Investigation of the effect of e-platform information security breaches: an SME supply chain perspective

Abstract

Many small and medium enterprises (SMEs) engage in dyadic information integration partnerships or partial integration with their direct suppliers and customers. They often utilize e-commerce or cloud computing technology platforms hosted by third-party providers to leverage such partnerships. However, information security breaches and disruptions caused by cyber-attacks are commonplace in the IT industry. The effects of said disruptions and breaches on e-commerce businesses under varied disruption conditions are still uncertain. Furthermore, the effect of security breaches on non-participating members of the supply chain is poorly understood, especially under various disruption profiles. Using discrete event modeling, this study explores the impact of disruption caused by information security breaches on supply chain performance and the externality effect of partial integration on non-participants. We also examine the impact of breach disruption frequency and remediation length on supply chain performance with varying levels of information sharing. These impacts were studied under two typical inventory replenishment policies for SMEs. It was determined that remediation length should be a prioritized factor in impact management and that flexibility in the inventory replenishment policy can help mitigate the impact of information disruption on the inventory performance of businesses, especially that of non-participants, in information-sharing partnerships.

Keywords: information security breach, simulation, information integration, disruption impact, supply chain integration.

1. Introduction

Small and medium-scale enterprises (SMEs) are heavily reliant on IT, mostly hosted by third-party technology service providers on e-commerce platforms such as Shopify and BigCommerce (Meng, 2017). These technologies or platforms are used by SMEs to facilitate the exchange and sharing of relevant information such as demand and inventory data (Holland & Gutiérrez-Leefmans, 2018). As increasing numbers of firms rely on information technology (IT) to run their day-to-day operations, the impact of disruptions caused by information security breaches (ISBs) or cyber-attacks on these firms and their supply chains becomes increasingly important. Thus far, the focus has largely been on those platform providers that are directly breached with little attention being paid to the small businesses that utilize said third-party platforms for their own operations and supply chain transactions. For example, analysts estimated the effect of the data breach experienced by eBay in 2014 to be a loss of approximately $200 million in revenue (Drinkwater, 2014), but that figure does not reflect the cost to the small businesses using the e-commerce platform. Despite small businesses accounting for the majority of private businesses in most developed and developing economies (Wright, 2018), there is a paucity of research into how their supply chains are impacted by disruptions caused to their service providers. The effects reported usually include loss of revenue, costs of remedial action or litigation and share price drops, but the effect on inventory management, arguably the most important cost component for small businesses, is seldom discussed (Kim, 2020). A 2019 Zogby Analytics survey of 1006 small-business decision-makers, conducted on behalf of the National Cyber Security Alliance, revealed that 10% of SMEs fail after experiencing a data breach (*Small Business Cybercriminal Target Survey Data*, 2019). Therefore, it is vital to understand the nature and extent of the impact of ISBs affecting e-platform providers on the performance of SMEs and their supply chains.

Another factor that can affect the nature and extent of the impact of ISBs on SMEs is the extent to which information is shared. It has been reported that it is beneficial to supply chain members to engage in the sharing of important information such as demand, inventory, supply lead time and capacity information (Devaraj, Krajewski, & Wei, 2007; Kovtun, Giloni, & Hurvich, 2019; Mukhopadhyay & Kekre, 2002; Rached, Bahroun, & Campagne, 2015; Yu, Ting, & Chen, 2010). In order to take advantage of said information-sharing benefits, SMEs try to share real-time information with their suppliers, utilizing varying degrees of information-sharing partnerships ranging from sharing solely with their direct suppliers (partial information integration) to sharing all along the supply line, all the way to the manufacturer (full information integration). Many SMEs adopt partial information integration partnerships due to the higher costs associated with full integration partnerships. This decision often has inadvertent consequences on non-participating members of the chain (such as the manufacturer), hereafter referred to as the ‘externality effect’. This externality effect in an information disruption scenario is poorly understood, especially on non-participating members of the supply chain. Although past research reveals that partial and full information integration benefits participating businesses, it is still not clear how the disruption of the integration platform (e-commerce sites) in the event of an ISB erodes those benefits for participating members and affects non-participating members.

Another critical factor that can affect the nature and extent of ISB impact on performance is the profile of the ISB itself, defined as the frequency with which it occurs and the level of sophistication of the breach. The incidence of ISBs disrupts access to technology, which means businesses may be deprived of useful, time-sensitive information needed to run their operation and supply chain efficiently. Several surveys have shown that technology service providers experience the highest frequency of ISBs or cyber-attacks compared to other industries (Bromiley, 2016; Miller, Horne, & Potter, 2015). The cost implications of the frequency of ISBs to these small and medium businesses are not sufficiently reported or understood. Additionally, the level of sophistication determines how long it takes to detect and remediate the breach. The remediation duration is understood as the time taken to restore functionality and accessibility to users to the software or hardware technology in order to allow them to resume business after being compromised by an ISB. The remediation duration, also referred to as disruption duration, is also an indicator of the resilience of the platform. The longer the remediation time, the less resilient the platform is deemed to be. Similarly, the shorter the remediation duration, the more resilient the platform is. The remediation period brings delays in information transmission, which has inventory management cost implications. This has not been sufficiently explored for SMEs. This study, therefore, aims to explore the impact of the frequency and remediation length of ISBs on supply chain performance and the purported benefits of information integration partnerships formed by SMEs, which are hosted on third-party platform providers.

Motivated by the above empirical evidence and the research gap in the literature, this paper aims to deepen our understanding of the impact of ISB incidences at third-party e-platforms on SMEs and their supply chains by using different information integration profiles. To this end, the study addresses the following questions:

a) What is the nature and extent of ISB impact on SME supply chain performance?
b) How is the benefit of information integration via shared platforms affected by the frequency and remediation length of an ISB?
c) To what extent are non-participants affected by the externality effect of partial supply chain information integration, and to what extent is this externality effect exacerbated or improved by ISBs?

To answer the above questions, we examined two levels of information integration partnerships where the sharing platform is inclusive of i) the downstream partners only (partial information integration mode); and ii) both upstream and downstream partners (full information integration mode). There are different ISB types, which cause varying levels of difficulty in remediating and varying frequencies of occurrence. We have focused on ISB profiles in terms of remediation duration and frequency of occurrence rather than on individual ISB types. The three ISB profiles, hereafter called 'disruption profiles' (DP), used in this study are i) low remediation length, low frequency of breach incidences (BP1); ii) low remediation length, high frequency of breach incidences (BP2); and iii) high remediation length, low frequency of breach incidences (BP3). Additionally, because our focus is on goods supply chains rather than services, we examined the impact of DP under two replenishment policies i) parameter-based replenishment (base stock policy) and ii) non-parameter-based replenishment (batch ordering policy). Since our focus is on SMEs using e-commerce platforms, we expect that their greatest expense would be inventory management costs; therefore, our focus is on the inventory performance of the supply chain and the typical inventory costs, including backlog, inventory holding and ordering costs. We have not considered other costs associated with information security breaches such as punitive costs, reputational costs, remediation costs or lost sales as these losses are borne, to a large extent, by the platform provider.

The rest of this paper is organized as follows: Section 2 examines the gap in the literature and the validity of the approach used. Section 3 presents the model setup and the validity of the simulation models and experimental parameters. Section 4 discusses the results, and Section 5 concludes this paper and proposes future work.

