Abstract

This paper extends existing research on the dynamic behaviour of supply chains by including the influence of online reviews. We model an online supply chain which contains customers and one e-commerce retailer. By using simulation, we compare the dynamic performance in a supply chain for two scenarios, namely adopting online review systems and without adopting the systems. The supply chain dynamic performance is measured by bullwhip effect and inventory variance amplification. The results demonstrate that online review systems increase both the bullwhip effect and inventory variance amplification, and this impact can be moderated by product quality, unit mismatch cost, lead time, and customer volatility. We further explore how our model could be extended to include market competition, dual sourcing, online review manipulation, and product returns. As the increase in the bullwhip effect and inventory variance amplification can be associated with supply chain inefficiency, managers who are aware of such consequence induced by online review adoption can make better decisions in supply chain management.

Keywords: online review, supply chain dynamics, bullwhip effect, inventory variance amplification, simulation, production control.

Exploring the influence of online reviews on supply chain dynamics

1. Introduction

The development of internet technologies enables customers to share their product evaluations online (Avery, Resnick & Zeckhauser, 1999). Online reviews, as a kind of 'electronic word-of-mouth' communication, deliver the product evaluations of previous customers and influence future customer purchase decisions (Chen & Xie, 2008). Through online reviews, customers can learn about product attributes to update their perception and evaluation of products, and make purchase decisions accordingly (Li, Hitt & Zhang, 2011).

Although the influence of online reviews on customer demand and product sales are well-documented in marketing and information management fields (e.g. Purnawirawan, Eisend, De Pelsmacker & Dens, 2015; You, Vadakkepatt & Joshi, 2015), their influence on supply chain management (SCM) is still not very clear. In the context of SCM, scholars have started exploring the influence of online reviews on sales forecasting (e.g. Lau, Zhang & Xu, 2018; Chong, Li, Ngai, Ch'ng & Lee, 2016), product design (e.g. Jiang, Liu, Ding, Liang, & Duan, 2017), and product return (e.g. Minnema, Bijmolt, Gensler & Wiesel, 2016). However, as explorations of online reviews in SCM are still in their infancy, there is no research explicitly focusing on the influence of online reviews on supply chain dynamics, such as the bullwhip effect and inventory variance amplification.

As different demand patterns can bring different supply chain dynamics (Gaalman, 2006), and as online reviews can influence customer demand, it can be reasonably inferred that online reviews will bring new dynamics in a supply chain system. Previous literature suggests that good management of supply chain system dynamics can improve supply chain performance (Sterman, 1989; Lee, Padmanabhan & Whang, 1997) while misperceptions of a system's feedback structure and dynamics can lead sub-optimal and problematic decisions in supply chain and operations management (Bendoly, Croson, Goncalves & Schultz, 2010). Therefore, failing to understand the possible supply chain dynamics brought by online reviews can lead to inappropriate decision making and inefficient management, decreasing the performance of supply chains.

Motivated by this thought, this paper aims to evaluate the influence of online reviews on supply chain dynamics. To do this, the paper uses the bullwhip effect and inventory variance amplification (INVamp) as two measures for supply chain dynamic performance and conducts a simulation experiment to explore their influence. A well-established, generic supply chain model using stochastically generated demand is used in the simulation, adapted to account for online reviews.

In this paper, and following previous literature (e.g. Li & Hitt, 2008; Jiang & Guo, 2015), we only consider the influence from online reviews in our model. While acknowledging that other review sources exist, including paper-based feedback (such as newspaper reviews) or offline word-of-mouth, online reviews can be considered as the most important information source for customers before purchase. According to Worldpay (2017), 93% of US consumers use online reviews ahead of purchasing a new product, with over 50% doing so most or all of the time. Brightlocal (2019) found that 82% of customers will check online review information for local businesses. Further, online reviews are probably the only accessible information source for many products or services. Reviews in printed media like magazines are constrained by space requirements and may focus more on particular products. By contrast, offline word-of-mouth can be only spread in a relatively small group of people and depends upon the purchasing habits of these consumers. Online reviews like those provided by Amazon or TripAdvisor can expand the scale of information spreading, make the information much more accessible, and reach many customers (Hu, Povlou & Zhang, 2017). Therefore, as online reviews have a more significant influence on customer purchase decisions than other information sources, we limit the scope of our model to online reviews.

To achieve our research aim of evaluating online review influence on supply chain dynamics, the paper is structured as follows. The next section reviews relevant literature on online review research in SCM and relevant bullwhip and INVamp research. Then, the proposed simulation model and experimental designs are detailed in Section 3. Section 4 analyses the results of the simulation, considering both main and interaction effects. Section 5 discusses the insights drawn from the results. Section 6 thoroughly discusses our model and makes several extensions accordingly to relax different assumptions within the model to address potential limitations, followed by the conclusion in Section 7.

2 Literature review

This research is primarily related to two streams of literature. The first concerns online reviews in SCM, while the second examines research in bullwhip and INVamp.

2.1 Online reviews in SCM

The influence of online reviews has been investigated for different facets of SCM, with significant research focusing on using online reviews to enhance demand forecasting (See-To & Ngai, 2018). Key factors to improve forecasting accuracy include review valence and volume (Chong et al., 2016; Chong, Ch’ng, Liu & Li, 2017), as well as the sentiment within the online reviews (Yuan, Xu, Li & Lau, 2018). Li, Ch’ng, Chong, and Bao (2016) found online review features can significantly influence product sales, but such influence is moderated by other variables, such as product type and promotion activity.

