reduce information asymmetry and increase ease of communication (Tan et al. 2019). Additionally, online retailers and other businesses have actively engaged in and responded to online reviews on digital platforms to engage consumers (Kumar et al. 2018). Our work complements the previous work on information disclosure technologies in e-commerce by demonstrating that the blockchain, as an emerging technology, can serve as a signaling tool, to directly – or jointly with other online technologies such as consumer review technologies – mitigate information asymmetry between online retailers and consumers.

Figure 2.2. Theoretical Position of Our Work



2.2. Hypothesis Development

In this subsection, we develop three hypotheses regarding the impact of BCT on consumer purchases and the moderating effects of consumer review inconsistency and product origins based on the signaling theory (effectiveness and reliability) introduced in subsection 2.1.1.

2.2.1. Effects of BCT Signaling on Consumer Purchase. Due to the information asymmetry between a producer/retailer and consumers, the true quality of products often cannot be accurately evaluated by consumers. One notable example is the common phenomenon of copycats that have a high degree of similarity with the genuine (usually brand) products and can confuse many consumers (Shen et al. 2022). We propose that BCT can act as an effective signal to help consumers differentiate high- and low-quality (brand or copycat) products, since BCT signaling possesses the two fundamental characteristics of effective signals, i.e., signal observability and (lower) signal cost. First, the BCT icon/informational page of a traced product on the e-retailer platform is easily observable by consumers when they browse the e-retailer site or visit the app (as shown in Figure 1.1). Second, producers with higher-quality products are likely to incur lower costs than lower-quality producers when implementing BCT, because their supply chains tend to be better prepared to implement BCT. Lower-quality producers may need to invest more, not only to implement BCT, but also to improve other aspects of their supply chain, e.g., production facilities and logistics infrastructure (Babich and Hilary 2020). As such, a low-quality producer/retailer has little incentive to imitate the BCT implementation strategy, and consumers can separate it from higher-quality producers by observing the BCT icon/information. Thus, BCT signaling can serve as a novel advertising tool before an actual consumer makes a purchase (Kirmani and Wright 1989, Milgrom and Roberts 1986).

Although effective signaling can help consumers reduce quality information asymmetry, consumers may still be concerned about the reliability of the signals. For example, traditional quality certification systems (e.g., ISO 9000 or an eco-label) are built on centralized information systems, and the focal company (the signal sender) can conveniently manipulate the signal. Another example is the existence of counterfeiters, especially in weakly regulated markets, who produce fake products that look identical to genuine products and consumers can easily be deceived. Yao and Zhu (2020) report a case in which the focal company distributes quality labels to unqualified sellers for profit. In summary, the possible manipulation of centrally stored data and the existence of deceptive counterfeiting can lead consumers to perceive weak signal reliability.

BCT can enhance signal reliability (honesty and fit) because of certain unique characteristics of the blockchain. First, since blockchain is a decentralized data storage system and all agents on the chain have the authority to safeguard, and are accountable for the data integrity, data stored in the blockchain is almost immutable, and the focal company would incur extremely high costs for tampering with the data. Therefore, signaling through the blockchain is less likely to be manipulated by the signaler and thus has higher signal honesty. Second, the subsequent BCT information disclosed to consumers (when they scan the QR code upon receiving the product) can enhance supply chain transparency. The rich back-end supply chain information aggregated and distributed through the blockchain from multiple participants includes product origins, fertilizer used, and weather conditions of the growing environment, among other details (Babich and Hilary 2020). The relevant back-end supply chain information tends to be significantly correlated with the unobservable product quality, suggesting a higher degree of signal fit to consumers. Moreover, the back-end supply chain information is specific to the product and the supply chain, and can hardly be copied by counterfeit producers. Therefore, BCT can ensure data integrity, reduce the possibility of deceptive counterfeits (Pun et al. 2021), and increase consumer confidence in the signal's honesty and fit.

In summary, BCT signaling is effective in reducing information asymmetry between the retailer and consumers. Moreover, consumers tend to have strong trust in the reliability of BCT signaling. Therefore, we hypothesize the following:

Hypothesis 1 (H1). Signaling BCT to consumers for a product will increase consumer purchases of the product.

2.2.2. Moderation Effects of Consumer Review Inconsistency. Consumer-generated reviews and ratings offer a form of peer learning (electronic word of mouth) by enabling prospective consumers to learn from other consumers' experiences and opinions (Wu et al. 2015). According to an online marketing survey, a large body of surveyed e-shoppers stated that online reviews were somewhat or very important to their purchase decisions and influenced their online purchases (eMarketer 2016). Previous studies have also shown that the consistency of ratings indeed affects consumer purchase decisions (Chevalier and Mayzlin 2006, Floyd et al. 2014, Sun 2012, Wang et al. 2015). Theoretically, the high consistency (low variance, i.e., consistently high or low consumer ratings) of consumer-generated ratings should mitigate information asymmetry between buyers and sellers (Chen and Xie 2008). However, previous research has reported mixed findings on the effects of consumer review inconsistency/variance on consumer purchases. See He and Bond (2015) and Wang et al. (2015) for a summary of the effects of consumer review variance on consumer behavior. These inconsistent findings may suggest that the effects of consumer review variances are context-specific, suggesting that additional contextual variables should be explored.

In our study context, the e-retailer provides a review-and-rating system that allows consumers to give overall ratings as well as narrative descriptions of the products they purchase. Consumers can make inferences about product quality from existing consumer reviews to mitigate their uncertainty about product quality and/or the product's fit with their needs, since the inconsistency (variance) in consumers' ratings is primarily attributed to differences in product quality and mismatch of consumer tastes with the product (Zimmermann et al. 2018). Product quality differences indicate the extent to which the quality of search and experience attributes deviates from the intended quality, i.e., the probability of a product failure, while consumer taste mismatch indicate a cost for customers' ability to enjoy the product. In the following, we highlight the moderating role of consumer review inconsistency on the signaling effect of BCT by examining these two sources.

First, high consumer review inconsistency of a product due to a high variation of the product failures amplifies the information asymmetry on product quality between the retailer and consumers. It creates uncertainty (i.e., the risk of purchasing an undesirable product) for consumers in deciding to purchase the product. BCT signaling, as previously discussed, serves as an effective signal to consumers and can mitigate consumer uncertainty to a greater extent when information asymmetry is larger. Additionally, with the implementation of BCT, goods movements along the supply chain and related supply chain information will become more standardized. When this more standardized, accurate information is disclosed to consumers, consumer perceptions of product failures are likely to be lower.

Second, consumer review inconsistency can also be partially attributed to a mismatch between the product and consumer tastes. Under this circumstance, the seller has an incentive to provide detailed information regarding the fitness of the product that can help facilitate the match between consumer taste and the product (Sun 2012). According to Sun and Tyagi (2020), such information (e.g., experience with the product and multimedia description of the product) reduces the uncertainty regarding the potential match of a consumer's needs and preferences with the features of the product. The provision of quality-related supply chain information integrated and disclosed through BCT (e.g., provenance, cultivation, or processing) informs consumers where the products are sourced and how products are processed, and transported, which can help consumers evaluate the fitness of the products. Furthermore, we note that the diversity associated with consumer preferences in our research context is likely to be small since our product categories are food and nutrition products, which tend to have small variations in consumer tastes. Further, all consumer purchases take place on the same e-commerce platform, which again suggests relatively low variation of consumer tastes since consumers with very different tastes may go to different platforms. Therefore, the mismatch costs tend to be small in our research context.

In summary, consumer review inconsistency of a product in our study mainly reflects the degree of information asymmetry between the e-retailer and consumers, and the signal effectiveness of BCT tends to be stronger in this circumstance. Thus, we hypothesize the following:

Hypothesis 2 (H2). Signaling BCT to consumers for a product with higher consumer review inconsistency will increase consumer purchases of the product to a greater extent.

2.2.3. Moderation Effect of Product Origins. Many entities are involved in the physical flow and information flow within a supply chain or supply network, thus creating various physical, informational, and temporal threats (Marucheck et al. 2011). For example, data distortion or tampering exists when information exchanges among the entities on the supply chain and counterfeiters are likely, since the true provenance of a product is difficult to trace. These threats tend to be greater in global supply chains than in domestic supply chains since the former are more complex and involve more hands-off exchanges. Data tampering is more likely when information exchange occurs between cross-regional and cross-cultural agents, and supply chain traceability is more difficult to accomplish. Consequently, the probability of product failure or deceptive counterfeiting increases in a global supply chain (Yi et al. 2022). Therefore, depending on the product origins, consumers may have different degrees of concern surrounding the product and back-end supply chain information. In what follows, we investigate the moderating effect of product origins on the signal reliability (honesty and fit) of BCT.

First, the signal honesty of BCT is stronger for products sourced globally. Previous studies show that signalers sending costlier signals are perceived to be more honest and credible by the signal receivers (Duan et al. 2021, Lee 2001). Implementing BCT incurs substantial costs to standardize supply chain processes and data, upgrade the technology infrastructure, and meet compliance and sustainability regulations (Hastig and Sodhi 2020). These costs can be considered part of the signal costs for the adoption firms. In a global supply chain, these BCT implementation costs can be substantially higher than in a domestic supply chain, because firms have to invest more resources and time to implement BCT and maintain supply chain transparency, resulting in much higher signal costs. Moreover, the data immutability enabled by the blockchain has a stronger effect on the global supply chain. Blockchain can be conveniently used to collect and integrate information from participants in different geographical locations, and this information can be securely shared between agents along the supply chain (Wang et al. 2021). Therefore, when online consumers realize the higher implementation cost and greater immutable effects associated with products sourced globally, they will perceive the signaler to be more honest, which increases their confidence in the product sold by the signaler (the e-retailer).

Second, the back-end supply chain information that BCT discloses has a stronger signal fit in a global supply chain. Blockchain traceability features record-and-trace product movement through the entire supply chain, which can enhance the quality and safety of products, e.g., food items (Rábade and Alfaro 2006). Specifically, supply chain traceability enabled by blockchain can help retailers target where in the supply chain problems may arise and what products are more likely to have quality or safety incidents, as the pilot project conducted by Walmart on sourcing mango overseas demonstrates (McKenzie 2018). Therefore, consumers may perceive blockchain-traced products they purchase to have a lower failure rate. Additionally, consumers may have a greater need for the back-end supply chain information for products sourced overseas, partly because counterfeiters have stronger incentive to imitate international brands, usually high-end brands, as doing so is more profitable. Therefore, the quality-related information provided by the blockchain, e.g., the product provenance and the customs inspection report, have stronger effects in increasing consumer's confidence in globally sourced products.

In summary, the global supply chain has a higher risk of information distortion and product failure, leading to greater needs among consumers for reliable signals (both signal honesty and fit). Therefore, the signaling effect of BCT perceived by consumers should be greater for globally sourced products.

Hypothesis 3 (H3). Signaling BCT to consumers for an imported product will increase consumer purchases of the product to a greater extent than for a domestically sourced product.