2. Literature Review

This study falls at the intersection between two research areas, namely: i) information sharing and ii) the disruption impact caused by information security incidents. The subsequent review is not intended to be exhaustive but rather to indicate where the current study fits within these two research areas.

Over the years, extensive studies in operations research have been conducted in the area of information-sharing partnerships and how agents in the supply chain derive benefit from it (Bourland, Powell, & Pyke, 1996; Chan & Chan, 2009; Huang, Ho, & Fang, 2017; Li et al. 2006; S. Li & Lin, 2006; Zhenxin, 2001). Other studies have shown that the benefit may be disproportionately distributed among supply chain members (Sahin & Robinson Jr, 2005; Yao & Dresner, 2008). Therefore there has been some discussion about ways to incentivize members in the chain that participate in, but do not benefit from, an information-sharing partnership (Dominguez et al. 2018b; Yao, Dong, & Dresner, 2010), while incentives are not offered for non-participating members. To our knowledge, the focus of past research into information-sharing benefits has been on one of the following three scenarios: i) a dyadic partnership in a two-stage supply chain setting (Cachon & Fisher, 2000; Huang et al., 2017; Khan, Hussain, & Saber, 2016; Kovtun et al., 2019; Lee, So, & Tang, 2000; Teunter et al. 2018; Zhou & Benton Jr, 2007), ii) dyadic partnership in a multi-stage supply chain setting without any consideration for the other members in the supply chain (Dominguez et al. 2018a), or iii) full partnership in a multi-stage supply chain setting (Dominguez et al., 2018b; Ganesh, Raghunathan, & Rajendran, 2014; Lau, Huang, & Mak, 2004). Studies of scenario i) are very limited in scope because the interaction is only between two players, which does not account for the complexities of supply chain interactions where processes in one part of the supply chain have a bearing on what goes on in other parts (Chatfield, 2013). For example, Huang et al. (2017) concluded that sharing too much information in a dyadic partnership can result in a negative outcome, which suggests that the amount of information shared should be moderated for optimal benefits. While informative, it is difficult to conclude that the same strategy for optimizing benefits will apply in a multi-stage setting. Studies in scenarios ii) and iii) tend to overcome some of the limitations of scenario i) by examining dyadic partnerships and full partnerships in multi-stage settings. However, most of these studies utilize a single inventory replenishment policy which limits generalizability as different replenishment policies behave differently under specific conditions, leading to different outcomes or conclusions (Lau, Xie, & Zhao, 2008). For example, Dominguez et al. (2018b), Ganesh et al. (2014) and Lau et al. (2004) found that some supply agents favor information sharing at certain points in the supply chain over other points, but they all utilized single replenishment policies in their studies. They all utilized Order-Up-To (OUT) policy, which is a parameter-based replenishment policy where the quantity ordered from the upstream agent is determined by the difference between two key parameters: the inventory position (IP) and the target inventory level (S). It is, therefore, necessary to examine information-sharing benefit in a multi-stage supply chain setting under different replenishment policies. To the authors' knowledge, Dominguez et al. (2018a) is the only study that has attempted to do this, but this is also parameter-based like the rest of the studies. Only two different variances were utilized to compute the target inventory level (S). However, the size of the order quantity was still determined by the difference between the two parameters: IP and S. This parameter-based policy has been shown to behave differently to other policies such as the batch policy, where a certain fixed amount is ordered. Our study, in one sense, will try to fill this gap by examining the benefit of information integration under two distinct replenishment policies in order to gain an incremental picture of information-sharing benefits. This increased understanding is even more pertinent when studying this benefit under disruption conditions such as incidences of an information security breach. In addition, previous studies have not considered these issues within the context of SMEs' supply chains. Those that have considered the SME context for supply chain partnerships have mostly been focused around building innovation capabilities (Mei, Zhang, & Chen, 2019; Radziwon & Bogers, 2019; Rehm & Goel, 2017; Yanes-Estévez, 2019). Our study is unique in that it uses a three-stage supply chain with two separate replenishment policies to investigate the benefits of information sharing not only among participants but also on non-participants of said sharing.

In the area of disruption, some studies in the field of operations and technology management have focused primarily on the disruption effect on supply chains without any regard to specific causes (Munoz & Clements, 2008; Schmitt & Singh, 2009; Snoeck, Udenio, & Fransoo, 2019) while others have looked more specifically at how specific disruption types (threats) affect the supply chain (Altay & Ramirez, 2010; Craighead et al. 2007; Rodger & George, 2017; Świerczek, 2014). The former approach gives a more general assessment of the effect of disruption, while the latter gives a clearer understanding of the dynamics of specific threats and how they impact the chain. Table 1 provides a summary of work that has been done on disruption risk assessment at the organizational level as well as the supply chain level and brings to light those studies that have provided real and objective estimations of the cost impact of certain threats on business operations and those that have looked at specific IT security risks. The third column of the table reveals the approach taken in undertaking the study. From the last three columns of Table 1, it can be seen that no single study has covered all three aspects of disruption risk assessment, at least not for small businesses. While some of these studies have examined the effect of physical disruption such as natural disasters (Dani, 2009), it is notable that only a small number have examined the effect of IT security incidents (Deane et al. 2009; Kim et al. 2011; Loch, Carr, & Warkentin, 1992; Rees et al. 2011), despite it being described as a persistent business risk in the 2015 survey conducted by PwC. Rodger and George (2017) developed an optimized sustainability model that reduces supply chain global cybersecurity vulnerability in the natural gas industry, but the direct impact of cybersecurity disruption on supply chain performance remained unclear. In addition, only a handful of these research papers have examined the impact of ISBs on inventory management, and those that have been mostly conceptual (Durowoju & Chan, 2012; Durowoju, Chan, & Wang, 2011). It is, therefore, imperative to determine how these threats affect the inventory performance of supply chain agents, before agreeing to specific information integration initiatives, as this is crucial for effective disruption risk planning and management. To the authors' knowledge, there is no single study examining the impact of information security disruption on multi-echelon supply chain inventory cost performances under varying supply conditions such as ordering policy and level of information integration.

Table 1: Summary of some relevant disruption risk studies

Authors	Subject	Approach	Cost Impact study? Y/N	IT security incident? Y/N	Supply chain study? Y/N
Snoeck et al. (2019)	A stochastic program to evaluate disruption mitigation investments in the supply chain	Stochastic programming	Y	N	Y
Rodger and George (2017)	Reducing supply chain global cybersecurity vulnerability in the natural gas industry using an optimized sustainment model	Linear programming, fuzzy integrated linguistic operator, weighted average	N	Y	Y
Świerczek (2014)	The impact of supply chain integration on the "snowball effect" in the transmission of disruptions	Quantitative survey	N	N	Y