Beyond interest in demand forecasting, the literature demonstrates other supply chain implications from online reviews. For example, online reviews can influence service delivery. Çalı and Balaman (2019) analysed online hotel reviews by combining multi-criteria-decision-making with sentiment analysis to inform improvements in service delivery processes. When customers have a negative experience, a management response to online reviews can help service recovery. For example, Gu and Ye (2014) found that posting online review responses to unsatisfied customers (who give 1- or 2-star rating) can more effectively improve their satisfaction than responding to other customers, while Kim, Lim, and Brymer (2015) identified that management responses to online reviews (particularly negative reviews) can positively contribute to the hotels' performance.

Turning to financial dimensions of SCM, Hou, de Koster, and Yu (2018) examined the impact of e-retailers' investment in physical product delivery under the influence of online reviews. They compared the cases with and without online reviews and found that the existence of online reviews can make retailers gain higher profits. Other research investigates how online reviews influence the pricing decisions in a supply chain. Liu, Gao, Zhou, and Ma (2019) examined supply chain pricing decisions under the influence from online reviews. A two-period model was employed with four pricing strategies compared, and they found the strategy of differential pricing for suppliers and stage pricing for retailers is best. Cai, Li, Dai and Zhou (2018) considered the influence of online reviews on supply chain pricing for competitive manufacturers with a common retailer, and identified that online reviews can influence the optimal price and profit of manufacturers and the retailer, but this influence is affected by the number of competing manufacturers in the market.

Finally, for product return, online reviews can influence return rates and may be useful return rate indicators. For example, Minnema et al. (2016) found that overly positive review valance can lead to more product returns, while Sahoo, Dellarocas and Srinivasan (2018) found unbiased online product reviews can contribute to better purchase decisions and thus reduce product returns.

The reviewed literature shows that although the influence of online reviews on many facets of SCM has been examined, there is little research linking online reviews to supply chain dynamics, such as bullwhip effect and INVamp. One paper by Hofmann (2017) considered the possible connections between the two, but their focus is upon 'big data' generally rather than modelling online review systems. Online reviews bring new dynamics to supply chain systems, and so ignoring them could make SCM inefficient. Therefore, investigating the influence of online reviews on supply chain dynamics can enhance the understanding of the value of online reviews in SCM and support managers to make more rational decisions in the current e-retailing era.

2.2 Bullwhip and INVamp

Since Forrester's (1961) seminal work on industrial dynamics, there has been extensive work on supply chain dynamics. Reflected in the "Beer-Game" (Sterman, 1989), the dynamics behind supply chains can lead to fluctuation and variance amplification of order and inventory in each node of the chain. Later in Lee et al. (1997), order amplification was further researched, and named as the 'bullwhip effect'. Although many themes are explored from a supply chain dynamics perspective, such as system stability (e.g. Wang, Disney & Wang, 2012), supply chain resilience (e.g. Spiegler, Naim & Wikner, 2012) and chaos (e.g. Hwarng & Xie, 2008), the bullwhip effect and INVamp are two of the most frequently researched themes. Following the definitions from previous research (Chen, Drezner, Ryan & Simchi-Levi 2000a; Disney & Towill, 2003c, Cannella, Dominguez, Ponte & Framinan, 2018), bullwhip is defined as the ratio of order variance to customer demand variance, while INVamp is the ratio of inventory variance to customer demand variance. Both measures can reflect the supply chain efficiency, with a lower value of them meaning higher efficiency (Cannella et al., 2018).

Since this paper is founded upon assumptions about supply chain demand ('online-review-influenced' demand), we thus review the literature of bullwhip effect and INVamp from the perspective of demand assumptions. Further, as bullwhip effect and INVamp are the two frequently used supply chain dynamics measures, we summarise each paper based on these measures and present the summary of literature in Table 1. To fit the purpose of this paper, demand assumptions are broadly categorised into *probability distribution* demand and *factor-influenced* demand. The probability distribution demand here means the demand is assumed as a probability distribution such as normal distribution, ARIMA family, or Poisson distribution. We also categorise the step increase demand assumption into this type as a special case. The factor-influenced-demand, on the other hand, means the demand is assumed not only as a probability distribution, but such distribution is influenced by other specified parameters. For example, the demand can be influenced by price, demand trend, and seasonality. Also, it can be influenced by the demand intercorrelation induced from the substitution effect (e.g. Raghunathan, Tang & Yue, 2017) and competition between two or more products (e.g. Ma & Ma, 2017). Finally, although less commonly used from a supply chain dynamics perspective, factors such as lifecycle and inventory level are also considered as the influencers of the demand. Table 1 also reveals that although bullwhip is more frequently used than INVamp, both are common measures for supply chain dynamic performance.