3. Empirical Setting

Our research setting is a leading global online retailer based in China. The e-retailer operates an online mall that sells appliances, digital devices, computers, housewares, clothing, baby and maternity products, books, food, and other product categories from tens of thousands of brands, sourced worldwide or domestically. In 2017, the e-retailer launched a BCT pilot program as a venture into blockchain technology. The program involved cooperation between the e-retailer and suppliers on the supply chains to record keeping and publishing services through various tiers, including production, processing, distribution, and retailing, using blockchain technologies. Before the BCT pilot program began, participants who were interested in BCT (the authors visited several of them) mainly expected improved upstream supply chain information quality and visibility, but few mentioned that they expected BCT to directly boost consumer purchases.

Our field survey of the e-retailer's BCT project team members and representatives from suppliers confirmed the above observations. The low expectation among the e-retailer and suppliers regarding increased consumer purchases was exacerbated by the fact that few, if any, high-profile BCT implementations in China had shown direct benefits of BCT to consumers. However, as a leader in innovation in retail supply chains, the e-retailer decided to launch the BCT pilot program along its own supply chains, and to observe and learn about its impacts on the entire supply chain. A senior manager from the e-retailer further commented, "We only ran the pilot on a few selected product categories to see what may come out of this pilot (on the both upstream and downstream of the supply chains). This was a valuable learning opportunity for us." The pioneering project specifically focuses on four product categories: agricultural products, nutrition supplements, powder milk, and liquor. Food and nutrition-related products were chosen by the e-retailer because of the potential effects of BCT on the upstream supply chains, and track and trace for product integrity is critically important in food supply chains. There had been reports on several BCT pilot projects by other retailers, including Walmart, which implemented BCT on food sourcing, also aiming at upstream supply chains (McKenzie 2018).

Although large suppliers account for a greater share of business for the e-retailer, it wanted to promote the BCT pilot project among suppliers of various sizes. The e-retailer's BCT pilot project team sent invitations to randomly selected suppliers to solicit their participation. The team informed the suppliers that the e-retailer was willing to work collaboratively with them to implement BCT. Almost all of the suppliers invited agreed to participate in the BCT pilot program, because they wanted to maintain a good relationship with the e-retailer, a global leader in B2C ecommerce. Some participating suppliers were aware of the potential benefit of BCT for the back-end supply chain processes, but few expected a strong impact of BCT on consumer purchases. Therefore, each of the participating suppliers randomly selected only a small number of SKUs (also referred to as products in this article) to implement the BCT. As of the date of our data collection, there were around 120 SKUs being tracked and traced by the blockchain, a small fraction of all SKUs from the suppliers in the four selected product categories.

Since the e-retailer had no expectations regarding the effects of BCT implementation on the consumer end, the e-retailer did not specifically advertise or promote the traced products. In fact, the e-retailer was more focused on promoting products to individual consumers using a sophisticated algorithm that targeted individual consumers, which considers both product attributes and consumer profiles. The managers also suggested that the algorithm did not appear to have systematically pushed SKUs with BCT icons to the top of the product list presented to consumers. The only difference between the traced and non-traced products to consumers is the traceability icon and the related back-end supply chain information on the webpage or within the app.

To investigate the effects of BCT signaling, we collected weekly data from each traced/treated SKU (i.e., products with BCT) and its comparable control SKU (i.e., products without BCT) for the 40 weeks before and the 40 weeks after BCT implementation. This data set allowed us to design a quasi-natural experiment to identify the causal relationship between BCT and changes in consumer purchases. First, the BCT was implemented on different SKUs at different points in time throughout the study period. The staggered implementation of BCT enabled us to mitigate the impacts of certain macroeconomic shocks that would simultaneously affect all treated SKUs. The statistics on the BCT effects on consumer purchases are not disclosed until the end of our study. As such, early BCT adopters did not influence the adoption decision of later adopters. Moreover, with a pretreatment window of 40 weeks, we were able to estimate and control for time-varying heterogeneity between products. The long post-treatment window of 40 weeks allowed us to tease out the effects of temporal shocks (e.g., promotional events) from the effects on consumer purchases that can be attributed to BCT.

3.1. Identifying the Control Group

At the beginning, we obtained data on 158 SKUs (treatment group) from the e-retailer, for which BCT was implemented between the second half of 2017 and the first half of 2019. We employed a two-step matching process to create a control group. We first identified the non-BCT products that matched key attributes of the BCT products. The attributes are explicitly defined on the product page, and consumers can use these attributes to search for their desired products online. Thus, we labeled these attributes as “searchable attributes”. Next, we further refined the matched set using propensity score matching (PSM) to identify the control SKUs that most closely matched the treated SKUs in terms of historical sales performance, in addition to several key product attributes. Causal inference relies on a counterfactual assumption that in the absence of the treatment (BCT implementation), average changes in the treatment and control groups would follow parallel trends (Abadie 2005, Kumar et al. 2018). In each step (i.e., searchable attribute matching and PSM), we performed parallel trend tests on the outcome variables between the treated and the control SKUs before BCT implementation.

3.1.1. Searchable Attributes Matching. The searchable attributes of a product can easily be observed by consumers before making a purchase and can therefore offer clues for product positioning and the target market from the perspective of consumers. Products with similar searchable attributes are likely to have similar target consumers. Searchable attributes matching helped us to locate potential control SKUs for each treated SKU, and this potential control matching strategy is consistent with the literature (Heckman et al. 1997, Hendricks and Singhal 2005, Levine and Toffel 2010). We matched the products based on the following attributes: product subcategory, manufacturer suggested retail price (MSRP), and several searchable keywords (see Appendix I for details). First, product subcategories for each SKU could be identified from its product catalog. For instance, the baby formula catalog contains subcategories based on babies’ ages (levels 1 to 5 age grades). Second, we used MSRP as another matching criterion to ensure that the price difference between the treated product and the potential control product is less than 20%, and therefore their target consumer segments are similar (Floyd et al. 2014).

Third, with the inputs from several sales managers of the e-retailer, we employed a series of searchable keywords within each product category to ensure that the search results matched these key attributes, from which the treated and the potential control products were then identified. For example, for powder milk, we constructed a product search query using 13 keywords, including the tier of brands, product origins, nutrition supplements, and taste, among others. All of the keywords of each unique SKU were represented with a one-hot vector, in which an element will have a value of 1 if the particular keyword appears in the product title or description, and 0 otherwise. Following Seamans and Zhu (2014), the attribute differentiation between a pair of SKUs was measured by the angle distance (in radians) between the keyword vectors, normalized by $\pi/2$, so that the value lay between 0 and 1. A potential control must match the treated SKU in all keywords, i.e., the angle distance between the vectors of the treated and the control should equal 0. Next, we employed the following procedure to match each product in the treatment group:

Step 1. We identified all of the SKUs that had been traced with the blockchain since March 2019 as treated SKUs. We removed the traced SKUs that had been on the shelf for less than 26 weeks (6 months) before the BCT implementation.

Step 2. From the full sample containing the traced and non-traced SKUs, we removed the traced SKUs identified in Step 1. The remaining SKUs became the pool of non-traced SKUs.

Step 3. We matched each treated SKU with potential controls based on the three criteria (i.e., product subcategory, MSRP, and several searchable keywords).

Step 4. From the matched SKUs of each treated SKU, we removed those with an on-shelf history of less than 26 weeks to remain consistent with the treated SKU.

Step 5. We eliminated the treated SKUs with no potential control SKUs.

Following the above procedure, we found 449 potential control SKUs for the 91 treated SKUs, as reported in Table 3.1. Due to the lack of potential control SKUs during the study period, the other 67 treated SKUs were removed from our treatment group. We verified the differences in consumer reviews between the treated SKUs and the potential control SKUs and found no significant differences between them. The statistics from the Wilcoxon Test show that the distributions of the weekly average ratings of the two sample groups in the pretreatment period did not differ significantly. The matching process helped to ensure that the treated and the control SKUs were similar in terms of searchable attributes, rendering them comparable from the perspective of consumers.

Table 3.1. Results of Searchable Attribute Matching by Product Category

Product category	No. of treated SKUs	No. of potential control SKUs per treated SKU			
		Total	Mean	Min	Max
Powder milk	41	214	5.22	2	10
Nutrition supplement	17	86	5.06	1	10
Liquor	17	38	2.29	1	4
Agricultural product	16	111	6.94	1	10

Overall	91	449	4.95	1	10

3.1.2. Propensity Score Matching. Before conducting PSM, we tested the parallel trends of the four outcome variables between the treated SKUs and the potential control SKUs. The test results indicate that pre-BCT implementation trends of the treated SKUs are significantly greater than those of the potential control SKUs for all outcome variables. Therefore, the parallel trends assumption does not hold using the observations from the searchable attributes matching, as outlined in subsection 3.1.1. As Kumar et al. (2018) suggest, PSM can alleviate endogeneity concerns when the selection process is driven by observable characteristics, which cause the differences between the treatment and the control groups to change over time. To ensure that the sample selection bias does not confound the effects of BCT signaling, we employ PSM to derive a smaller group of control SKUs that closely resemble treated SKUs, and we test the parallel trends assumption again.

As the first step of PSM, we fitted the treatment dummy variables with both the cross-unit and the cross-time variables from the pretreatment period. The *Probit* model was used to predict the propensity score of each SKU:

$$\begin{aligned} Pr(Treated_i = 1) & \\ &= \beta_0 + \beta_1 AvgPrice_i + \beta_2 AvgRating_i + \beta_3 AvgDeliveryCycle_i + \beta_4 Imported_i \\ &+ \sum_{l=1}^{5} \theta_l^T Quantity_{i,t-l} + \sum_{l=1}^{5} \gamma_l^T Visit_{i,t-l} + \sum_{l=1}^{5} \delta_l^T Return_{i,t-l} + \alpha_i + \varepsilon_{it}. \quad (1) \end{aligned}$$

In the above model, $Treated_i$ is a dummy variable that equals 1 if an SKU is the treated product, and 0 otherwise. Cross-unit variables, $AvgPrice_i$, $AvgRating_i$, and $AvgDeliveryCycle_i$ are the average price, average consumer review rating, and delivery cycle time in hours of SKU i before the BCT implementation, respectively; $Imported_i$ is a dummy variable that equals 1 if SKU i is imported, and 0 otherwise. The lagged variables, $Quantity_{i,t}$, $Visit_{i,t}$, and $Return_{i,t}$ represent the covariates derived from the sales quantity, the number of visitors, and the five-week consumer return rate of SKU i before the BCT implementation, respectively. The cross-time variables can capture the sales performance of the sample SKUs after the invitation to participate in the BCT pilot program was sent to suppliers. These factors could influence BCT implementation decisions of suppliers and therefore must be accounted for in the treatment selection of the *Probit* model.

Based on the propensity scores from Model (1), we matched the treated SKUs with the most closely resembled control SKUs. This matching process resulted in 182 SKU observations, in which each traced SKU was paired with one non-traced SKU (control group). Following Xu et al. (2017), we compared the overall distribution of the propensity score of the potential control group and verified the standardized difference of the covariates before and after the PSM. The frequency distribution of the treatment group and the two control groups are presented in Appendix II. As expected, the control SKUs identified through PSM have a propensity score distribution that is more similar to the treated SKUs than those matched exclusively with the searchable attributes. The results of a *Kolmogorov-Smirnov* test between the distributions of the treated SKUs and the control SKUs after PSM also indicate that the two groups of SKUs are very similar.