Altay and Ramirez (2010)	Impact of disasters on firms in different sectors: implications for supply chains	Fixed-effect regression	Y	N	Y
Schmitt and Singh (2009)	Quantifying supply chain disruption risk	Monte Carlo and discrete event simulation	Y	N	Y
Deane et al. (2009)	Managing supply chain risk and disruption from IT security incidents	Mixed-integer linear programming	N	Y	Y
Munoz and Clements (2008)	Disruptions in information flow: a revenue-costing supply chain dilemma	Discrete event simulation of beer distribution game	Y	N	Y
Rees et al. (2011)	Decision support for cybersecurity risk planning	Genetic algorithm	N	Y	N
Whitman (2003)	Profiling threats to information security	Interviews and survey	N	Y	N
Wilson (2007)	The impact of transportation disruptions on supply chain performance	Dynamic simulation modeling	Y	N	Y
Bellefeuille (2005)	Quantifying and managing the risk of information security breaches to the supply chain	Descriptive research	N	Y	Y
Yeh and Chang (2007)	Threats and countermeasures for information system security: A cross-industry study	Questionnaires and analysis of covariances (ANCOVAs)	N	Y	N
Goel and Shawky (2009)	Estimating the market impact of security breach announcements on firm values	Event-study methodology	Y	N	N
Craighead et al. (2007)	The severity of supply chain disruptions	Multiple-method, multiple-source empirical research design	N	N	Y
Kim et al. (2011)	The dark side of the Internet: Attacks, costs and responses	Explorative research	N	Y	N
Loch et al. (1992)	Threats to information systems: Today's reality, yesterday's understanding	Questionnaires	N	Y	N

3. Simulation Approach

This study focuses on the disruption in information flow resulting from a breach of information security. According to Lau et al. (2004), the simulation approach has an advantage over the analytical approach in that the effect of information sharing on supply chains can be investigated under various scenarios. Discrete event simulations (DES) are a powerful tool used in mimicking the dynamics of a real system as it evolves over time (Ingalls, 2008; Law, 2007). A multi-agent approach where each tier of the supply chain has at least one agent (or member as they are sometimes called) making decisions is accurately representative of a real-world situation, hence making it the approach of choice (Swaminathan, Smith, & Sadeh, 1998). For this study, we have used the Java program JDK 1.6, which is widely used for simulation studies, as the simulation tool.

3.1 Modeling the Supply Chain

The supply chain is conceptualized as a series of agents working autonomously to deliver goods to the end consumer. For simplicity, the number of echelons within the supply chain is limited to three, consisting of the retailer, wholesaler and manufacturer, as this represents an ideal supply chain scenario. The decision on when to order and how much to order is determined internally by each agent, who operate independently and strive to achieve the minimum operating cost possible. Depending on their position in the supply chain, each agent places an order to the upstream agent, and the upstream agent delivers goods to the downstream agent. Essentially, the retailer experiences the demand from the end customer (market demand) and determines when and what quantity of order to place with the wholesaler. In turn, the wholesaler works out when to order and how much to order from the manufacturer. The manufacturer then produces the product and delivers it to the wholesaler who, in turn, determines the quantity of goods to deliver to the retailer and then supplies it. The sequence of activities involved in determining when to order and how much to order for each agent is similar to Lau et al. (2004) and is shown below. Each agent makes their decision using key parameters, which are shown in Table 2.

Table 2: Key modeling parameters

Parameter	Notation	Retailer	Wholesaler	Manufacturer
Market demand	D	*		
Order quantity	Q	*	*	
Production quantity	PQ			*
Mean of orders from downstream agent	μ	*	*	*
Standard deviation of orders	σ	*	*	*
Stock received by agent	SR	*	*	
Stock shipped by agent	SS	*	*	*
Stock from production	SFP			*
On-hand inventory	OH	*	*	*
On-order/pipeline inventory	OO	*	*	*
Backlog quantity	BL	*	*	*
Inventory position	IP	*	*	*
Transportation lead time	L		*	*
Production lead time	PL			*
Production capacity	PC			*
Re-order point	ROP	*	*	*
Order-up-to-level	OUT	*	*	*
New order quantity	NQ	*	*	
New production quantity	NPQ			*
Unit shortage cost	*b*	*	*	*
Unit holding cost	*h*	*	*	*
Unit ordering cost	*o*	*	*	
Unit production cost	*om*			*
Fixed ordering cost	*f*	*	*	
Production setup cost	*p*			*
Safety factor	*k*	*	*	*

Table 2 shows the parameters of operation and their mathematical representation (notation). The use of '*' indicates whether the parameters relate to a specific agent or not. For example, Market demand (D) relates only to the retailer and stock received by the agent (SR) relates only to the retailer and wholesaler, while stock from production refers only to the manufacturer. To help distinguish information describing the activities of a particular agent from that relating to other agents, subscripts x and y are used. Subscript 'y' represents information relating to the upstream agent, while 'x' refers to parameters relating to the downstream agent. The sequence of activities and the mathematical model are described as follows.

Step 1: At the beginning of each operating day, an agent receives stock delivered by an upstream agent

The stock sent by the upstream agent is received at the current period by the downstream agent after the transportation lead time of the upstream agent. This stock is received at the start of business.

$$SR_t = SS_{y,t-L} \tag{1}$$

For the manufacturer, SS_y is replaced with SFP, which is stock received from production after the production lead time.

i.e. $SR_t = SFP_{t-PL}$ (2)

Step 2: Update of inventory position

Once the stock is received, the state of the on-hand inventory and the on-order inventory is updated as follows:

$$OH_t = OH_{t-1} + SR_t \tag{3}$$

$$OO_t = OO_{t-1} - SR_t \tag{4}$$

The inventory position is then updated as shown below:

$$IP_t = OH_t + OO_t - BL_{t-1} \tag{5}$$

Step 3: A decision is made as to whether an order should be placed and what quantity to order

A decision to order is made when the inventory position is below the re-order point, and the quantity to order (Q_t) at a given period, t, is governed by the ordering option adopted by the agent. This is discussed later in the study. It is assumed in the simulation model that each supply chain agent orders from the upstream agent when the inventory position, IP, (also called installation stock) falls to the re-order point, ROP, (eq. (6)) and the magnitude of order is decided by the choice of ordering policy adopted.

$$ROP_t = \mu(L_y + 1) + k\sigma\sqrt{L_y + 1} \tag{6}$$

The safety factor (k) is computed using eq. (7), which gives the optimal value of k, which is the solution to the standard newsvendor problem as expressed in Lau et al. (2002).

$$k = \Phi^{-1}\left(\frac{b}{b+h}\right) \tag{7}$$

Step 4: Update of on-order inventory

The order information above (if any) is passed to the upstream agent, and the on-order inventory is updated.

$$OO_t = OO + Q_t \tag{8}$$

Step 5: Receipt of order from downstream agent

The order information for the day is received from the adjacent customer (downstream agent), and this is added to the pending order previously placed to determine the new order quantity for that period. If the agent is the retailer, the adjacent customer is the end customer, and the customer order is called market demand.

$$NQ_{x,t} = Q_{x,t} + BL_{t-1} \tag{9}$$

Step 6: Calculation of quantity to deliver to fulfill orders from downstream agent

Each agent tries to fulfill all demands/orders placed by a downstream customer. However, whatever the agent is unable to fulfill is back-ordered.

$$SS_t = Min(NQ_{x,t}, OH_t) \tag{10}$$

$$BL_t = NQ_{x,t} - SS_t \tag{11}$$

Step 7: Update of on-hand inventory information

$$OH_t = Max(OH - SS_t, 0) \tag{12}$$

Step 8: Calculation of mean and standard deviation for orders

The mean of orders and standard deviation of orders is computed using the moving average (MA) technique. For the retailer, the mean of orders is represented as mean of demand instead.