Table 1. Literature summary of supply chain dynamics research

Research Papers	Bullwhip	INVamp	Demand distribution & Factors-influencing demand
Probability distribution category			
Sterman (1989)	✓	✓	Step increase demand
Disney and Towill (2003a)	✓		Step increase demand
Disney and Towill (2003b)	✓		Step increase demand
Warburton (2004)	✓		Step increase demand
Cannella, Bruccoleri, and Framinan (2016)	✓	✓	Step increase demand; Normal distribution demand
Dejonckheere, Disney, Lambrecht and Towill (2003)	✓		Normal distribution demand
Dejonckheere, Disney, Lambrecht and Towill (2004)	✓		Normal distribution demand, AR(1), MA(1), ARMA(1,1)
Disney, Farasyn, Lambrecht, Towill, and Van de Velde (2006)	✓	✓	Normal distribution demand
Cannella et al. (2018)	✓	✓	Normal distribution demand
Dominguez, Cannella, Ponte and Framinan (2019)	✓	✓	Normal distribution demand
Lee et al. (1997)	✓		AR(1)
Chen et al. (2000a)	✓		AR(1)
Chen and Disney (2007)	✓		ARMA(1,1)
Gilbert (2005)	✓		ARIMA(p,d,q)
Pastore, Alfieri, Zotteri, and Boylan (2020)	✓		AR(1)
Factor-influenced demand category			
Ma, Wang, Che, Huang, and Xu (2013a)	✓	✓	Price-dependent demand
Ma, Wang, Che, Huang, and Xu (2013b)	✓		Price-dependent demand
Wang et al. (2014)	✓		Price-dependent demand
Wang, Lu, Feng, Ma and Liang (2016)	✓		Price-dependent demand
Tai, Duc, and Buddhakulsomsiri (2019)	✓		Price-dependent demand
Zhang and Burke (2011)	✓		Demand intercorrelation
Ma and Ma (2017)	✓		Demand intercorrelation
Sirikasemsuk and Luong (2017)	✓		Demand intercorrelation
Raghunathan et al. (2017)	✓		Demand intercorrelation
Chen, Ryan and Simchi-Levi (2000b)	✓		Trend and seasonality
Metters (1997)	✓		Trend and seasonality
Bayraktar, Koh, Gunasekaran, Sari, and Tatoglu (2008)	✓		Trend and seasonality
Nagaraja, Thavaneswaran and Appadoo et al. (2015)	✓		Trend and seasonality
Bayraktar, Sari, Tatoglu, Zaim and Delen (2020)	✓		Trend and seasonality
O'donnell, Maguire, McIvor and Humphreys (2006)	✓		Promotion influenced demand
Nepal, Murat and Chinnam (2012)	✓		Product life-cycle influenced demand
Lin, Jiang, and Wang (2014)	✓		Inventory-level influenced demand

The literature review on demand assumptions reveals that no supply chain dynamics research considers online review as a factor to influence demand. More importantly, we argue subsequently that the influence of online reviews cannot be directly modelled in a similar way to other factors in Table 1 (e.g. price, trend, seasonality), where authors simply added a parameter into the demand functions to indicate the influence of the factor. To model the influence of online reviews on supply chain demand from a dynamic perspective, more feedback and different model structures need to be conveyed in the research, revealing that there are more dynamics involved in the system. Therefore, our model provides a way to understand the influence of online reviews on supply chain dynamics, which leads to our work being significantly different to previous papers and underlines the novelty and value of our research. These contributions when compared to previous research are shown in Table 2.

Table 2. Comparison between this paper and previous research

Previous supply chain dynamic research	**Contribution of this paper**
• Online reviews are not considered in previous supply chain dynamic research.	• Online reviews are considered as a factor to influence supply chain dynamics.
• Supply chain demand is directly assumed as a random distribution.	• Supply chain demand is derived from consumer utility to examine the influence of online reviews .
• Customers are usually assumed as homogenous.	• Customers are assumed as heterogenous.
• Some papers consider the influence of online reviews on supply chain performance under market competition, dual sourcing, and product return, but they fail to link online reviews to supply chain dynamics in these directions.	• The model extension in this paper discusses market competition, dual sourcing, product return and other situations to examine online review influence on supply chain dynamics.

3. Methodology

To evaluate the influence of online reviews on supply chain dynamics, we develop a model to compare the bullwhip effect and INVamp of a supply chain in two different scenarios: with and without an online review system. A pictorial description can be seen in Figure 1. First, customers visit the e-commerce platform, and they will decide if they will buy the product based on their estimated evaluation of product quality and their own preferences. If an online review system is adopted, the average rating shown in the system will influence the purchase decision of customers. After that, customers who decide to buy the product will order it online from the retailers, and retailers will fulfil customer orders, with unfulfilled customers lost due to a lack of inventory. When an online review system is used, the fulfilled customers can decide if they will rate the product after receiving and using the product. When customers post ratings, these evaluations can influence the average product rating shown in the online review system albeit after a time delay to allow for the rating system to update. The average product rating in the system can be thus updated, which further generates influence on future customers. If there is no online review system, the fulfilled customers will just receive the product and do nothing else. Finally, for the supply side, the retailer will replenish products by ordering from its supply source. All notations of the following mathematical models are listed in Appendix 1.