The improvement of standardized differences also indicates that PSM is successful in producing a comparable control group. A standardized difference refers to the absolute difference between the two means, as standardized by the overall standard deviation (i.e., *Mahalanobis* distance). Table 3.2 lists all of the covariates for fitting the propensity score of the treatment group in the first column, and the standardized differences before and after PSM in the second and the third columns, respectively. As expected, the standardized differences decreased after PSM for each covariate. For most covariates, the standardized differences after PSM decreased to less than 0.10, or 10% of the overall standard deviation. Thus, our matching methods collectively (i.e., searchable attribute matching and PSM) produced statistically similar pairs of treated and control SKUs.

To further ensure that PSM has ruled out the different pre-implementation trends between our treated and control groups, we conducted a series of parallel trend tests with the new sample set after PSM (Appendix III). We found that for all of the outcome variables, the coefficients of the interactions between the trend variable and the treated group indicator were insignificant, i.e., the parallel trends assumption holds. Kumar et al. (2018) suggest that the combination of the PSM and DID approach can eliminate bias from the unobservable differences between the treatment and the control groups as long as such differences between the treatment and the control groups are stable over time (parallel trends assumption holds). Therefore, the confirmation of the parallel trends assumption indicates that there are no potential confounding factors that may lead to an increase in consumer purchases specific to the treated SKUs, satisfying the condition for a valid causality inference.

Table 3.2. Standardized Differences of Covariates Before and After PSM

Covariates	**Before PSM**	**After PSM**	**Improvement (%)**
Average price ($AvgPrice$)	0.2578	0.0291	88.71
Consumer review rating ($AvgRating$)	0.1299	0.0919	29.23
Delivery cycle hour ($AvgDeliveryCycle$)	0.2253	0.0166	92.61
Overseas provenance ($Imported$)	0.4975	0.1903	61.75
Sales quantity 5 weeks ahead ($Quantity_{-5}$)	0.0788	0.0445	43.55
Sales quantity 4 weeks ahead ($Quantity_{-4}$)	0.0494	0.0386	21.87
Sales quantity 3 weeks ahead ($Quantity_{-3}$)	0.0856	0.0607	29.10
Sales quantity 2 weeks ahead ($Quantity_{-2}$)	0.0838	0.0803	4.16
Sales quantity 1 week ahead ($Quantity_{-1}$)	0.1098	0.0980	10.70
Visitor number 5 weeks ahead ($Visit_{-5}$)	0.0479	0.0094	80.42
Visitor number 4 weeks ahead ($Visit_{-4}$)	0.0571	0.0036	93.77
Visitor number 3 weeks ahead ($Visit_{-3}$)	0.1051	0.0284	73.02
Visitor number 2 weeks ahead ($Visit_{-2}$)	0.0963	0.0447	53.60
Visitor number 1 week ahead ($Visit_{-1}$)	0.1164	0.0509	56.28

Return rate 5 weeks ahead ($Return_{-5}$)	0.4385	0.4181	4.88
Return rate 4 weeks ahead ($Return_{-4}$)	0.3772	0.3153	16.41
Return rate 3 weeks ahead ($Return_{-3}$)	0.2574	0.2405	6.59
Return rate 2 weeks ahead ($Return_{-2}$)	0.1544	0.1285	16.76
Return rate 1 week ahead ($Return_{-1}$)	0.1279	0.0898	29.83

Note: Absolute values of the standardized difference, before and after matching.

4. Data and Summary Statistics

Our analyses employed 80-week consumer purchase records of 91 traced SKUs and 91 matched non-traced SKUs. The data set has a balanced panel structure and allows for the control of unobserved product-specific and time-invariant fixed effects. The sample statistics show that the BCT pilot program was launched in 2017, experienced rapid growth in the first half of 2018, and slowed considerably in the second half of 2018 and even more so in the first half of 2019. The powder milk category accounted for more than 45% of all SKUs, more than twice as many as any other categories. The agricultural product was the smallest, with only 32 SKUs. Some 46.15% of the products were sourced from Europe, 29.67% were domestic (in China), and the rest were imported.

We used four dependent variables to estimate the effect of BCT on consumer purchases: (1) the average purchase quantity for all buyers of the SKU; (2) the weekly number of all buyers of the SKU; (3) the weekly number of new buyers of the SKU and (4) the weekly number of unique visitors to the product page of the SKU. The average purchase quantity directly captures the individual consumer purchase increase after BCT implementation. This measure, combined with the weekly number of all buyers, reflects the impacts of BCT on the overall sales performance of the SKU (sales = number of buyers × average quantity per buyer), a meaningful metric for the e-retailer. We also measure purchases from new buyers, which are defined as consumers who had no pre-purchases of any other products in the same category of the focal SKU from the e-retailer in the past 60 days. The new buyers represent a consumer group with less knowledge about the quality of the product purchased, i.e., relatively stronger information asymmetry between the retailer and the consumers. Finally, the measure of online traffic reflects general consumer interest in the traced products, which could strengthen the characterization of the conversion path toward the number of all buyers and new buyers. Table 4.1 presents the definitions for each variable in our regression models. Table 4.2 presents the correlation matrix.

Table 4.1. Variable Definitions

Variable name	Description	N	Mean	Std. dev.	Min	Max
Dependent variables						
$QttyPerBuyer_{it}$	Average purchase quantity per buyer of SKU i on week t.	[1]13,292	9.38	1.90	3.57	15.14

$AllBuyer_{it}$	Natural log of the total number of consumers purchasing SKU i in week t.	13,385	5.29	2.17	0.00	10.95
$NewBuyer_{it}$	Natural log of the number of consumers who purchased SKU i in week t but had not purchased any product from the same category in the past 60 days	13,385	4.92	2.10	0.00	10.59
$Visitor_{it}$	Natural log of the total number of unique visitors to the product page of SKU i in week t.	[2]12,918	8.10	1.77	2.89	12.85
Independent variables						
$After_{it}$	A dummy variable indicating whether the weekly period came after the implementation of BCT on SKU i.	13,385	0.54	0.50	0	1
$Treated_{i}$	A dummy variable indicating whether the BCT was implemented on SKU i.	13,385	0.49	0.50	0	1
$Discount_{it}$	Percentage price discount from MSRP for SKU i in week t.	13,385	0.32	0.20	0	0.90
$Inconsistency_{i}$	A dummy variable indicating whether the variation (standard deviation) of weekly consumer review of the treated SKU i was higher than the control SKU.	13,385	0.25	0.43	0	1
$Imported_{i}$	A dummy variable indicating whether the SKU is imported.	13,385	0.73	0.44	0	1

[1]Some SKUs do not have any buyers in certain weeks, and for these weeks we have null values in the average purchasing quantity of each buyer for the specific SKU-week observation.
[2]The platform started to record online traffic from March of 2017, which is later than the beginning date of our experiment (approximately January of 2017). Thus, the number of visitors is not recorded for some weeks of the SKUs that implemented BCT very early.

Table 4.2. Correlation Matrix

		1	2	3	4	5	6	7	8
1	$QttyPerBuyer_{it}$	1							
2	$AllBuyer_{it}$	0.89*	1						
3	$NewBuyer_{it}$	0.87*	0.98*	1					
4	$Visitor_{it}$	0.89*	0.92*	0.91*	1				
5	$After_{it}$	0.11*	0.08*	0.07*	0.11*	1			
6	$Treated_{i}$	0.02	0	0.05*	0	0.01	1		
7	$Discount_{it}$	-0.26*	-0.23*	-0.21*	-0.36*	0.02	0.06*	1	
8	$Inconsistency_{i}$	-0.21*	-0.22*	-0.20*	-0.19*	-0.03*	0.04*	0.06*	1
9	$Imported_{it}$	-0.01	-0.06*	-0.06*	-0.02	-0.02	0.03*	0.07*	0.19*

*Note: * indicates significance at 10% level.*

Signaling BCT became effective when the e-retailer began to display the BCT icon on the product page of a traced product and presented the details of the BCT information through QR code scanning. The week in which the e-retailer began to signal BCT for a SKU is defined as the launch week. In the DID estimation, we captured whether a week in our study period was before or after the launch week of BCT on SKU i using a dummy variable $After_{it}$, with a value of 1 indicating after, and 0 before. The variable allowed us to compare the pre-treatment with the post-treatment performance of all SKUs for both the treated and control SKUs in our sample. To distinguish between the treated SKUs and their controls, we included another dummy variable, $Treated_i$, which equals 1 when BCT was implemented on a SKU, and 0 otherwise. Changes in consumer purchases of a product can also be attributed to the marketing promotions for the product run by the e-retailer. Thus, we included a variable, $Discount_{it}$, which measures the percentage discount of the weekly average transaction price of SKU i from its MSRP. This variable can account for changes in consumer purchases for SKU i that may be attributable to price discounts.

Consumer review inconsistency can affect consumer judgment of product quality. In our study context, the e-retailer allows consumers to post reviews and provide ratings ranging from one to five stars to indicate their level of satisfaction with the product they purchased and/or the associated services. The e-retailer does not graphically display the distribution of consumer ratings of the products. Consumers can only see the percentage of positive reviews on the product page (e.g., 95% positive rating). Still, consumers can get a sense of review inconsistency by browsing the list of review comments and ratings. The inconsistent consumer reviews can reflect the uncertainty of consumers' quality inspections. To compute the review inconsistency of a product, we obtained the weekly average ratings of each SKU in the pretreatment period and computed the variance of ratings. The intuition behind this measure is that if the perceived quality of consumers of an SKU is inconsistent, the review ratings should vary considerably across the weeks. By comparing the review rating variance of each treated product with its corresponding control products, we defined a dummy variable $Inconsistency_i$, which equals 1 if the treated product has a higher review rating variance than that of its controls, and 0 otherwise.

Imported products, which have a higher risk of supply chain information distortion and fraud imitation, could benefit to a greater extent from the signal reliability of BCT. We defined a dummy variable $Imported_i$, which takes a value of 1 if the treated SKU i is imported from overseas regions (i.e., Europe, North America, Oceania, or other countries from Asia), and 0 if the treated SKU is produced and sourced domestically in China.

5. Analysis Results

5.1. Main Effects of BCT Signaling

We began with an analysis of the main effects of BCT signaling on consumer purchases. For each SKU-week observation, our dependent variables took the logarithm scales of the average purchase quantity of each buyer ($QttyPerBuyer_{it}$), the number of all buyers who purchased the product ($Allbuyer_{it}$), the number of new buyers who purchased the product ($Newbuyer_{it}$), and the number of unique visitors to the product page ($Visitor_{it}$).

Following the DID framework, our variable of interest, $Treated_i * After_{it}$, is an interaction term indicating whether product *i* is blockchain traced ($Treated_i$), and whether the observation corresponds to the period after the BCT was implemented ($After_{it}$). This interaction term allows us to estimate the main effects of BCT on consumer purchases. Our model also included the fixed effects for each SKU (γ_i) and week (η_t), and price discount ($Discount_{it}$) as controls, as shown in Model (2).