Step 9: Calculation of the operating cost for the day

The operating costs this study is interested in are the holding cost, the backlog cost, and the ordering cost. These are computed using eq. (13), (14) and (15) respectively.

$$HC_t = h * OH_t \tag{13}$$

$$BC_t = b * BL_t \tag{14}$$

$$OC_t = p * Max(Q_t, 0) + o * Q_t \tag{15}$$

For the manufacturer, the fixed ordering cost is known as production setup cost (*p*), and the unit ordering cost is called the unit production cost (*op*). Each cost is computed at the end of the day and averaged over the effective simulation period only.

3.2 Modeling the Ordering Policies

The first alternative (Option I), which determines its order size by computing the difference between two decision parameters (which we call parameter-based ordering) is the order-up-to base stock policy. The second alternative, which uses a predetermined batch size (batch ordering), is represented in this study as Option II- the optimal economic order quantity (EOQ*) in a stochastic environment specified by Axsäter (Axsäter, 1996). These two policies were selected as they have been extensively researched and validated in literature and are quite dissimilar in their computation. Therefore, the aim is to find out if the incentive for some supply agents to favor certain types of information-sharing partnerships remain the same, given the behavior of ordering policies under various disruption scenarios.

3.2.1 Option I (The base stock policy)

The base stock policy has been used by several authors (Agrawal, Sengupta, & Shanker, 2009; Beamon & Chen, 2001; Bensoussan, Cakanyildirim, & Sethi, 2007; Chen et al. 2000). Here, an order is placed to raise inventory to the base stock level (otherwise called order-up-to level, OUT) when the inventory position falls below the base stock level. This option is also called an adaptive model because the order-up-to-level, or base stock level in this case, is recalculated every replenishment period. The base stock level is calculated in a similar way to eq. (6). The ordering decision for this policy is shown in eq. (16).

$$Q_t = \begin{cases} \max(OUT_t - IP_t, 0), & IP_t < ROP_t \\ 0, & IP_t \geq ROP_t \end{cases} \tag{16}$$

Here, the order quantity is determined by two decision parameters: the order-up-to level and the inventory position (Cimino, Longo, & Mirabelli, 2010), which is why it is referred to as parameter-based ordering.

3.2.2 Option II (The optimal EOQ model)

In contrast to the base stock policy, in an (R, Q) option, when the inventory position falls to the re-order point (R), a batch (Q) is ordered. However, according to Vasconcelos and Marques (2000), Q is usually set to the economic order quantity (EOQ), which is predetermined, while R is the re-order point computed for each replenishment period. The EOQ model, being deterministic, usually fails and causes a significant increase in cost when used in a stochastic environment. However, Axsäter (1996) proposed an optimal solution for Q. The standard solution for EOQ in a stochastic environment is given by eq. (17).

$$EOQ_t = \sqrt{\frac{2\mu f(b+h)}{bh}} \tag{17}$$

However, according to Axsäter (1996), multiplying the EOQ by square root of $1+\alpha^2$ becomes optimal when $\alpha=2$. This optimal model is used as one of the ordering options in the current study.

$$Q_t = \begin{cases} \max(EOQ_t * 2.2361, 0), & IP_t < ROP_t \\ 0, & IP_t \geq ROP_t \end{cases} \tag{18}$$

3.3 Modeling the Extent of Information Integration Partnership

This study adopts the conceptual model of information-sharing levels validated in Lau et al. (2002) and Lau et al. (2004). Information integration (also termed information sharing) is conceptualized here as a strategy where an upstream agent is privy to the demand and other related inventory information of a downstream agent such as the inventory position, safety factor, lead time, ordering cost, backlog cost and holding cost. The extent of information integration (EII), therefore, refers to how far up the chain information is being shared. Figure 2 (b) and (c) show the two main EII scenarios examined in this study, including the non-integrated model called the base model. The performance of each of the two EII scenarios is evaluated against the base model. The base model, in Figure 2 (a), represents a supply chain where each supply agent acts independently and does not share information with any other agent. In this model, only the order information is passed from a downstream agent to the preceding upstream agent.

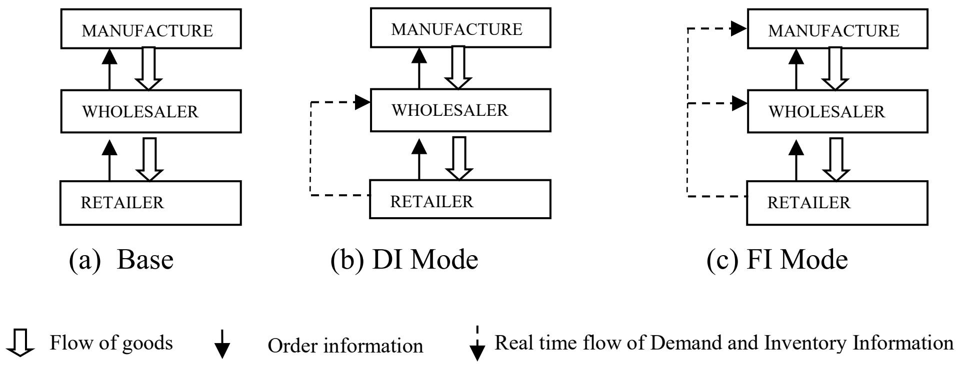


Figure 2 Three levels of information sharing

3.3.1 Downstream integration (DI mode)

This is the integration between retailer and wholesaler only. In Figure 2 (b), the DI mode is a supply chain where the retailer shares market demand information and other related inventory information with the wholesaler. The wholesaler, in turn, uses this information to make inventory decisions. The retailer and manufacturer control their inventory as previously described, but certain decision parameters are changed for the wholesaler. Instead of using the installation stock, the wholesaler uses the echelon stock instead, represented as IP′, as shown in eq. (19). The echelon inventory position at the current period t is the sum of the inventory position of the agent calculated normally in eq. (5) and that of the retailer, also calculated using eq. (5). The re-order point also changes to ROP′, as shown in eq. (20) while the EOQ computation changes from (17) to (21).

$$IP'_t = IP_t + IP_{x,t} \tag{19}$$

$$ROP'_t = \mu_x(L_y + L + 2) + k_x\sigma_x\sqrt{L_y + L + 2} \tag{20}$$

$$EOQ'_t = \sqrt{\frac{2\mu(f+f_x)(b+h)}{bh}} \tag{21}$$

Here, μ_x and σ_x are the average market demand and standard deviation of market demand, respectively, rather than the retailer order, since the wholesaler is now privy to this information from the retailer.

3.3.2 Full integration (FI Mode)

The final information-sharing mode considered is the FI mode (Figure 2 (c)), which is a scenario in which the wholesaler and the manufacturer are privy to the retailer's market demand and other related inventory information. The manufacturer is also privy to the wholesaler's inventory information. The decision parameters of the retailer do not change but that of the wholesaler and the manufacturer change. The wholesaler's parameters are similar to those in the DI mode, and the manufacturer's parameters now include the retailer's inventory information. Therefore, the echelon stock for the manufacturer becomes the summation of the inventory position of the manufacturer, calculated normally, and the entire downstream agent (wholesaler and retailer) as shown in eq. (22). Equations (20) and (21) also changes to (23) and (24) for the manufacturer.

$$IP'_t = IP_t + \sum IP_{x,t} \tag{22}$$

$$ROP'_t = \mu_x(L_x + L + PL + 3) + k_x\sigma_x\sqrt{L_x + L + PL + 3} \tag{23}$$

$$EOQ'_t = \sqrt{\frac{2\mu_x(p+f_x+f_r)(b_x+h_x)(b_r+h_r)}{(b_xh_x)(b_r+h_r)}} \tag{24}$$

μ_x and σ_x in eq. (23) represent the average and standard deviation of retailer order, respectively, while μ_x and subscript 'r' in eq. (24) represent the average market demand information and retailer parameter, respectively.