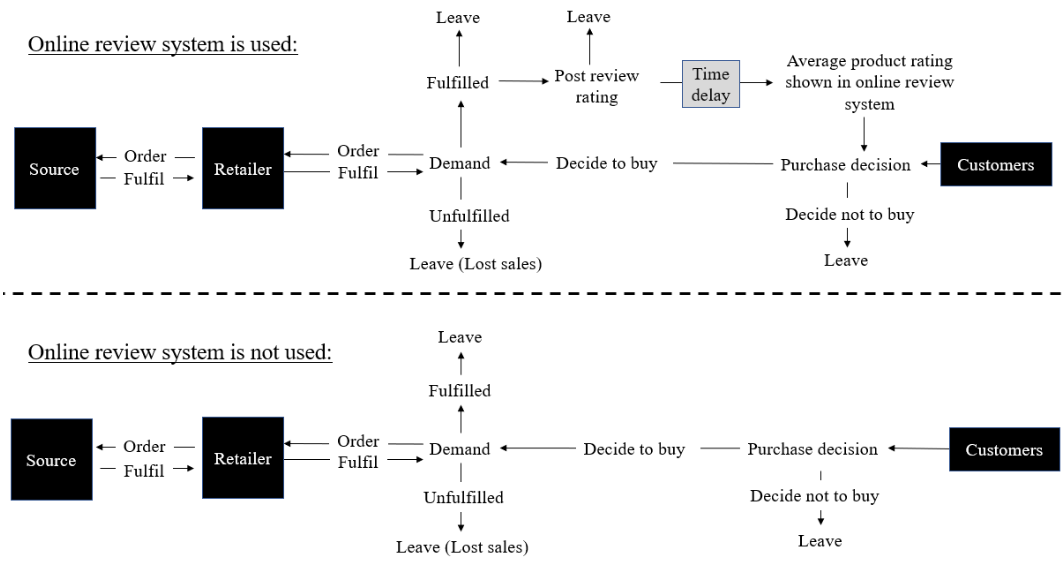


Figure 1. Comparison of a supply chain with/without online review system

3.1 Model development

We assume that in each period t, there are D_t^a customers visiting the website. D_t^a here is assumed to be stochastic, following an integer normal distribution with specific parameters provided in subsection 3.3. Among all customers, there are only $D_t^{(h)}$ customers who decide to purchase the product ($D_t^{(h)} \leq D_t^a$), with h = N for no online review and h = R for providing online reviews. There are only $n_t^{(h)}$customers fulfilled ($n_t^{(h)} \leq D_t^{(h)}$). $D_t^a, D_t^{(h)}$ and $n_t^{(h)}$ here are all modelled as integers, and $D_t^{(h)}$ here is essentially the demand for the supply chain under two scenarios in each period. We also assume a backlog at the retailer is not permitted, and unfulfilled customers will leave. This assumption is consistent with the real world situation, especially in e-commerce era, because when customers find one product is out of stock, they can leave or easily turn to buy other alternatives in the e-commerce platform and therefore seldom wait until the product is replenished.

We first derive the customer demand $D_t^{(N)}$ from the utility perspective in the case without online reviews. Following previous literature (Li & Hitt, 2010; Sun, 2012; Jiang & Guo, 2015), the customer expected utility before purchase without online review influence is modelled as $U_{it}^e = q^e - p - \beta * x_{it}$ in which U_{it}^e is the customer i's expected utility in period t before purchase, q^e the expected quality, and p the product price, x_{it} the customer preference. For each customer i ($1 \leq i \leq D_t^a$) in period t, they have the same value of expected quality (i.e. q^e) before purchase, but they are heterogeneous on preference to the product (Li & Hitt, 2010). To model this heterogeneity x_{it}, we follow Li and Hitt (2010) to assume x_{it} is a random variable uniformly distributed in [0,1] to indicate different preferences, and each value of x_{it} is "the position of a customer's ideal product in a product space". By assuming the product is located at 0, x_{it} essentially reflects the mismatch degree between the real product and each customer's 'ideal product' (Li & Hitt, 2010). β here is the unit mismatch cost. According to Sun (2012), higher β means the product is more niche, while a lower value indicates the product is more mainstream. To illustrate this, we adopt the example of books, as discussed in Sun (2012). The author identifies niche books as those that draw strong positive or negative reactions from people (for example, those with graphic, violent content or representing extreme political views), where even a small change in content preference (i.e. x_{it}) will significantly impact on mismatch cost. Mainstream books, such as popular fiction titles (e.g. the Harry Potter series) will still create like/dislike reactions, but there will be greater indifference in opinion as well. Therefore, such books have a relatively low β.

As p is not the decision variable in this model, price is normalised as 0 without loss of generality, and its influence can be absorbed into q^e. Thus, the expected utility is modelled as $U_{it}^e = q^e - \beta * x_{it}$, and here q^e can be interpreted as 'net expected quality utility' which means the utility obtained from the expected product quality's utility less the disutility of price. What should be noticed here is, in the following content, we use the term 'quality' to represent *net quality* which means the utility drawn from product quality has taken the effect of price into consideration. Consistent with previous literature (e.g. Li & Hitt, 2010), we further normalise the value of the best alternative to the focal product as 0 without the loss of generality. If customers are rational then, without the influence of online reviews, a customer will purchase the product only when $U_{it}^e > 0$. We also assume $\beta > q^e$, so that the product cannot cover the whole market. Under these assumptions, $D_t^{(N)}$ thus can be derived. To simplify the formulation processes below, we denote $\sum_{i=1}^{0} variable_i$ =0 for all following formulae in this paper. Therefore, $D_t^{(N)}$ can be derived as:

$$D_t^{(N)} = \sum_{i=1}^{D_t^a} f(U_{it}^e), where\ f(a) = \begin{cases} 1, & a > 0 \\ 0, & else \end{cases} \tag{1}$$

Following the above logic, we denote the expected utility of customers under the influence of online review as U_{it}^{er} (where $1 \leq i \leq D_t^a$), and the $D_t^{(R)}$ can be derived as:

$$D_t^{(R)} = \sum_{i=1}^{D_t^a} f(U_{it}^{er}), where\ f(a) = \begin{cases} 1, & a > 0 \\ 0, & else \end{cases} \tag{2}$$

However, as discussed later, U_{it}^{er} is not only generated based on U_{it}^{e}, but also under the online review influence; it is not the same as U_{it}^{e}. Therefore, to model U_{it}^{er}, it is necessary to firstly model the generation of online review rating and how it can influence U_{it}^{er}.

To model the process of online review rating generation, we start from modelling the real utility U_{it}^{r} for customer i in period t. We model $U_{it}^{r} = q - \beta * x_{it}$, where q is the utility of real (net) quality. As real quality can only be perceived after receiving the products, only customers who buy the products and get fulfilled can know their real utility. We assume there is no quality fluctuation for the product, meaning that q is a constant value for every customer rather than a random variable (Jiang & Guo, 2015). In this paper, we only consider the scenario that q^e is equal to q, in which case the expected quality correctly reflects the real quality. It means that customers' information is adequate, and their perception about real quality is not influenced by biased information such as excessive advertising. As our focus is the influence of online reviews, such simplification is reasonable. We note it can also be a potential direction for the future research to explore the scenario of different values for q^e and q, indicating customers can over-/under-estimate the real quality before purchase.