We note that the main effect of $Treated_i$ cannot be identified in the model, because the effect of any time-invariant factors across the products is subsumed by the product-specific dummies (γ_i). Therefore, our model specification below does not include the main effect $Treated_i$:

$$\begin{aligned} &QttyPerBuyer_{it} \text{ or } AllBuyer_{it} \text{ or } NewBuyer_{it} \text{ or } Visitor_{it} \\ &\qquad = \beta_0 + \beta_1 After_{it} + \beta_2 Treated_i * After_{it} + \beta_3 Discount_{it} + \gamma_i + \eta_t + \epsilon_{it}. \end{aligned} \tag{2}$$

The estimation results for this model are presented in Table 5.1. Overall, the four models yielded consistent results. All of the models had very high R-squares (about 90%), suggesting that omitted variables, a major cause of endogeneity, are unlikely to be a concern. The variable $After_{it}$ had an insignificant coefficient, indicating that the outcome variables of the control SKUs did not change significantly after the BCT signaling took effect. The coefficient of the control variable $Discount_{it}$ was positive and significant (p<1%) in all models, suggesting that providing price discounts increases consumer purchases. While this finding was as expected, it lent face validity to our data.

The main variable of interest, $Treated_i * After_{it}$, had positive and significant coefficients in all models. The magnitude of the coefficients shown in Column (1) of Table 5.1 suggests that buyers were willing to purchase 10.3% more units of product due to the signaling effect of BCT. The results in Column (2) of Table 5.1 suggest that the weekly number of buyers increased by 6.67% after the BCT signaling took effect, implying an increase of sales income for adopters. The weekly average number of new buyers increased by 10.96%, which was larger than the percentage increase of all buyers (Column (3) of Table 5.1). Thus, the signal effectiveness of BCT is stronger when the information asymmetry is larger, where consumers have less or no prior experience with a product. Finally, in Column (4) of Table 5.1, the 8% increase in the weekly average number of unique page visitors implies that BCT boosted sales performance for the e-retailer not only by increasing the willingness to purchase more units, but also by attracting more online traffic. These findings consistently support H1.

Table 5.1. Effects of BCT Signaling on Consumer Purchases

Variable	(1) $QttyPerBuyer$	(2) $Allbuyer$	(3) $Newbuyer$	(4) $Visitor$
$After_{it}$	-0.0059	-0.0264	0.0045	-0.0020
	[0.0228]	[0.0279]	[0.0297]	[0.0200]

$After_{it} * Treated_i$	0.1030***	0.0667**	0.1096***	0.0800***
	[0.0195]	[0.0263]	[0.0271]	[0.0178]
$Discount_{it}$	1.1330***	1.8645***	1.5814***	1.4977***
	[0.0655]	[0.0872]	[0.0906]	[0.0523]
Constant	8.9987***	4.6949***	4.3878***	7.6044***
	[0.0242]	[0.0311]	[0.0326]	[0.0197]
SKU fixed effects	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
Observations	13,292	13,385	13,385	12,918
Adjusted R^2	0.917	0.899	0.882	0.926

*Note: Standard errors in brackets; **, *** respectively stand for significance levels at 5% and 1%.*

To verify the robustness of the results, we tried different matching algorithms and replicated the DID framework using new sample sets. First, we used one-to-one and one-to-many algorithms by restricting a caliper size for the PSM matching. The “caliper” restriction improves matching quality by eliminating the pairs of the treated SKU and the potential control SKU for which the difference between the predicted propensity scores exceed a given caliper size. With a caliper size of 0.2 times the standard deviation of the propensity score, the one-to-one matching yielded a smaller but more similar set of SKU pairs. We also tried one-to-many matching with the same caliper size, so that each treated SKU can have more than one control SKU as long as they have similar propensity scores. The re-estimated coefficients of the interactions ($Treated_i * After_{it}$) using the new matched sample sets were consistent with the results of the previous sample sets (panels A-B of Appendix V). In addition, we used a new propensity score predictive model by replacing the weekly values of covariates in Model (1) with the average values of covariates from all pretreatment weeks. Based on the newly predicted propensity score, we tried one-to-one matching with and without the caliper, and one-to-many matching with the caliper. The key estimators were also consistent with those from the previous regressions (panels C-E of Appendix V). Further, we conducted look-ahead PSM to tease out confounding factors of BCT signaling. Specifically, we compared the searchable attributes of only those SKUs traced by the blockchain and matched each SKU with others that are also tracked and traced by the blockchain. Then, among all matched SKUs, we identified the treated SKUs if their BCT implementation week occurred relatively early in the study period. Third, for each treated SKU, we matched it to a control SKU that had not implemented BCT during an observation window (20 weeks) and had the closest predicted propensity score (one-to-one matching). The set of the observation window ensured that we had at least 20 weekly observations to estimate the changes in the outcome variables caused by the BCT signaling. Using the look-ahead PSM, we accounted for not only the observed characteristics in traditional PSM, but also the unobserved characteristics linked to the BCT adoption decision. We then re-estimated the DID framework using the new data sample (panel F of Appendix V). The results were also consistent with those in Table 5.1, suggesting that our matching successfully created a proper control group for the blockchain-traced SKUs. The above robustness analyses provide strong support for our main results regarding the signaling effects of BCT.

5.2. Moderating Roles of Consumer Review Inconsistency and Product Origins

Given the impact of BCT signaling identified in Model (2), we further examined how the two product-related characteristics – namely, consumer review inconsistency and product origins – moderate the effects of BCT signaling on consumer purchases. In terms of consumer review inconsistency, we estimate the following models:

$$\begin{aligned} QttyPerBuyer_{it}\ or\ AllBuyer_{it}\ or\ NewBuyer_{it}\ or\ Visitor_{it} \\ = \beta_0 + \beta_1 After_{it} + \beta_2 Treated_i * After_{it} + \beta_3 After_{it} * Inconsistency_i \\ + \beta_4 Treated_i * After_{it} * Inconsistency_i + \beta_5 Discount_{it} + \gamma_i + \eta_t + \epsilon_{it}, \end{aligned} \quad (3)$$

where the variable $Inconsistency_i$ indicates whether the blockchain-traced SKUs have a larger deviation than their control SKUs in historical ratings, i.e., high consumer review inconsistency. The three-way interaction term $Treated_i * After_{it} * Inconsistency_i$ is included to estimate the moderating role of consumer review inconsistency on the effects of BCT signaling on consumer purchases.

Table 5.2 reports the estimation results of the above models. In column (1) of Table 5.2, the coefficient of the three-way interaction term $Treated_i * After_{it} * Inconsistency_i$ is positive (0.2987) and significant (p<1%), suggesting that relative to the products (SKUs) without inconsistent consumer reviews, inconsistently rated products experienced an increase of 29.87% in purchase per buyer after the products were traced by the blockchain. The results, with the number of all buyers and new buyers in columns (2) and (3) of Table 5.2, are consistent with the results reported in column (1). The corresponding positive coefficients (0.4056; 0.3347) of the three-way interactions are both statistically significant (p<1%), suggesting that higher consumer review inconsistency creates greater information asymmetry for both experienced and new buyers. In column (4), the coefficient of the three-way interaction term $Treated_i * After_{it} * Inconsistency_i$ is positive (0.4244) and statistically significant (p<1%). Therefore, when the traced products had inconsistent consumer reviews, BCT signaling on average attracted 42.44% more visitors to view the product. These results strongly support H2.

Table 5.2. Moderation Effects of Consumer Review Inconsistency

	(1) *QttyPerBuyer*	(2) *AllBuyer*	(3) *NewBuyer*	(4) *Visitor*
$After_{it}$	0.0014	-0.0530*	-0.0044	0.0321
	[0.0241]	[0.0315]	[0.0331]	[0.0216]
$After_{it} * Treated_i$	0.0405*	-0.0148	0.0401	-0.0155
	[0.0221]	[0.0288]	[0.0301]	[0.0200]
$After_{it} * Inconsistency_i$	-0.0488	0.0549	0.0027	-0.1430***
	[0.0317]	[0.0506]	[0.0514]	[0.0292]
$After_{it} * Treated_i * Inconsistency_i$	0.2987***	0.4056***	0.3347***	0.4244***

	[0.0466]	[0.0667]	[0.0678]	[0.0434]
$Discount_{it}$	1.1234***	1.8387***	1.5646***	1.4904***
	[0.0657]	[0.0869]	[0.0907]	[0.0521]
Constant	9.0006***	4.7026***	4.3925***	7.6047***
	[0.0243]	[0.0311]	[0.0327]	[0.0196]
SKU fixed effects	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
Observations	13,292	13,385	13,385	12,918
Adjusted R^2	0.917	0.900	0.883	0.927

*Note: Standard errors in brackets; *, **, *** respectively stand for significance levels at 1%, 5%, and 10%.*

We also tested the above models using an alternative and reverse measure of consumer review inconsistency. We set a threshold for the high and low rating tiers, with the median value of all of the review ratings within a product subcategory. The new measure of consumer review consistency of an SKU was derived by computing the proportion of weeks the SKU had been rated to the more frequent rating tier (either high or low). The intuition behind this measure is that the more frequently the ratings fall within a particular tier, the more reliable and convincing the reviews tend to be (due to more observation points) to consumers. The ratings and the associated comments can in turn better reflect the quality level of the product. By replacing the old measure in Model (3) with the new measure that is in reverse scale, we re-estimated the moderation effect of consumer review consensus (Appendix VI). The coefficients of the three-way interactions were all significantly negative in the results, yielding consistent results as the main analyses.

Next, we estimate the moderation effect of product origins using the following models:

$$\begin{aligned} &QttyPerBuyer_{it} \text{ or } AllBuyer_{it} \text{ or } NewBuyer_{it} \text{ or } Visitor_{it} \\ &\quad = \beta_0 + \beta_1 After_{it} + \beta_2 Treated_i * After_{it} + \beta_3 Imported_i * After_{it} \\ &\quad + \beta_4 Treated_i * After_{it} * Imported_i + \beta_5 Discount_{it} + \gamma_i + \eta_t + \epsilon_{it}, \end{aligned} \tag{4}$$

where the variable $Imported_i$ indicates whether the blockchain-traced product is sourced overseas. The three-way interaction term $Treated_i * After_{it} * Imported_i$ allows us to estimate the moderating role of product origins (imported or domestic products) on the effects of BCT signaling on consumer purchases.