3.3 The Disruption Model

A 2017 cybersecurity survey (Klahr et al., 2017) revealed that 1 in 5 organizations experience a security breach which results in temporary loss of access to files/network or have had their software/systems corrupted or damaged. This is a major concern, as many organizations rely on access to these files/networks in order to store and retrieve real-time demand and/or inventory information. Various breach surveys have reported typical frequencies of ISBs to be a few times per day, one per day, one per week, one per month, less than one per month, and one per year. However, having studied data from various surveys, and based on our investigation, we have only considered frequencies of one per quarter (low frequency)-BP1, and one per week (high frequency)-BP2, in order to show the effect of an increased frequency of ISBs on supply chain performance.

According to the SANS Institute survey of 591 respondents in 2016, remedial actions are largely manual and can include activities such as rebuilding a server or replacing a workstation (Bromiley, 2016). The survey further revealed that remedial action can typically take less than one day (29% of respondents) or between 2 to 7 days (33% of respondents). Therefore, in our study, we examined the impact of an average of 1-day (low) and 5-day (high) remediation length as they are typical figures in the industry. Comparing the impact of low remediation length (BP1) with the impact of high remediation length (BP3) gives an indication of the effect of increased remediation length (or rather decreased resilience) on supply chain performance.

Breach Model Assumption:

It is assumed that the service provider's interfaces with end consumer and supply chain operators are off-line during the remediation period, but become available after the disruption period. Therefore, the remediation time is seen in this study as the 'delay period' for the supply chain operators in getting access to real time demand and inventory information. During this period, the supply chain partners are unable to know what the actual demand is, but they continue to forecast demand based on moving average forecasting technique. The demand is not actually lost during the remediation period but only delayed. The assumption that demand is not lost is supported by various industry experts who comment that since 2013, most retail customers and shareholders are becoming desensitized and are more forgiving owing to the frequency with which security breaches occur in the retail industry (C. Chen, 2018; Kvochko & Pant, 2015).

3.4 Simulation Experiments

The simulation was run for 800 days. Using the time series method (Kelton, Sadowski, & Swets, 2010), the warm-up period was set to 100 days, resulting in an effective period of 701 days, and the average statistics were computed over this period. The number of replications required to obtain a 98% confidence level was determined to be 45, using the confidence interval method described in Law (Law, 2007). The same random number streams were used for each experiment to ensure that input bias is eliminated and to ensure direct comparison between scenarios. To test for significance during result comparison, we employed the Paired-t Confidence Intervals for Mean Differences with Bonferroni Correction and standard-t Confidence Intervals for Mean Differences with Bonferroni Correction at 95% confidence level (Law, 2007; Robinson, 2004). The following assumptions, which are routine assumptions used in most simulation studies of this nature, were made in the model:

- In the serial supply chain model, there is only one product and a single agent in each tier of the supply chain; the downstream agent places an order to the adjacent upstream agent. As supply structures may be more complex in reality, and this complexity consequently affects the outcome, this study only focuses on the interaction between the integration and disruption profiles. Hence the simplest structure (serial type) was adopted in this evaluation.
- Demand is normally distributed with a mean of ten quantities and a standard deviation of two quantities.
- All the lead times are constant.
- All members of the supply chain use the same ordering policy.
- If on-order quantity cannot be met with current on-hand inventory, then the on-hand inventory is shipped, and the rest is back-ordered, leaving the agent with zero inventory.
- Each unfulfilled order is back-ordered, and a shortage or backlog cost is incurred by the supplier per unit item.
- The total production capacity at the manufacturer tier is assumed to be 80 units.
- A unit of production capacity makes a unit of the product for the duration of the production lead time.

Table 3 shows the parameters considered for these experiments, similar to those used in Lau et al. (2002); Lau et al. (2004). The demand follows a normal distribution with a mean of ten units and a standard deviation of two units and is reviewed at the end of each day.

Table 3: Simulation parameters

Parameter	Value
Demand (units)	NORM (10,2)
Demand Arrival	End of Day
Production Lead Time	3 days

Manufacturer Capacity	80
Transportation Lead Time from Wholesaler to Retailer	2 days
Transportation Lead Time from Manufacturer to Wholesaler	5 days
Retailer Unit Holding Cost, Backlog Cost, Ordering Cost	£5, 10, 5
Wholesaler Unit Holding Cost, Backlog Cost, Ordering Cost	£3, 10, 5
Manufacturer Unit Holding Cost, Backlog Cost, Production Cost	£3, 10, 5

3.5 Sensitivity of the Simulation Model

To ensure that the result is not biased against our input parameters, we conducted a sensitivity analysis by examining the simulation output under two varying conditions. The first sensitivity analysis was conducted on the only variable input parameter (demand stream) by changing the demand variance from low to high (2 to 4) and the second by halving the lead time across the supply chain. The result revealed that, at 95% confidence level, changing the demand variance does not affect the 'nature of impact', and, as expected, the higher the demand variance, the higher the magnitude of impact of information security breach. However, the nature of the effect, whether negative or positive, of high recurrence rate and high disruption duration remains the same. On the other hand, reducing the lead time by half did not have a significant impact on the performance of the batch ordering system in either the non-breached or breached scenarios. Although halving the lead time in the parameter-based system appears to increase cost performance, the impact of an information security breach under scenarios of high disruption and low recurrence rate was significantly reduced. This is because reducing the lead time in a parameter-based ordering system increases the flexibility of the ordering system in a disruption scenario where supply agents are able to respond more rapidly to changes in demand level. Therefore, changing the demand variance or the lead time only affects the magnitude of the breach impact and does not affect the nature of the impact, which is the focus of our findings. Conclusively, the findings of this study are robust under the conditions studied. In addition, the simulation models were verified using the simple walkthrough or traces technique described in Sargent (2010).

4. Result and Discussion

This section discusses the output of the simulation experiments and answers the research questions posed in the introduction. The results of the experiments have been intentionally presented in different formats for ease of exposition when discussing different questions. Using the t-test, a pair-wise comparison reveals that each ordering policy and each integration level are significantly different (at $p \leq 0.05$) from each other when there is no disruption to the supply chain. This conforms to the findings in other validated models and, to some extent, confirms the validity of our modeling of them in the base model.