Turning to the online review generation process, we employ a 5-star rating system consistent with that of online commerce platforms like Amazon and others. We assume that customers can receive the product within the same period they place the order online. For customer i in period t who receives the product, if he/she is willing to post rating, he/she will give rating 1- to 5-star based on his/her real utility U_{it}^{r} (Jiang & Guo, 2015). To transform U_{it}^{r} to each customer i's rating score in period t which is R_{it}, we adopt Jiang and Guo (2015)'s transform function:

$$R_{it} = k + 1; \tag{3}$$

$$where\ k = argmin_{k^r=0,1,2,3,4}\left\{\left|\frac{k^r}{5-1} - w_{it}\right|\right\}, and$$

$$w_{it} = \frac{e^{U_{it}^r}}{(1 + e^{U_{it}^r})}$$

Customers will rate products as an integer on a 1- to 5- star scale (reflecting common real-world practice), based on their utility experienced after purchase. Equation (3) uses a logistic transform to convert all customers' utility to a unit line. Then, the unit line is divided into 5 parts, with each part corresponding to a star level. As customers can only have five choices when rating the product (i.e. 1 to 5 star), this is essentially a discrete choice problem. Therefore, to follow the norm of modelling consumer discrete choice behaviour by other researchers (e.g. McFadden, 1973; Train, 2009), the logistic transformation is adopted here. In addition, the model needs the rating is bounded within an interval (i.e. from 1 to 5) regardless of how small or large U_{it}^r is. As the range of logistic function is also lower and upper bounded, such property enables our model to guarantee all customers with any value of U_{it}^r will rate products within the range from 1 to 5 star. For example, if in period t, customer i's U_{it}^r is 1, his/her w_{it} is equal to 0.73, and the $k = arg\ min_{k^r=0,1,2,3,4}\{|\frac{k^r}{5-1} - w_{it}|\}$ will be equal to 3. Thus, this customer will post a 4-star (3+1) rating. For those customers in period t who do not buy the products, or who are unfulfilled and leave, their real utility U_{it}^r as well as ratings R_{it} are counted as 0 for computational purposes as these customers do not know their real utility and so will not post ratings.

After modelling the rating score R_{it} from each customer, we can calculate the average rating for the product $\overline{R_t}$ in period t. This average rating is the rating shown in the review system and can influence future customers' decisions. Only n_t^r people (where $n_t^r \leq n_t^{(R)}$) are willing to post rating scores in the online review system, consistent with previous literature where not all fulfilled customers are willing to post reviews (Ye, Law, Gu & Chen, 2011). Therefore, we follow Ye et al. (2011) in assuming a constant probability for each customer to post reviews and, consistent with Bhole and Hanna (2017), we set this probability as 0.1. Being a yes/no decision, we use a Bernoulli distribution $\varphi_{it} \sim B(1{,}0.1)$ to model posting process. Using a Bernoulli distribution to model this process captures the features of online rating systems as customers can only have two choices: posting or not posting; there are no further choices for customers after purchase. Here, the Bernoulli distribution will generate 1 with probability as 0.1 and 0 with probability as 0.9, where 1 indicates the customer is "posting review" while 0 indicates this customer "not posting". Thus,

$$n_t^r = \sum_{i=1}^{D_t^a} \varphi_{it} * f(R_{it}),\ where\ f(a) = \begin{cases} 1, & a > 0 \\ 0, & else \end{cases} \tag{4}$$

To check the influence of the Bernoulli distribution parameters on our results, the results under probability 0.1 were compared with 0.8 (a high probability) and 1 (all fulfilled customers post a review). We found our results still hold, and are therefore robust to the Bernoulli distribution parameter.

Major e-commerce platforms like Amazon and Taobao do not disclose the frequency they update the rating scores. Therefore, we assume the rating score update frequency is equal to one period of our model, which is also consistent with previous research (e.g. Li & Hitt, 2008). This means, all customers in period t will see the same average rating score. Even though ratings are posted on the product in period t, the average rating will not be updated until next period, $t+1$. Thus, in period t the rating score shown is the rounded average value of all rating scores posted from first period to period $t-1$. What should be also noted is that if no one posts a rating in period $t-1$, the score $\overline{R_t}$ will remain as $\bar{R}_{t-1}$:

$$\overline{R_t} = \begin{cases} round\left(\frac{\sum_{j=1}^{t-1}\sum_{i=1}^{D_{t-1}^a} R_{ij}*\varphi_{it}}{\sum_{c=1}^{t-1} n_c^r}, digit = 1\right), & n_{t-1}^r > 0\ and\ t > 1 \\ \bar{R}_{t-1}, & n_{t-1}^r = 0\ and\ t > 1 \\ 0\ , & t = 1 \end{cases} \tag{5}$$

Consistent with how online reviews are presented to customers, just one decimal point is retained. Thus, $\overline{R_t}$ can only be 1, 1.1, 1.2 up to 4.9 and 5. The formula shows that in the first period, the average rating will be zero as no one posts score in period 'zero'.

After deriving the average rating shown in the system, we can model how U_{it}^{er} is generated under the influence of online reviews. For customers, their initial expected utility before purchasing is still U_{it}^{e}, and it will be influenced by the online review and then updated to U_{it}^{er}. Under such circumstances, they will buy the product if U_{it}^{er} is greater than zero (even if his/her U_{it}^{e} is not necessarily greater than zero).