Table 5.3. Moderation Effects of Product Origins

	(1) *QttyPerBuyer*	(2) *AllBuyer*	(3) *NewBuyer*	(4) *Visitor*
$After_{it}$	0.0882***	0.0830*	0.0183	0.0654**
	[0.0325]	[0.0488]	[0.0509]	[0.0321]
$After_{it} * Treated_i$	-0.0214	-0.1279**	-0.0465	-0.0894**
	[0.0386]	[0.0545]	[0.0568]	[0.0375]
$After_{it} * Imported_i$	-0.1292***	-0.1501***	-0.0182	-0.0914***
	[0.0315]	[0.0491]	[0.0508]	[0.0321]
$After_{it} * Treated_i * Imported_i$	0.1712***	0.2692***	0.2195***	0.2352***
	[0.0447]	[0.0625]	[0.0649]	[0.0425]
$Discount_{it}$	1.1469***	1.8808***	1.5836***	1.5066***

	[0.0658]	[0.0878]	[0.0911]	[0.0522]
Constant	8.9946***	4.6895***	4.3852***	7.6006***
	[0.0243]	[0.0314]	[0.0329]	[0.0197]
SKU fixed effects	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
Observations	13,292	13,385	13,385	12,918
Adjusted R^2	0.917	0.899	0.883	0.926

*Note: Standard errors in brackets; *, **, *** respectively stand for significance levels at 1%, 5%, and 10%.*

Table 5.3 reports the estimation results. The coefficient of the three-way interaction term $Treated_i * After_{it} * Imported_i$ is positive and significant in all three columns, suggesting that due to the BCT signaling effects, imported products on average had 17.12% more purchases per buyer, 26.92% more buyers, 21.96% more new buyers, and 23.52% more site traffic compared with domestically sourced products. These results strongly support H3.

Interestingly, the results also illustrate a spillover effect of BCT signaling for non-blockchain-traced imported products. These products on average had significant reductions in purchase quantity per buyer (-0.1292, p<1%), the number of all buyers (-0.1501, p<1%), and page visitors (-0.0914, p<1%) when compared with blockchain-traced imported products. The imported products not traced by the blockchain lose sales and site traffic in accordance with the corresponding imported products traced by the blockchain.

To verify the robustness of the results, we reproduced the analyses shown in Table 5.2 and Table 5.3 with new model specifications. First, we estimated a full model, including all variables, to ensure that the correlation between the two moderators would not significantly change our results. The key estimators of the new models (see Table 5.4) remain consistent. Our findings are also consistent when the models employ the standard errors clustered at the brand level and the week level (see Appendix VII).

Table 5.4. Key Estimation Results of the Full Models

Outcome Variable		Changes due to BCT signaling			
		$QttyPerBuyer_{it}$	$AllBuyer_{it}$	$NewBuyer_{it}$	$Visitor_{it}$
Products with inconsistent consumer reviews	$After_{it} * Inconsistency_i$	-0.0248	0.0869	0.0055	-0.1316***
	$After_{it} * Treated_i * Inconsistency_i$	0.2754***	0.3664***	0.3016***	0.3939***
Products with overseas provenance	$After_{it} * Imported_i$	-0.1270***	-0.1709***	-0.0221	-0.0699**
	$After_{it} * Treated_i * Imported_i$	0.1322***	0.2171***	0.1745***	0.1765***

Note: **, *** respectively stand for significance levels at 5% and 1%.

Second, we replicated the regressions with the weekly sales quantity (computed as the average purchase quality per buyer × the number of all buyers) as the dependent variable, since this is an important metric to the e-retailer. We found that the BCT led to a sales increase of 12.14% (0.1214, p<1%) for the blockchain-traced products relative to the non-traced ones. The coefficients for the three-way interactions $After_{it} * Treated_i * Inconsistency_i$ and $After_{it} * Treated_i * Imported_i$ are all positive and statistically significant. Based on these results, the blockchain-traced products on average experienced a 16.33% sales increase if their consumer reviews were inconsistent, and a 40.16% sales increase for the imported products (see Appendix VIII).

Third, given the hype surrounding blockchain technology, we cannot completely rule out the possibility that consumers purchase blockchain-traced products purely out of excitement or curiosity, without any awareness of the potential enhancement of value or quality of the traced products. To tease out the impact of consumer impulse purchases, which would usually occur in the short term, we constructed and estimated a skipping period model intended to determine whether the signaling effects persist over time. The new model replaces the original post-BCT indicator $After_{it}$ with a new variable which equals 0 if week t is from 40 weeks before BCT implementation and equals 1 if week t is from 21 to 40 weeks after BCT implementation. The observations from 1 to 20 weeks in the post-implementation period are not included in the new data set. As shown in Appendix IX, the sign and significance levels of the key coefficients are similar to those from the main analyses, suggesting that the signaling effects on product quality and value persisted.

Finally, to provide additional evidence on our selection of the two moderating factors, we conducted a first-order difference causal forest (FDCF) analysis. Following Wang (2022), we calculated the average change of the outcome variables from the pre-treatment to post-treatment period (i.e., average treatment effect) for each SKU. We then applied the causal forest approach using the average treatment effect of the outcome variables. The forest focused its splits of the samples using the features that we expect to have heterogenous effects on the outcome variables. The feature group includes consumer review inconsistency and product origins, as well as several additional variables: an indicator of whether the treated SKU is more expensive than its controls, four indicators of the product category, and the order delivery cycle time. Consumer review inconsistency was the most important, because it maximized the differences in the conditional average treatment effect between all of the feature-split SKU groups. Overseas provenance became the next most effective feature, which maximized the conditional average treatment effect differences. The results provide supportive evidence for the moderating roles of consumer review inconsistency and product origins. Appendix X reports the statistical results of the FDCF analysis.

6. Conclusions and Implications

BCT has the potential to substantially improve supply chain transparency by signaling and disclosing important quality-related back-end supply chain information to consumers. The unique characteristics of BCT render it a more effective and reliable signal of product quality than many other quality signals, such as quality certification labels. However, empirical evidence on the benefits of BCT to consumer purchases is scant. To fill this gap, our study investigates the effects of BCT on consumer purchases using a quasi-natural experiment design and offers rigorous empirical evidence of these effects. Further, our findings suggest that the effects of BCT on consumer purchases increase for products with inconsistent consumer reviews and products sourced globally. While consumers sharing product reviews on online platforms have substantial implications for e-retailing operations (Qiu and Whinston 2017), our findings suggest that consumer review technology and BCT technology can jointly affect consumer purchases. Disclosing BCT information complements the consumer review information available on the e-retailing platforms to reduce information asymmetry, especially when consumer reviews are inconsistent. Finally, the effects of BCT are stronger on imported products due to BCT's high signal reliability, and these effects may negatively spill over to non-blockchain-traced imported products.

This study contributes to prior research in several ways. First, our study reveals the effects of BCT on consumer purchases, which is in contrast to the vast majority of existing research on blockchain that focuses on the impacts of BCT on back-end supply chain operations. Second, our study contributes to the signaling theory by providing a nuanced view of BCT implementation and subsequent information disclosure from a signaling perspective. Finally, our work complements the literature on supply chain transparency by investigating the effect of quality-related back-end supply chain information disclosure enabled by BCT on actual consumer purchases, rather than on consumers' willingness to pay or purchase intentions.

6.1. Managerial Implications

This research provides important managerial implications for retailers and suppliers. First, it is crucial for online retailers to recognize that BCT not only can streamline the information flow throughout the supply chain, as many recognize, but can also directly affect consumer purchases, when BCT is signaled and BCT information is disclosed to consumers. BCT can serve as an effective and reliable signal to convey product quality information to consumers and increase consumer purchase confidence. Thus, our study can help proponents of blockchain technology make a strong business case about the benefits and viability of blockchain business applications. For retailers, implementing BCT is only part of necessary efforts, and it is equally important to collect and disclose back-end supply chain information through BCT to consumers and perhaps also to other stakeholders.

Second, retailers will usually selectively implement BCT in the beginning. It is important to select the low-hanging fruits that can reap maximum benefits from BCT implementation. Our findings suggest that firms should implement BCT on products with greater information asymmetry between sellers and consumers, and on products with higher supply chain information distortion risks. Specifically, products with a high degree of consumer review inconsistency or products sourced globally are likely to be good candidates. BCT enables the aggregation of multi-sourced historical information associated with the traced products throughout the supply chain, and this information, when made available to consumers, can increase supply chain transparency and, accordingly, consumer purchases.

6.2. Limitations and Future Research Directions

This research has several limitations, each presenting future research opportunities. First, our study uncovers the causal effects of BCT on consumer purchases. It would be useful for future studies to examine the effects of BCT on post-consumer purchase behavior, such as consumer returns, or on long-term consumer purchase behavior, such as purchase frequency. Further, future studies can investigate the types of supply chain information that are most effective in stimulating consumer purchases. Such findings will allow retailers and suppliers to selectively disclose information to consumers to maximize the impacts of BCT.

Second, our study only examines the effects of BCT on the downstream supply chain, specifically, on consumer purchases. However, the implementation of BCT requires coordination of all participants along the supply chain (Hastig and Sodhi 2020). Thus, the effects of BCT on the upstream supply chain need to be further studied. While there is rich OM literature on supply chain coordination (see Cachon 2003, Cachon and Lariviere 2005), few studies have rigorously addressed supply chain coordination via blockchain. Some relevant questions include the following: What are the main obstacles for suppliers to engage in BCT? How should retailers design blockchain-based value sharing mechanisms for suppliers to be able to participate in supply chain coordination?

This research is also limited to four product categories. It is conceivable that consumers may react differently to retailers' implementation of BCT in other product categories with different characteristics, such as electronics, which tend to have a higher degree of standardization. Retailers selling various categories of products will benefit from future research examining the effects of BCT across a broader array of product categories. In closing, we hope this study can stimulate future research interest in blockchain applications in the supply chain, especially those that may increase supply chain transparency.

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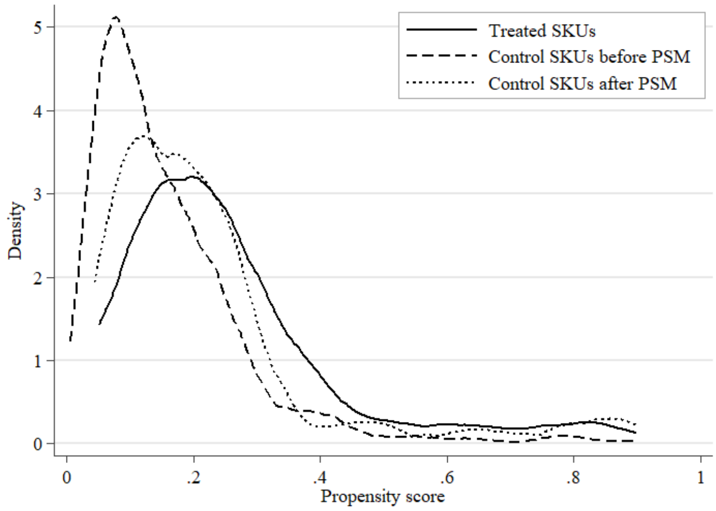
Appendix I. Searchable Attributes for Matching