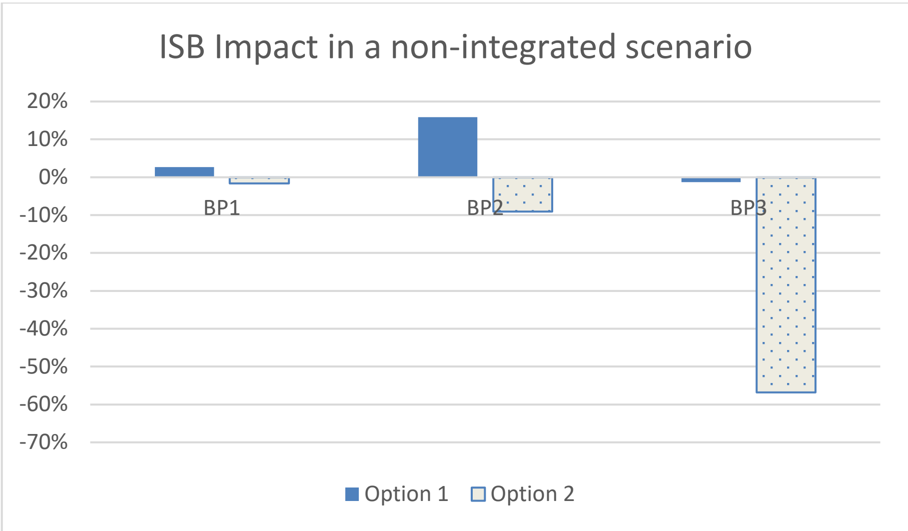
Table 4 shows the supply chain daily average cost performance for the base model and the relative performance of the partial and full information-sharing scenarios under the three disruption profiles. For ease of exposition, we have extracted relevant information from the table and displayed it in a different format in order to focus on specific questions.

Table 4: Daily average supply chain cost performance.

Disruption Profile	Integration Type	Ordering Policy	
		Option1 (£)	**Option2 (£)**
Base Model		397.0	309.8
No disruption	DI	355.8	302.1
	FI	314.0	287.3
BP1	Base(NI)	386.5	314.8
	DI	350.3	305.6
	FI	312.8	291.1
BP2	Base(NI)	333.9	338.0
	DI	308.8	331.3
	FI	314.8	324.6
BP3	Base(NI)	402.2	485.7
	DI	395.2	480.0
	FI	385.1	471.8

4.1 Impact of Frequency and Remediation Length of ISBs on SCM Performance

Recall from Section 3.3 that the only difference between BP1 and BP2 is that BP2 has a much higher frequency of disruption; therefore, the difference in performance between the two is solely due to the effect of increased disruption frequency as the disruption duration in both BP1 and BP2 is low. Similarly, the only difference between BP1 and BP3 is that BP3 has a higher remediation length. Therefore, a comparison between the performances of BP1 and BP3 signifies the sole effect of increased remediation length as the frequency of disruption in BP1 and BP3 are the same. Figure 3 shows the impact of all three ISB profiles on the base model without any form of integration. The percentage values are derived by expressing the difference between the daily average cost under the base model and the daily average cost under each ISB profile as a percentage of the former. Negative values indicate an increase in cost, which is a negative impact, while positive values indicate a reduction in cost, which is a positive effect on the daily average cost. Therefore, Figure 3 clearly shows the nature (polarity of impact, whether negative or positive) and extent (magnitude of impact) of ISB on supply chain performance, which helps us answer research question 'a'. We see that high frequency of disruption has a positive effect under Option I as the benefit increases from 3% in BP1 to 16% in BP2, but under Option II, a negative impact was observed with the negative impact increasing from -2% in BP1 to -9% in BP2. This shows that the frequency of occurrence of an ISB will have either a negative or positive effect depending on the inventory policy being adopted, as long as the disruption duration is very low each time it occurs. However, as expected, a high disruption duration had a negative impact on cost performance, especially for the batch policy, where impact increased from -2% in BP1 to -57% in BP3. This high negative impact provides empirical evidence to support the argument that most small businesses experiencing a significant breach incidence are unable to recover from the impact and consequently cease trading or file for bankruptcy (*Small Business Cybercriminal Target Survey Data*, 2019). This is despite the fact that for small businesses using third-party platforms, most of the reputational, legal and remediation cost of ISB is borne by the platform provider that was attacked. We have shown here that such attacks significantly affect or lead to the closure of small businesses using such platforms exclusively for their daily operation without any information integration partnership with other members of the supply chain.



Negative sign indicates negative impact where ISB has increased the daily average cost.

Figure 3: Impact of ISB profile on supply chain inventory performance

As for the positive effect of frequency of occurrence on the base stock policy, it is important to know that there is some inherent flexibility in the base stock policy owing to it being a parameter-based ordering policy, whereby the quantity ordered depends on the difference between the inventory position and the re-order point. This flexibility allows operators to place smaller order quantities at frequent intervals, unlike the batch ordering type (Option II), where larger order quantities are placed at infrequent intervals. The comparatively higher order quantity of a batch ordering policy makes it more cost-effective than the parameter-based policy with a lesser order quantity. However, our study shows that the inherent flexibility of the base stock policy is increased under higher frequencies of disruption, resulting in a better performance than in a non-disruptive scenario. This is because BP2 has a low remediation length (1 day) and when this is combined with a high frequency of occurrence, it creates a condition where the usually low order quantities associated with base stock policy become larger, giving rise to an overall better cost performance than in the non-disruptive scenario. However, this does not hold true in a scenario with a disruption with larger remediation length even when this occurs less frequently (as in BP3).

Therefore, supply chain operators should undertake an impact assessment of this kind to know how their inventory policy would fare during a breach incident. This, in turn, will determine the necessary cybersecurity KPI to include in their contract with platform providers in order to further protect themselves.

4.2 Effect of Frequency and Remediation Length of ISBs on the Purported Benefits of Partial and Full Integration

The singular effect of the disruption profile on integration is computed as the distance between the relative performance in a non-disruptive scenario (expressed as a percentage of the base model) and the relative performance in each disruption scenario (also expressed as a percentage of the base model). This distance is shown for both partial (DI) and full integration (FI) under all three disruption scenarios (or profiles) in Figure 4, which helps us to answer research question ‘b’. From Figure 4, we see that the magnitude of the impact generally increases as one goes from BP1 to BP2 and BP3. This means that remediation length (BP3) has a higher impact on the purported benefits of integration than frequency of occurrence (BP2).

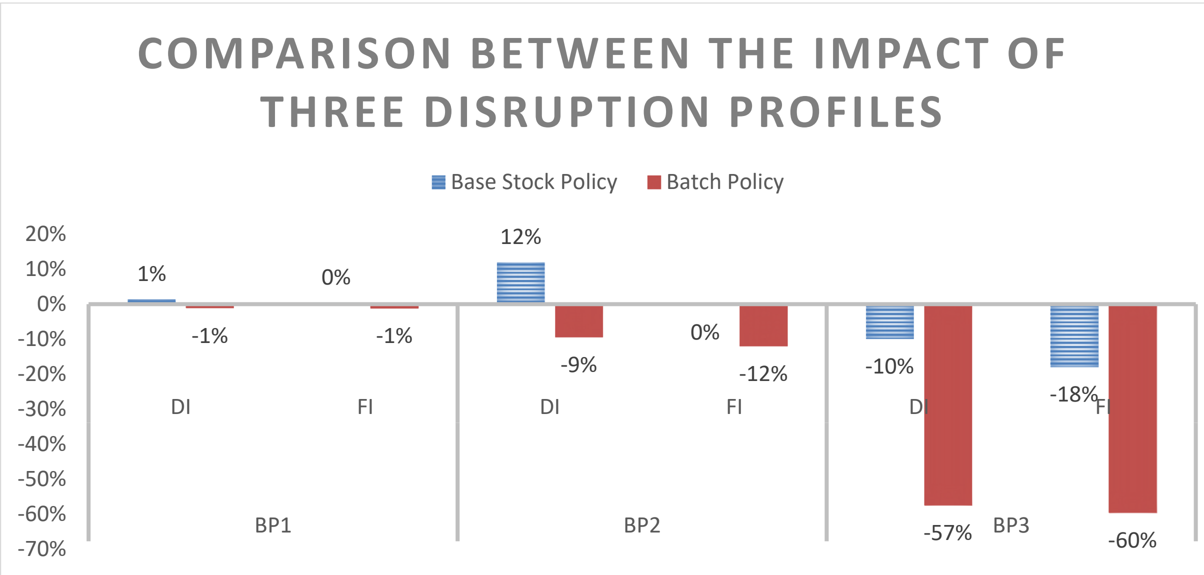


Figure 4 Effect of Disruption Profile on Integration Benefit under two distinct inventory policies.