To model how customer i in period t updates their expected utility (i.e. U_{it}^{e}) to review-influenced expected utility (i.e. U_{it}^{er}), we first model the utility obtained from product's average rating score. Generally, customers tend to believe that a product having higher rating score will have better quality. Therefore, a higher rating score will give customers a higher utility. We notate the utility generated from seeing a rating score as U_{it}^{score}. To quantify U_{it}^{score}, we use the inverse form of the transformation in Equation (3):

$$U_{it}^{score} = Ln\left(\frac{Z}{1-Z}\right); where\ \mathrm{z} = \frac{\overline{R_t}-1}{4}\ and\ \overline{R_t} \neq 0 \tag{6}$$

where $Ln(\,)$ calculates the natural logarithm. As it is possible that no one rates the product in the first several periods (i.e. $\overline{R_t} = 0$) , U_{it}^{score} does not exist under such case and will not pose any influence on customer expected utility. In effect, this equation converts a rating value with one decimal point into a value of customer utility. As $\overline{R_t}$ has the range from 1 to 5 (once customers rate the product), and therefore a different scale with U_{it}^{e}, such transformation enables U_{it}^{score} to be compatible to U_{it}^{e}. It can be seen from the formulae that, as $\overline{R_t}$ remains the same for all customers in period t, their utilities generated from the rating score are the same.

For simplicity, we do not model the customer behaviour of reading online review content. Such simplification can also be seen in Li and Hitt (2008). It is possible that an individual customer randomly picks online reviews to read (Mayzlin, 2006), and such reading behaviour can lead to customers forming different utility values. For example, customers who read more negative online reviews would be expected to have a lower expected utility compared to those reading more positive reviews can generate a higher utility. A more sophisticated way to model such behaviour is to assign each customer a utility from reading online reviews randomly (e.g. with a normal distribution) with mean equal to $Ln(\frac{z}{1-z})$ and a variance σ_{score}, i.e. $U_{it}^{score} \sim N\left(Ln\left(\frac{z}{1-z}\right), \sigma_{score}\right)$. However, as long as the σ_{score} is not huge and our simulation periods are long enough, the result should not be influenced significantly by simplifying U_{it}^{score} to a fixed number rather than a distribution.

What should be noted here is when $\overline{R_t}$ is 1 star or 5 star, z is 0 or 1 respectively and the U_{it}^{score} is equal to negative infinity and positive infinity. This is unrealistic. Therefore, to better model real life situation, we arbitrarily assign z $= \frac{4.99-1}{4}$ when $\overline{R_t}$=5 and z $= \frac{1.01-1}{4}$ when $\overline{R_t}$=1. As $\overline{R_t}$ can only be 1, 1.1, 1.2, etc. with a 0.1 interval, we believe using 4.99 (and 1.01) is a good approximation for 5 star (and 1 star) as the 0.01 difference between the rating and this approximation is much smaller than the 0.1 interval and it means such approximation gives a large (and small) enough value for 5 star (and 1 star). We also check the results when using 4.999 (and 1.001) and 4.9999 (and 1.0001) to approximate 5 star (and 1 star), and our results still hold. This means our experiment results are robust under the approximation.

Finally, adapting previous literature (e.g. Bhole & Hanna, 2017; Jiang & Guo, 2015), we quantify the online-review-influenced expected utility U_{it}^{er} as a weighted average of expected utility without online review (i.e. U_{it}^{e}) and utility generated from the online review rating score, U_{it}^{score}. Such an updating process is also consistent with previous research on combining forecasts (Clemen, 1989; Lawrence, Goodwin, O'Connor & Önkal, 2006). Specifically,

$$U_{it}^{er} = \begin{cases} \theta_{it} * U_{it}^{score} + (1-\theta_{it}) * U_{it}^{e}, & \overline{R_t} \neq 0 \\ U_{it}^{e}, & \overline{R_t} = 0 \end{cases} \tag{7}$$

Here, θ_{it} is the weight put on U_{it}^{score} for customers in each period as we do not assume each customer will have the same attitude towards online reviews, as some may draw more on their previous expectations for a product, while others may rely on online review information more. This assumption is reflected in the previous research which has shown that customers have different attitudes towards the usefulness and credibility of online reviews due to their personal characteristics, experiences, and cultural background (Park, Wang, Yao & Kang, 2011, Park & Lee, 2009). Therefore, this heterogeneity is modelled such that each customer will put different weights on the rating score, and we let θ_{it} follow a uniform distribution bounded in [0,1] as $\theta_{it} \sim U(0,1)$ in Equation (7). For each individual customer i in period t, they will generate a unique pair of weights to form U_{it}^{er}. To check the robustness of the distribution choice, different distributions of weights including normal distribution and triangular distribution are examined in Appendix 2. It reveals that the results are robust and will hold under different distributions.

In the first period, customers will not be influenced by the average rating score as there is no review from period 'zero'. From the second period onwards, customers can be influenced by the average rating score and change their U_{it}^{e} to U_{it}^{er}. For the scenario of no review, customers' expected utility remains U_{it}^{e}. What should be noticed is that it is possible that no one posts a review in the first period, in which case the second period's (or even the following periods') rating score remains zero. In this special case, customers will not be influenced by the rating score until there are ratings posted in period t, and the subsequent customers will be influenced from the following period $t+1$.

Turning to the supply side operations, we build our supply chain model based on Dejonckheere et al.'s (2003, 2004) work as their mathematical model is widely adopted in literature and can model real world supply chains well (e.g. Disney & Grubbström, 2004; Potter & Lalwani, 2008). It is an established inventory and order based production control system

(IOBPCS) that is representative of real world systems, and we refer interested readers to Lin, Naim, Purvis and Gosling (2017) for a detailed review on the model applications. To generate the online review supply chain model, we make the following assumptions:

(1) We consider a supply chain model where there is only an e-retailer with their customers, consistent with previous literature like Dejonckheere et al. (2003), and Disney et al. (2006). Being an exploratory model, we do not consider the multi-echelon supply chain based for the following reasons. As online reviews are a tool in e-retailing sites, their influence will directly affect the retailer, while upstream companies like wholesalers or factories can only be influenced indirectly through the retailer. Therefore, our focus is to clarify the relationship between online reviews and retailer dynamic performance first. Further, the adoption of online reviews is normally made by the retailer at the downstream end of supply chain. Therefore, limiting the analysis of online review benefits or drawbacks on retailer rather than the whole supply system can be a reasonable perspective.