Product Category	**Searchable Attributes**
Nutrition Supplement	1. Subcategories by functionality (i.e., body fitting/bone strong/sleep improvement/kidney health/stomach maintain) 2. MSRP 3. Gender* (i.e., female/male) 4. Age* (i.e., the middle-old/old/middle)
Powder milk	1. Subcategories by stage (i.e., stage pre-stage/1/1+/2/2+/3/3+/4/4+) 2. MSRP 3. Target group* (i.e., the pregnant/mother/elder/adult/juvenile/children) 4. Tier of brands* 5. Imported/domestic* 6. Supplementary element* (i.e., calcium/ferrum/zinc) 7. Package weight* (i.e., 0 – 400g/400 – 900g/900 –1200g/above 1200g) 8. Other features* (i.e., formula/organic)
Agricultural Product	1. Subcategories (i.e., rice/oil/seafood) 2. MSRP 3. Rice* (i.e., normal rice/millet rice/fragrant rice/wuchang rice) 4. Oil* (i.e., edible oil/canola oil/ready-to-eat food/light food) 5. Seafood* (i.e., fish/shrimp/sea cucumber) 6. Age* (i.e., the elder/pregnant/children) 7. Processing* (i.e., frozen/fresh/waterless) 8. Organic* 9. Package weight* (i.e., 0 – 400g/400 – 900g/900 –1200g/above 1200g)
Liquor	1. Subcategories by type (i.e., red wine/white wine/liquor/sparkling wine/champagne) 2. MSRP 3. Flavor* (i.e., sweet/dry) 4. Imported/domestic* 5. Quality* (i.e., vdt/vdm/vdp/vdlt/aoc/do) 6. Package weight* (i.e., 1/2/6/12 bottle)

Appendix II. Distribution of Propensity Scores for Treated SKUs and Control SKUs (Before and After PSM)



Appendix III. Parallel Trends Test

The parallel trends test examines the potential existence of different pretreatment trends in our treatment and control groups. In Panel (A) to (C), we used the fixed effect model:

$Visitor_{it}$ *or* $Allbuyer_{it}$ *or* $Newbuyer_{it}$ *or* $QttyPerBuyer = \beta_0 + \beta_1 Trend_{it} + \beta_2 Treated_i * Trend_{it} + \beta_3 Discount_{it} + \gamma_i + \eta_t + \epsilon_{it}$, where $Trend_{it}$ counts the weeks before the BCT implementation week t of product i. The fixed effect model includes the price discount ($Discount_{it}$) and the product-specific dummy variable (γ_i) as control variables. The main effect of $Treated_i$ cannot be identified because the fixed effect cross products are controlled by γ_i. The trend of the outcome variables is estimated by the cross-time variable $Trend_{it}$. And the interactive term between $Trend_{it}$ and $Treated_i$ estimated the differences of pretreatment trends between the treatment and control groups. We also visualize the parallel path with predictive margin plots of the four outcome variables. Specifically, based on the results shown in Panel A, the predicted paths of the treated SKUs (treated = 1) and the control SKUs are illustrated with the blue line and the red line respectively (see Figure A).

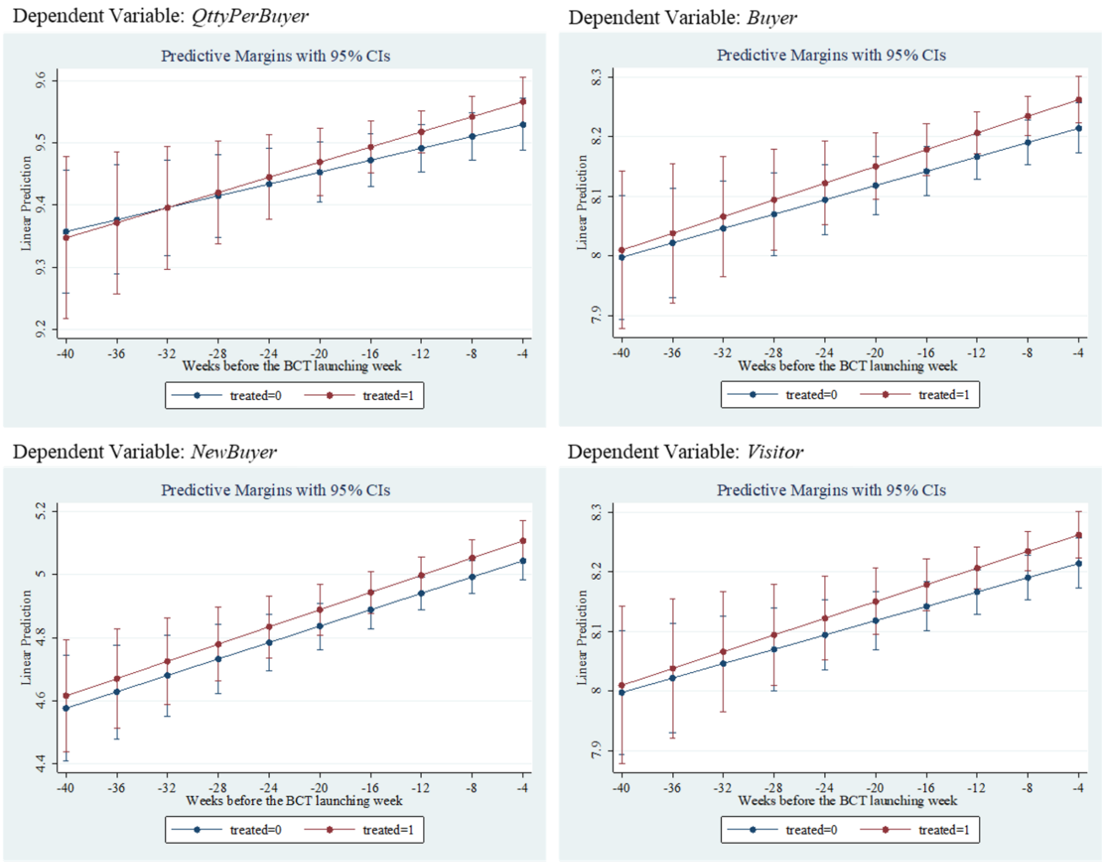
In Panel (D), the trend variable is replaced by four weekly dummies in the regression. The weekly dummies can estimate the time varying changes of the observations and its interaction with $Treated_i$ test whether the treatment and control groups have similar changes in different weeks before BCT implementation. As reported in the above table, the corresponding coefficients of the cross-time variables and the treatment variable are not significant for all dependent variables. Standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%.

Panel A. Parallel Trends Test with 40-week Pretreatment Trend

Variables	*QttyPerBuyer*	*AllBuyer*	*NewBuyer*	*Visitor*
$Trend_{it}$	0.0044***	0.0108***	0.0124***	0.0046**
	[0.0016]	[0.0028]	[0.0027]	[0.0019]
$Trend_{it} * Treated_i$	0.0034	0.0016	0.0011	0.0024
	[0.0027]	[0.0039]	[0.0039]	[0.0028]
$Discount_{it}$	1.6573***	2.4896***	2.1407***	1.8651***
	[0.2441]	[0.3508]	[0.3580]	[0.1537]

$Constant$	8.9890***	4.7565***	4.4141***	7.5914***
	[0.0752]	[0.1092]	[0.1113]	[0.0540]
SKU fixed effects	Yes	Yes	Yes	Yes
Observations	6125	6212	6212	5774
Within R-sq	0.086	0.108	0.089	0.132

Figure A. The visual plots of regressions in Panel A



Panel B. Parallel Trend Test with 20-week Pretreatment Trend

Variables	*QttyPerBuyer*	*AllBuyer*	*NewBuyer*	*Visitor*
$Trend_{it}$	-0.0031	0.0044	0.0076	-0.0088**
	[0.0030]	[0.0046]	[0.0050]	[0.0043]
$Trend_{it} * Treated_i$	0.0101	0.008	0.0099	0.0119*
	[0.0048]	[0.0062]	[0.0070]	[0.0060]
$Discount_{it}$	1.5322***	2.1038***	1.7106***	1.7677***
	[0.2375]	[0.3144]	[0.3255]	[0.1990]
$Constant$	8.9173***	4.7663***	4.4763***	7.5246***
	[0.0751]	[0.0991]	[0.1027]	[0.0673]
SKU fixed effects	Yes	Yes	Yes	Yes
Observations	3192	3224	3224	3053
Within R-sq	0.066	0.082	0.057	0.114

Panel C. Parallel Trend Test with 10-week Pretreatment Trend

Variables	*QttyPerBuyer*	*AllBuyer*	*NewBuyer*	*Visitor*
$Trend_{it}$	0.007	0.0290***	0.0355***	0.0071

	[0.0076]	[0.0109]	[0.0122]	[0.0066]
$Trend_{it} * Treated_i$	0.0019	-0.0043	-0.0006	0.0108
	[0.0121]	[0.0143]	[0.0169]	[0.0105]
$Discount_{it}$	1.9306***	2.2277***	1.9080***	1.9635***
	[0.4158]	[0.4390]	[0.4482]	[0.3117]
$Constant$	8.8098***	4.7412***	4.4591***	7.5285***
	[0.1312]	[0.1417]	[0.1466]	[0.0991]
SKU fixed effects	Yes	Yes	Yes	Yes
Observations	1544	1571	1571	1502
Within R-sq	0.083	0.094	0.073	0.158

Panel D. Parallel Trend Test with 4 pretreatment Dummies

Variables	*QttyPerBuyer*	*AllBuyer*	*NewBuyer*	*Visitor*
Four weeks ahead	-0.1888**	-0.2904***	-0.3108***	-0.1590***
	[0.0730]	[0.0659]	[0.0709]	[0.0533]
*Four weeks ahead*Treated*	-0.1406	-0.1341	-0.1383	-0.0533
	[0.1017]	[0.1076]	[0.1138]	[0.0814]
Three weeks ahead	-0.1209*	-0.2798***	-0.2952***	-0.1229**
	[0.0686]	[0.0654]	[0.0703]	[0.0620]
*Three weeks ahead*Treated*	-0.1578	-0.0172	-0.0391	-0.0598
	[0.1118]	[0.1207]	[0.1316]	[0.0949]
Two weeks ahead	-0.1622***	-0.2465***	-0.2649***	-0.1289***
	[0.0498]	[0.0548]	[0.0588]	[0.0437]
*Two weeks ahead*Treated*	-0.1237	-0.0122	-0.0102	0.0079
	[0.0857]	[0.0973]	[0.1065]	[0.0683]
One week ahead	-0.1505**	-0.2248***	-0.2450***	-0.1341***
	[0.0609]	[0.0615]	[0.0717]	[0.0393]
*One week ahead*Treated*	-0.0288	0.0548	0.0139	0.0433
	[0.0870]	[0.0858]	[0.0981]	[0.0553]
$Discount_{it}$	2.5163***	2.0317***	1.8384***	1.6119***
	[0.5882]	[0.5245]	[0.5536]	[0.3995]
$Constant$	8.7874***	4.8940***	4.5864***	7.7073***
	[0.1853]	[0.1737]	[0.1811]	[0.1347]
SKU fixed effects	Yes	Yes	Yes	Yes
Observations	882	905	905	868
Within R-sq	0.166	0.161	0.138	0.156

Appendix IV. Sample Statistics

	No. of SKUs	Percent (%)	Cum. (%)
Panel A. BCT Adoption period			
2017 2nd half	11	6.04	6.04
2018 1st half	43	23.63	29.67
2018 2nd half	26	14.29	43.96

2019 1st half	11	6.04	50.00
Total treated SKUs	91		
Total control SKUs	91	50.00	100.00
Total SKUs	182	100.00	
Panel B. Product category			
Powder milk	82	45.05	45.05
Nutrition supplement	34	18.68	63.73
Liquor	34	18.68	82.41
Agricultural product	32	17.58	100.00
Total SKUs	182	100.00	
Panel C. Product origin			
Asia (domestic)	54	29.67	29.67
Asia (abroad)	10	5.49	35.16
Europe	84	46.15	81.32
North America	22	12.09	93.41
Oceania	12	6.59	100.00
Total SKUs	182	100.00	

Appendix V. Results of re-estimation using data from different matching algorithms

We tried different matching algorithms and replicated the DID framework using new sample sets. Standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%.