The same peculiarity of impact observed with the frequency of occurrence in the non-integration scenario in Section 4.1 above is observed with the integration benefits here. In addition, we observe another peculiarity involving the differences in performance between DI and FI modes. Both peculiarities, however, only pertain to one aspect of the breach profile: the frequency of occurrence.

In terms of differences in performance between full and partial integration, we find that remediation length has a higher impact on full integration than on partial integration under both base stock and batch policies, but this is not the case with frequency of occurrence under the base stock policy. To explain this effect, we must examine this at the supply agents' level (see Table 5).

Table 5 Disruption Profile Impact on Supply Chain Agents

			No disruption		**BP1**		**BP2**		**BP3**	
		Base (£)	DI	FI	DI	FI	DI	FI	DI	FI
Option I	Retailer	194.9	12%	20%	14%	22%	29%	31%	9%	13%
	Wholesaler	112.7	18%	30%	19%	29%	19%	22%	-2%	4%
	Manufacturer	89.4	-3%	11%	-2%	10%	12%	-3%	-15%	-19%
Option II	Retailer	120.0	5%	5%	3%	3%	-10%	-11%	-103%	-103%
	Wholesaler	86.8	4%	6%	3%	5%	-8%	0%	-32%	-25%
	Manufacturer	103.0	-2%	11%	-2%	11%	-2%	-2%	-19%	-15%

A negative percentage indicates an increased cost, which signifies a worse performance compared to the base model.

From Table 5, the cost for the manufacturer in the DI mode improves from -3% in the non-disruptive scenario to 12% in BP2 scenario while the benefit of FI reduces from 11% in the non-disruptive scenario to -3% in BP2 scenario. For the wholesaler, the benefit of the DI mode remains the same under BP2 (at ~19%), but the benefits of the FI mode diminish from 30% in the non-disruptive scenario to 22% in the BP2 scenario. The effect of BP2 on the retailer's cost was an improvement in performance from 12% to 29% in the DI mode, which is greater in scale than the increase from 20% to 31% in the FI mode. The synergy of the impact on all three supply agents shows a resultant greater positive effect for the SME supply chain in the DI mode as compared with the FI counterpart. This shows that the frequency of disruption has a greater positive impact on SME supply chains with the partial integration mode than on the full integration mode under the flexible base stock policy. This effect is explained further in the next section under the externality effect of partial integration.

4.3 Externality Effect

To examine the externality effect on non-participants, we only look at integration scenarios where a particular member of the supply chain is not included, such as the manufacturer in the DI scenario. The externality effect is construed as the difference in the performance of the manufacturer in the base model when compared to the performance in the DI scenario. Therefore, subsequent analysis is based only on the DI mode. First, we examine this effect under normal settings and then under disruptive settings. Again, we see a counterintuitive phenomenon between the parameter-based policy (Option I) and the non-parameter-based policy (Option II).

From Figure 5, under the no-disruption scenario, we observe that there is an externality effect on the manufacturer's cost performance if SME supply chains engage in DI integration. In this scenario, the retailer and wholesaler enjoyed reduced costs at the expense of the manufacturer, and this was true for both inventory policies studied, making the observation more generalizable.

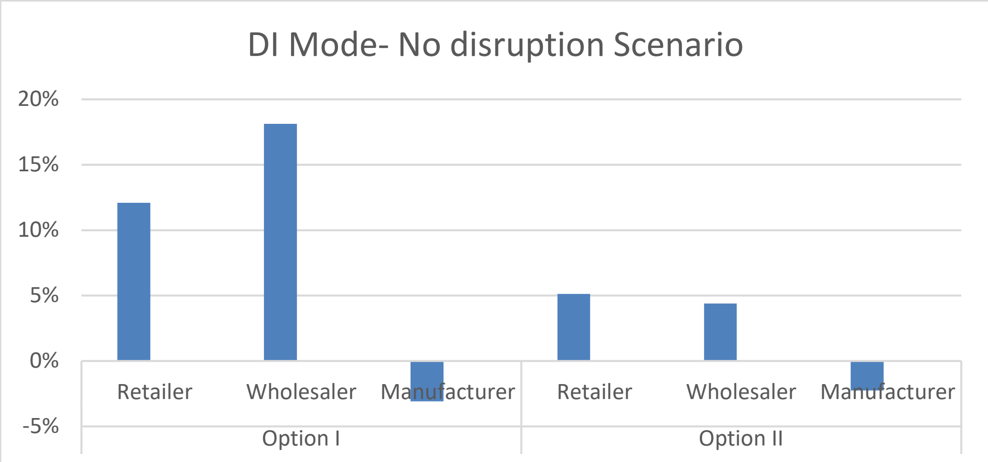


Figure 5 Effect of DI mode on supply chain agents' performance

The manufacturer incurred a 3% increase in cost, solely from the externality effect of DI partnership under a non-disruptive scenario. Further analysis revealed that while the retailer and wholesaler enjoyed a significant reduction in backlog cost, the manufacturer incurred an increase in backlog, which could not offset the decrease in holding cost observed at the manufacturer. Therefore, manufacturers in such scenarios may need to think about ways to mitigate or offset such disadvantages, either through price adjustment or any other means.

Furthermore, to estimate the effect of disruption on this externality effect, we take the percentage impact of disruption on the DI mode and deduct the percentage impact of disruption on a non-integrated mode (also called the base disruption impact). The resulting difference is the singular effect DI partnership has on the base disruption impact. This can be referred to as the impact of disruption on the DI effect. All impact percentages are expressed as a percentage of the base model to allow for direct comparison, and the result is shown in Table 6.

Table 6 Disruption impact on DI-externality effect on the manufacturer

Inventory Policy	Externality Effect in the No-disruption Scenario	Effect of DI Mode on the Base Disruption Impact		
		BP1	BP2	BP3
Option I	-3%	-2%	12%	8%
Option II	-2%	-2%	-2%	-14%

Note: Positive values mean the effect is desirable as there is reduction of the impact of disruption on cost performance, negative means a disadvantageous effect.