(2) The order-up-to policy is used to replenish inventory, the sequence of events following Dejonckheere et al. (2003). In each period t, first, the retailer received previously ordered products from its supplier. After that, customer demand is observed, and the retailer fulfils the demand. Then, the retailer observes the updated inventory level. Finally, the retailer places orders to its supplier. As the retailer receives orders from the supplier at the start of each period, the system lead time, L, consists of a one period ordering delay and T_p periods physical distribution lead time. In other words, even though there is no delay on physical distribution lead time (T_p=0), L is 1 rather than 0 as an order placed at the end of period t will be received in period $t+1$. Lead time is not a random variable but a fixed numeric value (as in Chen et al. 2000a; Dejonckheere et al., 2003 & 2004).

(3) Returns from the retailer company to its supplier are not permitted, which means the order rate for the retailer in period t, $O_t^{(h)}$ is not negative. This is also consistent with previous literature (e.g. Sterman, 1989; Wang, Disney & Wang, 2012).

(4) Under the assumption that unfulfilled customers will be lost, we then reasonably assume the companies can only know the fulfilled demand in each period (i.e. $n_t^{(h)}$). In e-commerce websites, customers can often see the stock-out information and may well directly leave under such circumstances without telling the retailer. Although the company might use click data or website cookies to estimate the lost sales, such estimation is not considered in this paper and can be investigated in the future research. Under such an assumption, the daily sales $n_t^{(h)}$ is then used in the forecasting process. The retailer is assumed to use simple exponential smoothing with parameter α to estimate the future demand. This forecasting method is widely used in literature and practices (e.g. Dejonckheere et al., 2003; Potter & Lalwani, 2008). α is specified as 0.2, as suggested in previous literature (e.g. Syntetos, Georgantzas, Boylan & Dangerfield, 2011).

(5) We assume the online review rating score is updated every period and so, to fit our model, we assume the lead time is the multiple of one period, while the retailer's orders are also placed in each period. Based on this, customers are assumed to both receive the purchased product and make their decisions on posting their review in the same period. In real world, customers may not receive the purchased product or post reviews in the same period because the delivery time from retailers can vary, and relaxing this assumption offers an opportunity for future research.

Based on all the above assumptions, in period t, the following event sequence occurs:

(1) First, D_t^a customers visit the platform, with $D_t^{(h)}$ customers ordering products.

(2) The retailer uses available inventory to fulfil customer demand as well as updating its inventory, and $n_t^{(h)}$ customers are fulfilled:

$$n_t^{(h)} = MIN(D_t^{(h)}, I_{t-1}^{(h)} + O_{t-L}^{(h)}) \quad (8)$$

$$I_t^{(h)} = MAX(I_{t-1}^{(h)} + O_{t-L}^{(h)} - D_t^{(h)}, 0) \quad (9)$$

$I_t^{(h)}$ is company's inventory on hand at period *t*, where *h* = *N* for no online review while *h* = *R* for using online review. The order fulfilment applies a first-come-first-served policy. $n_t^{(h)}$ is integer, and $O_{t-L}^{(h)}$ here is the integer rounded up or down from the number generated by the following Equation (12).

(3) The retailer updates work-in-process (or goods in transit) in period *t*:

$$WIP_t^{(h)} = WIP_{t-1}^{(h)} + O_{t-1}^{(h)} - O_{t-L}^{(h)} \quad (10)$$

(4) The retailer makes forecast by using simple exponential smoothing:

$$\widehat{D}_t^{(h)} = \alpha * \widehat{D}_{t-1}^{(h)} + (1-\alpha) * n_t^{(h)} \quad (11)$$

(5) Finally, the retailer places their orders to their supplier based on the rules in Dejonckheere et al. (2003) where nonnegative order constraint is applied:

$$O_t^{(h)} = MAX\left(0, (L+1) * \widehat{D}_t^{(h)} - I_t^{(h)} - WIP_t^{(h)}\right)$$

$$= MAX\left(0, \left(T_p + 2\right) * \widehat{D}_t^{(h)} - I_t^{(h)} - WIP_t^{(h)}\right) \quad (12)$$

$O_t^{(h)}$ is also be rounded up/down to the nearest integer, and $(L+1) * \widehat{D}_t^{(h)}$ takes L-period demand forecasting as well as one extra period forecasted demand as safety stock into consideration.

3.2 Verification

The simulation model was built and analysed in R (RStudio). In the process of verifying the simulation model, thorough verifications were conducted. Each submodule was first coded in R by one author and reviewed by another author. For difference equations, Excel was also used to check the results and verify the logic. Moreover, for submodules related to the supply chain side, t-tests were conducted to compare the numerical results generated from the submodules to theoretic values calculated from previous literature including Dejonckheere et al. (2003, 2004) as well as from our own analytical results. All tests were passed with p-value greater than 0.05, indicating that our numerical simulation results have no significant difference from theoretic and analytical results. Therefore, our model has good accuracy.

3.3 Experiment design

To test the influence of online review on supply chain dynamics, we designed a full factorial experiment. The independent variables are detailed in Table 3 and include (1) using/not using online review system, (2) product quality level (i.e. q); (3) product unit mismatch cost level (i.e. β); (4) physical distribution lead time (T_p); (5) customer volatility level, measured by the coefficient of variation (CoV) of D_t^a in each period. The first independent variable has a binary value (e.g. using/not using) while other variables have three values. The CoV of D_t^a is a measure of the variability of D_t^a relative to its mean value. The higher CoV means the customer arrival (i.e. D_t^a) is more volatile and a high CoV could reflect a strongly seasonal product while a low value is a more regular purchase. For the dependent variables, as discussed above, we selected bullwhip effect (order variance amplification) and INVamp as dynamic performance indicators:

$$\text{Bullwhip effect} = \frac{var(O^{(h)})}{var(D^{(h)})} \tag{13}$$

$$\text{INVamp} = \frac{var(I^{(h)})}{var(D^{(h)})} \tag{14}$$

Other parameters like the probability of posting a review and the smoothing parameter are constant coefficients as specified previously.