Panel A. One-to-one matching with a caliper restriction

Variable	*(1)QttyPerBuyer*	*(2)Allbuyer*	*(3)Newbuyer*	*(4)Visitor*
$After_{it}$	0.0594**	0.0767**	0.1329***	0.0068
	[0.0284]	[0.0342]	[0.0370]	[0.0247]
$After_{it} * Treated_i$	0.0668***	0.0415*	0.0722**	0.0682***
	[0.0250]	[0.0321]	[0.0337]	[0.0229]
$Discount_{it}$	1.7768***	2.8070***	2.6053***	1.8149***
	[0.1111]	[0.1490]	[0.1612]	[0.0804]
Constant	9.2516***	4.9434***	4.5241***	7.8605***
	[0.0316]	[0.0426]	[0.0460]	[0.0244]
SKU fixed effects	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
Observations	7,358	7,393	7,393	7,047
Adjusted R^2	0.906	0.883	0.862	0.906

Panel B. One-to-many matching with a caliper restriction

Variable	*(1)QttyPerBuyer*	*(2)Allbuyer*	*(3)Newbuyer*	*(4)Visitor*
$After_{it}$	0.0657***	0.0993***	0.1307***	0.0201
	[0.0208]	[0.0234]	[0.0256]	[0.0178]
$After_{it} * Treated_i$	0.0781***	0.0356*	0.0866***	0.0410**
	[0.0212]	[0.0259]	[0.0275]	[0.0189]
$Discount_{it}$	1.7961***	2.6057***	2.3458***	1.8949***
	[0.0815]	[0.1094]	[0.1159]	[0.0607]
Constant	8.9690***	4.6982***	4.3206***	7.5708***
	[0.0250]	[0.0330]	[0.0350]	[0.0193]
SKU fixed effects	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
Observations	14,117	14,164	14,164	13,664
Adjusted R^2	0.919	0.897	0.879	0.923

Panel C. New PSM predicting model; One-to-one matching without caliper restriction

Variable	*(1)QttyPerBuyer*	*(2)Allbuyer*	*(3)Newbuyer*	*(4)Visitor*
$After_{it}$	0.0475**	0.0694***	0.0809***	0.0415**
	[0.0203]	[0.0227]	[0.0248]	[0.0166]
$After_{it} * Treated_i$	0.1419***	0.0783***	0.1522***	0.0483***
	[0.0215]	[0.0258]	[0.0274]	[0.0183]
$Discount_{it}$	2.0961***	3.0516***	2.7472***	2.1190***
	[0.0864]	[0.1176]	[0.1230]	[0.0643]
Constant	9.1835***	4.8899***	4.5363***	7.7798***
	[0.0264]	[0.0351]	[0.0368]	[0.0199]
SKU fixed effects	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
Observations	15,119	15,178	15,178	14,699

Adjusted R^2	0.92	0.897	0.879	0.93

Panel D. New PSM predicting model; One-to-one matching with a caliper restriction

Variable	*(1)QttyPerBuyer*	*(2)Allbuyer*	*(3)Newbuyer*	*(4)Visitor*
$After_{it}$	0.0134	0.0486	0.0711*	0.0042
	[0.0324]	[0.0387]	[0.0420]	[0.0258]
$After_{it} * Treated_i$	0.1749***	0.1300***	0.1982***	0.1213***
	[0.0283]	[0.0380]	[0.0397]	[0.0235]
$Discount_{it}$	2.2721***	3.4568***	3.1693***	2.0128***
	[0.1499]	[0.2162]	[0.2271]	[0.1085]
Constant	9.3975***	5.0322***	4.6717***	8.0961***
	[0.0423]	[0.0604]	[0.0636]	[0.0309]
SKU fixed effects	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
Observations	6,506	6,531	6,531	6,298
Adjusted R^2	0.904	0.881	0.861	0.922

Panel E. New PSM predicting model; One-to-many matching with a caliper restriction

Variable	*(1)QttyPerBuyer*	*(2)Allbuyer*	*(3)Newbuyer*	*(4)Visitor*
$After_{it}$	0.0475**	0.0694***	0.0809***	0.0415**
	[0.0203]	[0.0227]	[0.0248]	[0.0166]
$After_{it} * Treated_i$	0.1419***	0.0783***	0.1522***	0.0483***
	[0.0215]	[0.0258]	[0.0274]	[0.0183]
$Discount_{it}$	2.0961***	3.0516***	2.7472***	2.1190***
	[0.0864]	[0.1176]	[0.1230]	[0.0643]
Constant	9.1835***	4.8899***	4.5363***	7.7798***
	[0.0264]	[0.0351]	[0.0368]	[0.0199]
SKU fixed effects	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
Observations	15119	15178	15178	14699
Adjusted R^2	0.897	0.920	0.930	0.879

Panel F. Searchable attribute matching and look-ahead PSM

Variable	*(1)QttyPerBuyer*	*(2)Allbuyer*	*(3)Newbuyer*	*(4)Visitor*
$After_{it}$	-0.1246***	0.0486	-0.0031	-0.1324***
	[0.0458]	[0.0430]	[0.0538]	[0.0338]
$After_{it} * Treated_i$	0.1243***	0.0396*	0.1253***	0.1479***
	[0.0380]	[0.0361]	[0.0449]	[0.0307]
$Discount_{it}$	2.5708***	2.9679***	1.3472***	3.5581***
	[0.2065]	[0.2123]	[0.2829]	[0.1870]
Constant	10.0430***	5.4753***	4.9763***	8.0224***
	[0.0489]	[0.0493]	[0.0648]	[0.0433]
SKU fixed effects	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
Observations	1920	1920	1920	1920
Adjusted R^2	0.931	0.957	0.926	0.949

Appendix VI. The Moderation effect of Consumer Review Consensus

We check the robustness of our result with another variable, consumer review consensus, which is measured below (part A and part B) and reverse to the consumer review inconsistency in the main analysis (section 5.2). In the results presented in Part C below, the effects of BCT on the outcome variables are smaller for products with a high consumer review consensus. Therefore, the results are consistent with the main analysis, which shows that the effects of BCT are greater for products with a high consumer review inconsistency

Part A: The Measurement of Consumer Review Consensus

We assumed that consumers perceive two rating tiers: high and low, from historical rating information.

1. For each week before BCT implementation, we calculated $SKU\ i$'s weekly rating tier v_{it} within its subcategory. If the weekly average rating was among the top 50% $SKUs$ in the subcategory, then $v_{it} = H$, otherwise $v_{it} = L$.
2. We then calculated the percentage of each rating tier (pct_i^H, pct_i^L) in the pretreatment period for $SKU\ i$.
3. The $SKU\ i$'s final consumer review consensus equaled to the corresponding value of the most frequent rating tier (i.e., $\max\{pct_i^H, pct_i^L\}$).

Part B: An Example of the Computation Procedure of Consumer Review Consensus

SKU (i)	Week (t)	Weekly average score	Weekly rating tier (v_{it})
1	1	3	H
2	1	1	L
3	1	3	H
1	2	4	H
2	2	2	L
3	2	4	H
1	3	2	L
2	3	1	L
3	3	4	H
1	4	3	L
2	4	4	H
3	4	3	L

SKU (i)	Percentage of weeks in low tier (pct_i^L)	Percentage of weeks in high tier (pct_i^H)	Final review consensus
1	0.5	0.5	0.5
2	0.75	0.25	0.75
3	0.25	0.75	0.75

Part C: The Moderation Effect of Consumer Review Consensus on BCT Signaling

	QttyPerBuyer	*AllBuyer*	*NewBuyer*	*Visitor*
$After_{it}$	-0.0428	-0.2145***	-0.1443*	-0.0735
	[0.0538]	[0.0734]	[0.0743]	[0.0510]
$After_{it} * Treated_i$	0.4760***	0.7759***	0.7748***	0.5755***
	[0.0771]	[0.0977]	[0.0982]	[0.0737]
$After_{it} * RatConsensus_i$	0.0525	0.2675***	0.2117**	0.1024
	[0.0681]	[0.0984]	[0.0996]	[0.0654]
$After_{it} * Treated_i * RatConsensus_i$	-0.5057***	-0.9753***	-0.9134***	-0.6752***
	[0.1029]	[0.1333]	[0.1342]	[0.0975]
$Discount_{it}$	1.1178***	1.8559***	1.5675***	1.4752***
	[0.0669]	[0.0913]	[0.0944]	[0.0531]

Constant	8.9979***	4.6901***	4.3847***	7.6044***
	[0.0245]	[0.0322]	[0.0337]	[0.0198]
SKU fixed effects	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
Observations	13292	13385	13385	12918
Adjusted R^2	0.917	0.899	0.883	0.927

*Notes. Standard errors in brackets; * significant at 1%; ** significant at 5%; *** significant at 1%.*

Appendix VII. Regression Results of All Variables (The Full Model)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	QttyPerBuyer	*AllBuyer*	*NewBuyer*	*Visitor*	*QttyPerBuyer*	*AllBuyer*	*NewBuyer*	*Visitor*
$After_{it}$	0.0871***	0.0626	0.0120	0.0807**	0.0871***	0.0626	0.0120	0.0910**
	[0.0329]	[0.0489]	[0.0511]	[0.0325]	[0.0329]	[0.0489]	[0.0511]	[0.0383]
$After_{it} * Treated_i$	-0.0503	-0.1631***	-0.0772	-0.1357***	-0.0503	-0.1631***	-0.0772	-0.1731***
	[0.0391]	[0.0545]	[0.0569]	[0.0380]	[0.0391]	[0.0545]	[0.0569]	[0.0461]
$After_{it} * Inconsistency_i$	-0.0248	0.0869*	0.0055	-0.1316***	-0.0248	0.0869*	0.0055	-0.0643
	[0.0318]	[0.0520]	[0.0528]	[0.0292]	[0.0318]	[0.0520]	[0.0528]	[0.0421]
$After_{it} * Treated_i * Inconsistency_i$	0.2754***	0.3664***	0.3016***	0.3939***	0.2754***	0.3664***	0.3016***	0.3852***
	[0.0469]	[0.0676]	[0.0686]	[0.0432]	[0.0469]	[0.0676]	[0.0686]	[0.0573]
$After_{it} * Imported_i$	-0.1270***	-0.1709***	-0.0221	-0.0699**	-0.1270***	-0.1709***	-0.0221	-0.0593
	[0.0315]	[0.0505]	[0.0521]	[0.0322]	[0.0315]	[0.0505]	[0.0521]	[0.0392]
$After_{it} * Treated_i * Imported_i$	0.1322***	0.2171***	0.1745***	0.1765***	0.1322***	0.2171***	0.1745***	0.2331***
	[0.0449]	[0.0633]	[0.0657]	[0.0423]	[0.0449]	[0.0633]	[0.0657]	[0.0526]
$Discount_{it}$	1.1360***	1.8558***	1.5685***	1.4976***	1.1360***	1.8558***	1.5685***	1.6451***
	[0.0659]	[0.0873]	[0.0911]	[0.0520]	[0.0659]	[0.0873]	[0.0911]	[0.0803]
Constant	8.9974***	4.6979***	4.3899***	7.6018***	8.9974***	4.6979***	4.3899***	7.8105***
	[0.0243]	[0.0313]	[0.0329]	[0.0196]	[0.0243]	[0.0313]	[0.0329]	[0.0276]
SKU fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13292	13385	13385	12918	13292	13385	13385	10708
Adjusted R^2	0.917	0.900	0.883	0.927	0.917	0.900	0.883	0.917