From Table 6, it is clear that disruption of type BP1 has no impact on the externality effect for the manufacturer under the base stock replenishment policy as the value remains virtually the same (at -2%). This observation is also more generalizable as it is true for both inventory policies studied. However, under more disruptive scenarios, disruption impact on externality effect is seen to differ based on the type of inventory policy. For the base stock policy (Option I), BP2 (high frequency, low remediation length) and BP3 (low frequency, high remediation length) are seen to be advantageous to the externality effect for the manufacturer. The manufacturer's cost goes from -3% in the no-disruption scenario to 12% and 8% in the BP2 and BP3 scenarios, respectively, thus revealing an improvement to the manufacturer's performance under highly disruptive modes. In fact, it appears that this is more favorable to the manufacturer in the DI supply chain than in the FI counterpart. These findings again appear counterintuitive, albeit not impossible. For instance, under the base stock policy, the DI mode is of greater benefit to the manufacturer's holding cost than the FI mode, whereas the backlog cost of the manufacturer is significantly increased under DI but decreased under the FI mode. This tips the scale in favor of the FI mode for the manufacturer under non-disruptive settings. This corroborates results from various other studies, which show that including the manufacturer in information sharing is more beneficial for the supply chain than if the manufacturer is not included (Xu, Dong, & Evers, 2001; Yao & Dresner, 2008). However, this finding does not hold true under certain conditions, as our study reveals. In the BP2 scenario, the backlog cost disadvantage of the DI in the non-disruptive scenario is significantly reduced, to the extent that it now outweighs FI superiority for the manufacturer. Again, this is because the flexibility of the parameter-based policy is enhanced by the increased frequency of disruption, and the non-participating manufacturer who ideally should be disadvantaged in the DI mode is able to improve its ability to satisfy demand, thereby reducing the backlog and only slightly increasing the holding cost. The benefits derived under this condition—higher frequency of disruption—outweighs the benefit provided by FI under normal circumstances. Having said that, we do not infer that disruption is desirable but instead aim to show that some counterintuitive implications exist, which operators should be aware of and plan for accordingly.

For the batch replenishment policy (Option II), BP2 has no effect on the DI externality for the manufacturer owing to the lack of flexibility in the batch replenishment policy. Therefore, regardless of the high frequency of disruption, there is no advantage or disadvantage regarding DI externality for the manufacturer owing to the low remediation length associated with BP2. However, BP3 (low frequency, high remediation length) has higher disruptive tendencies and therefore results in a higher negative impact on the externality effect under this replenishment policy. The manufacturer's performance is 11% worse as it goes from -2% in the no-breach scenario to -14% in BP3 scenario as a result of operating in the DI type supply chain. Therefore, a higher remediation length is more of a concern to the manufacturer under this partial information-sharing partnership than higher frequency of disruption.

5. Conclusion

We have studied the impact of information security breaches on SME supply chains under two distinct replenishment policies (parameter-based and non-parameter-based policies), to establish whether there are any significant differences in outcome. Using the most common ISB profiles reported, we studied the impact of ISB on the purported benefits of different modes of information integration, namely partial (DI) and full (FI) modes. In addition, we examined the impact of these ISB profiles on non-participants in information integration; this effect was termed the externality effect of information integration. Therefore, we have made three significant contributions to the literature on impact assessment in supply chain management.

First, we contributed to the IT-related disruption literature by showing that ISBs have a significant cost impact on the inventory management performance of SME supply chains linked to e-commerce/technology platforms, which is seldom reported. We empirically demonstrated that the inventory management cost, which represents a huge percentage of revenue for small businesses (Kim, 2020), is impacted significantly (up to 57% in some cases), eradicating any opportunity for profit, leading to business death. This answers the 'extent of ISB impact' question which previous supply chain studies have not focused on. Our study also found that different policies may lead to different outcomes, answering the 'nature of impact' question. This has two obvious theoretical implications. The first implication is that our study lends credence to our initial argument that using more than one distinct replenishment policy in supply chain impact studies is needed to gain a more comprehensive understanding, enabling relevant players to make better-informed decisions. The second implication is that, although an optimized non-parameter-based ordering policy performs better than a parameter-based type, the latter yields a better outcome than the former when an ISB with low remediation length (disruption duration) occurs relatively frequently. Therefore, small businesses need to undertake similar impact assessments to test the performance of their inventory policy in the incidence of a breach, in order to determine strategies that can be used to ameliorate the impact.

Second, we examined the impact of ISBs on the purported benefits of two main types of information integration partnerships proposed in the literature: partial (DI mode) and full integration (FI mode). We found that the specific ISB profile plays a significant role in determining the direction and magnitude of impact. It was established that the magnitude of the impact generally increases as one goes from BP1 to BP2 and BP3, meaning that ISB remediation length has a higher impact on the benefits of integration than ISB frequency of occurrence. We also found that, under the parameter-based policy, the DI mode outperforms the FI mode under ISB with increased frequency and low remediation length. Nevertheless, frequency of disruption occurrence has other impacts such as customer churn (Janakiraman, Lim, & Rishika, 2018), which have not been considered in this study but should not be taken lightly. Therefore, technology providers should invest more in effective remediation strategies, as these are crucial to the inventory performance of SME supply chains that depend on them for such services. Small business supply partners should include this as a KPI in any cybersecurity contract agreement with platform providers to further protect themselves against ISB impact.

Third, we looked at the effect of this impact on small businesses that are not directly involved in information-sharing partnerships in the supply chain. We found that non-participants are disadvantaged by such partnerships and are even worse off in the event of information disruption at the downstream end when the disruption is of the high remediation length type. This, of course, depends on the inherent flexibility of the inventory management policy being used by such non-participants. Therefore, for those not involved in information sharing in the supply chain, flexibility should be a priority, and flexible inventory policies such as the base stock policy should be employed, as our study has shown. Also, since the impact on non-participants is significant, contract agreements requiring integrated partners to share ISB incidences as soon as they occur are imperative. Sharing ISB occurrence promptly will afford non-participants adequate time to prepare for the reverberating effect of the impact.

Our research findings are highly valuable to firms seeking to understand what their ISB mitigation priorities should be. In general, this study has shed important light on the inventory performance of SMEs using different information integration strategies under disruptive conditions. Since the ISB profile is of the utmost relevance, those SMEs seeking an e-commerce/technology platform should be cautious of providers with a reputation for high ISB remediation length rather than those known to have a high frequency of ISB occurrence and low remediation length. It also highlights the precarious position of non-participants in information integration in SME supply chains. Non-participants need to be cautious when downstream players enter into information-sharing partnerships, as this will have an effect on inventory management costs, especially in the event of a highly disruptive ISB.

While the simulation model assumptions may affect the generalizability of the findings, the findings in this study have been validated by using simulation assumptions that have been used in past literature. A sensitivity analysis, which was discussed earlier in this study, has been included. Our simulation model utilized deterministic data on the breach profile as the focus was on what happened when the breach occurs. However, future research can utilize probabilistic models to incorporate 'when' and 'if' a breach occurs. The results of this study are based on a serial supply chain structure, but since many supply chains are more complex structurally, future studies should aim to understand the roles different supply chain structures play in these impact-benefit interactions. This study also focused on the operational implication of the impact of disruption caused by ISBs on the small players in the supply chain; the next line of inquiry should focus on the strategic implication by adopting a triple bottom line perspective, such as the one reported in Rodger and George (2017).

Acknowledgement

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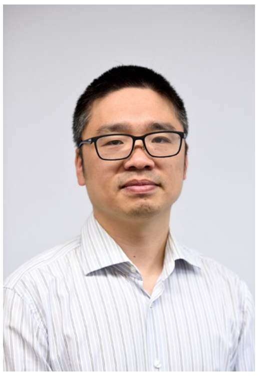

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