Appendix VIII. Effects of BCT Implementation on the Sales Quantity and the Moderation Effects of Consumer Review Inconsistency and Product Origins

	Basic	Completed
$After_{it}$	-0.0386	0.0605
	[0.0285]	[0.0413]
$After_{it} * Treated_i$	0.1214***	-0.0799
	[0.0245]	[0.0490]
$After_{it} * Inconsistency_i$		-0.1487***
		[0.0399]
$After_{it} * Treated_i * Inconsistency_i$		0.1633***
		[0.0561]
$After_{it} * Imported_i$		-0.0030
		[0.0407]
$After_{it} * Treated_i * Imported_i$		0.4016***
		[0.0593]
$Discount_{it}$	2.0416***	2.0386***
	[0.0917]	[0.0925]
Constant	5.1605***	5.1611***
	[0.0330]	[0.0332]
SKU fixed effects	Yes	Yes
Week fixed effects	Yes	Yes
Observations	13312	13312
Adjusted R^2	0.912	0.912

Note. Interactive fixed effect model; Standard errors in brackets; * significant at 10%; ** significant at 5%; *** significant at 1%

Appendix IX. Regression Results of Skipping Period Model

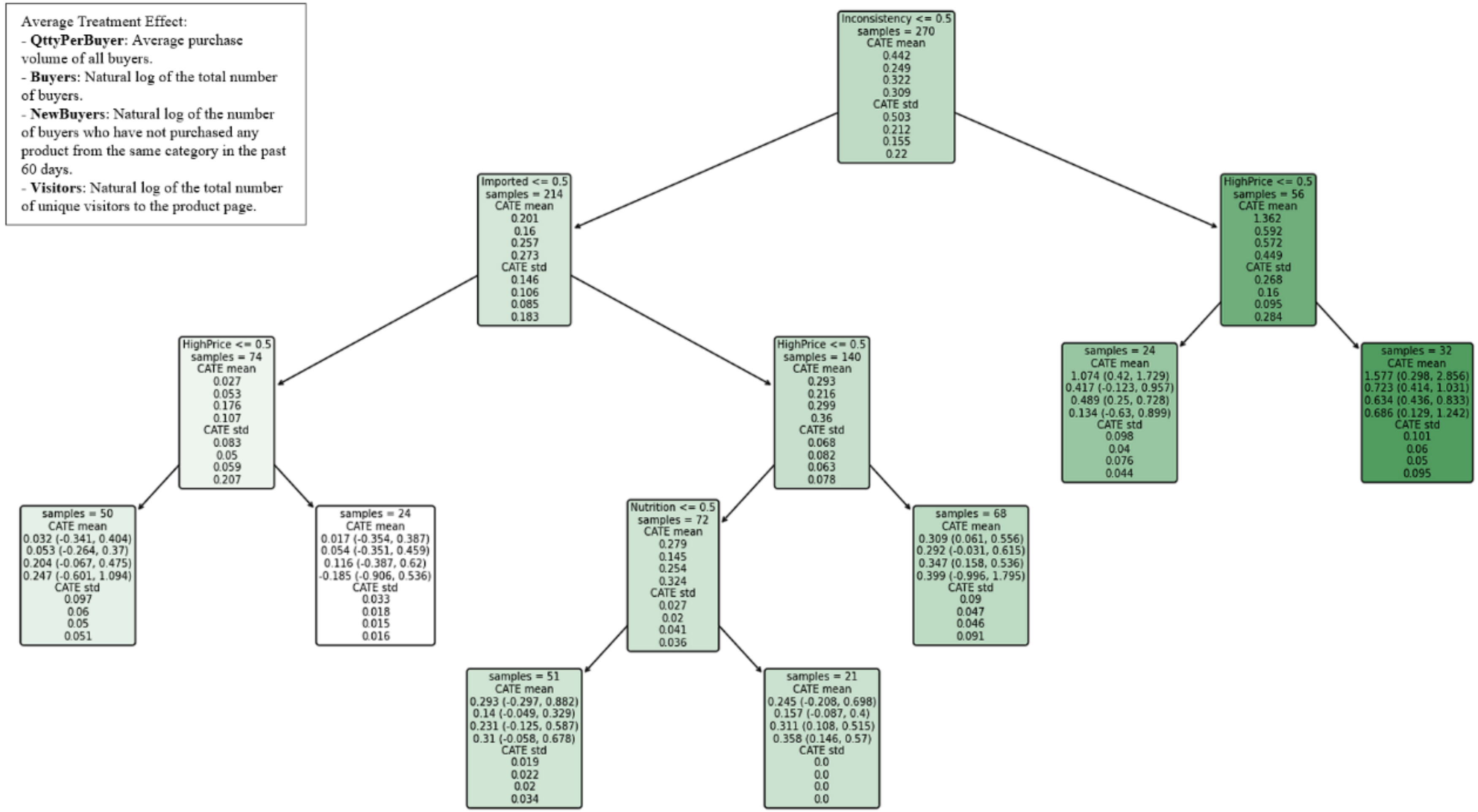
	QttyPerBuyer	*AllBuyer*	*NewBuyer*	*Visitor*	*QttyPerBuyer*	*AllBuyer*	*NewBuyer*	*Visitor*
$SkipAfter_{it}$	-0.0703**	-0.1730***	-0.1888***	-0.1030***	0.0513	-0.0618	-0.1876***	-0.0645
	[0.0324]	[0.0412]	[0.0434]	[0.0287]	[0.0461]	[0.0654]	[0.0679]	[0.0429]
$SkipAfter_{it} * Treated_i$	0.0784***	0.0440*	0.0862***	0.0588***	-0.0764	-0.2096***	-0.1256*	-0.1356***
	[0.0249]	[0.0319]	[0.0327]	[0.0224]	[0.0510]	[0.0678]	[0.0704]	[0.0470]
$SkipAfter_{it} * Inconsistent_i$					0.0193	0.1496***	0.0285	-0.0098
					[0.0389]	[0.0577]	[0.0584]	[0.0359]
$SkipAfter_{it} * Treated_i * Inconsistency_i$					0.3003***	0.4517***	0.4343***	0.3878***
					[0.0583]	[0.0804]	[0.0803]	[0.0530]
$SkipAfter_{it} * Imported_i$					-0.1678***	-0.2025***	-0.0182	-0.0478
					[0.0410]	[0.0614]	[0.0628]	[0.0398]
$SkipAfter_{it} * Treated_i * Imported_i$					0.1303**	0.2288***	0.1720**	0.1596***
					[0.0581]	[0.0778]	[0.0803]	[0.0526]
$Discount_{it}$	1.2094***	1.9692***	1.6530***	1.6033***	1.2071***	1.9479***	1.6241***	1.5806***
	[0.0706]	[0.0976]	[0.1012]	[0.0610]	[0.0708]	[0.0976]	[0.1015]	[0.0607]
Constant	9.0209***	4.7294***	4.4484***	7.6182***	9.0173***	4.7299***	4.4541***	7.6207***
	[0.0255]	[0.0343]	[0.0359]	[0.0222]	[0.0255]	[0.0343]	[0.0361]	[0.0220]
SKU fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9684	9773	9773	9329	9684	9773	9773	9329
Adjusted R^2	0.916	0.889	0.872	0.924	0.917	0.891	0.873	0.925

Appendix X. The Results of First-Order Difference Causal Forest (FDCF) Analysis

In order to get more insights regarding the potential moderators of BCT signaling effect, we conducted the first-order difference causal forest (FDCF) analysis on all outcome variables ($QttyPerBuyer$, $AllBuyer$, $NewBuyer$, $Visitor$). For each treated and control SKU, we firstly calculate the average change in the four outcome variables from the pretreatment to the posttreatment period (first-order difference). We then applied the causal forest approach using the average treatment effect of the four variables. The treatment variable is the dummy which discriminates the treated SKUs and the control SKUs. The forest focused its splits of the samples using the features that we expect to have heterogenous effects on the outcome variables. The feature variables include: an indicator of high score deviation ($Inconsistency$), an indicator of overseas product origins ($Imported$), an indicator whether the treated SKU is more expensive than its controls ($HighPrice$), and four dummies indicating the product category of the treated SKUs (i.e., $AgriFood, PowderedMilk, Liquor, Nutrition$), and a variable measure the order delivery cycle ($WaitTime$). According to Wang (2022), the causal forest approach using the first-order difference teases out the systematic difference and the time trends difference between the treatment and control groups.

Figure A interprets the heterogeneous effects of the features by splitting on the cutoff points that maximize conditional average treatment effect (CATE) difference in each leaf. As shown in the figure, $Inconsistency$ is the most important discriminator of the treatment effects. 56 SKU samples with inconsistent consumer rating ($Inconsistency$=1) have the CATE values equaling to 136.2%, 59.2%, 57.2%, and 44.9%, respectively. Otherwise, for the 214 samples without inconsistent consumer rating ($Inconsistency$=0), their CATE values are lower (respectively 20.1%, 16%, 25.7%, and 27.3%). Therefore, products with a higher consumer rating inconsistency experienced larger percentage changes in the sales outcomes due to BCT implementation. Then, for the 214 samples which have $Inconsistency$ equals to 0, $Imported$ discriminates the treatment effect -- when equals to 1, the CATE values of 140 samples are 29.3%, 21.6%, 29.9%, and 36%; the CATE values of the other 74 SKUs are 2.7%, 5.3%, 17.6%, and 10.7%. Interestingly, the relative market price of products ($HighPrice$) is also identified as an important discriminator. However, the impact direction is conditional upon the consumer rating and provenance of products. For example, among products with inconsistent consumer ratings, the subsample with more expensive traced products has larger CATE values. In contrast, with consistent consumer ratings and domestic provenance, the subsample with expensive traced products do not have significantly positive CATE values. Comparing with the subsample which do not have the expensive traced SKUs, the changes of sales outcomes maybe even lower. This phenomenon can be explained by the quality signaling effect and economic cost effect of high price (Dodds et al. 1991). On one hand, a high price would have a positive effect on consumer's willingness to buy if it signals the product quality to a level that outweighs the economic cost. On the other hand, a negative effect would take place if the signaled quality is less than the cost in exchange for the ownership of the product (Moore and Carpenter 2006). The results imply that the BCT adopters with inconsistent consumer rating and from oversea provenance can enjoy the benefits that come from the quality signaling of a high price.

Figure A. Single Tree CATE Interpreter



Note: EconML SingleTreeCateInterpreter is used. The maximum depth of the tree is restricted to 5; the minimum number of samples required at a leaf node is restricted to 20.

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