Table 3. Experiment design

Parameters	Value
Customers visiting platform (D_t^a)	$MAX(0, round[N(100, \sigma 2)])$ per period
Demand smoothing parameter α	0.2
Probability of posting review	0.1
Independent variable	Value
Online review system	Yes (for using the system); No (for not using the system)
Quality (q)	1 ; 2 ; 3
Unit mismatch cost (β)	4; 6; 8
Coefficient of variation (CoV) of D_t^a (σ/μ, where μ=100)	0; 15%; 30%
Physical lead time (T_p)	4; 8; 16
Dependent variable	
Bullwhip effect (Natural logarithmic form)	$Ln\ [\frac{var(O^{(h)})}{var(D^{(h)})}]$
INVamp (Natural logarithmic form)	$Ln\ [\frac{var(I^{(h)})}{var(D^{(h)})}]$

The total number of experiments are 2*3*3*3*3=162. We replicated each experiment 5 times, with each experiment running for 10,000 periods. The first 3,500 periods are warm-up periods and removed when calculating bullwhip effect and INVamp. Consistent with Kelton, Sadowski and Sadowski (2007) if the half-width of the 95% confidence interval for dependent variables (i.e. bullwhip effect and INVamp) is smaller than a pre-defined value, the replication is sufficient. We specified this value as 10% of the mean, consistent with the previous literature (e.g. Cannella et al., 2018; Yang, Wen & Wang, 2011). As our running periods are long, such criterion can be easily achieved under 5 replications. We conducted analysis of variance (ANOVA) to the simulation results, considering the main and interaction effects of each variable. Scatter plot of residuals as well as Levene's test based on median were used to check the assumption of homogeneity of variance, and the QQ-norm plot as well as the Shapiro-Wilk test were used to check assumption of normality. When a natural logarithmic transformation is conducted to dependent variables, all checks indicate two assumptions are not violated (specifically with p-values greater than 0.05 for the Levene's test and for Shapiro-Wilk test), and ANOVA results are valid. Thus, the natural logarithmic values are calculated for bullwhip effect and INVamp to form new dependent variables. As our research focus is on the online review system rather than all the variables and their interactions, we only report the influence of each individual variable's main effect on bullwhip effect and INVamp, and the first-order interaction effects between online review and other variables.

4. Results

We start our result analysis from the main effect of each variable. Table 4 indicates that the main effects of all independent variables on bullwhip effect and INVamp are significant at 95% confidence level.

Table 4. ANOVA results

	ln(Bullwhip)					ln(INVamp)				
	Df	Sum Sq	Mean Sq	F value	P value	Df	Sum Sq	Mean Sq	F value	P value
Online review	1	1	0.97	6259.00	<0.001	1	1.8	1.8	2041.04	<0.001
Quality	2	8.6	4.3	27830.00	<0.001	2	11.3	5.7	6538.69	<0.001
Unit mismatch cost	2	3.4	1.7	10980.00	<0.001	2	5.4	2.7	3106.80	<0.001
Coefficient of variation (CoV)	2	39.6	19.78	127900.00	<0.001	2	50.1	25.1	28963.01	<0.001
Lead time	2	344.6	172.32	1114000.00	<0.001	2	947	473.5	547180.64	<0.001
Quality*Online review	2	0.1	0.04	254.70	<0.001	2	0	0	13.55	<0.001
Unit mismatch cost* Online review	2	0	0	11.16	<0.001	2	0	0	14.50	<0.001
CoV*Online review	2	0.5	0.25	1616.00	<0.001	2	1.1	0.5	616.81	<0.001
Lead time*Online review	2	1.5	0.75	4866.00	<0.001	2	1.3	0.7	758.50	<0.001

We demonstrate the main effects in Figure 2 for the online review variable and Figure 3 for other variables. Figure 2 shows that the dynamic performance of supply chain is better without online review, as in this case the natural logarithmic values of bullwhip effect and INVamp are both lower. By comparison, when the online review system is adopted, the bullwhip effect and INVamp will be increased by 7.3% (calculated by $e^{(2.315-2.245)} - 1$) and 9.7% (calculated by $e^{(3.152-3.059)} - 1$), respectively.

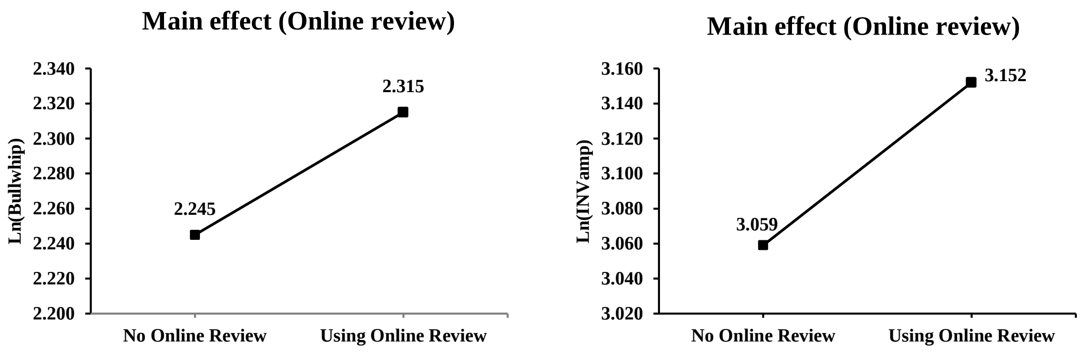
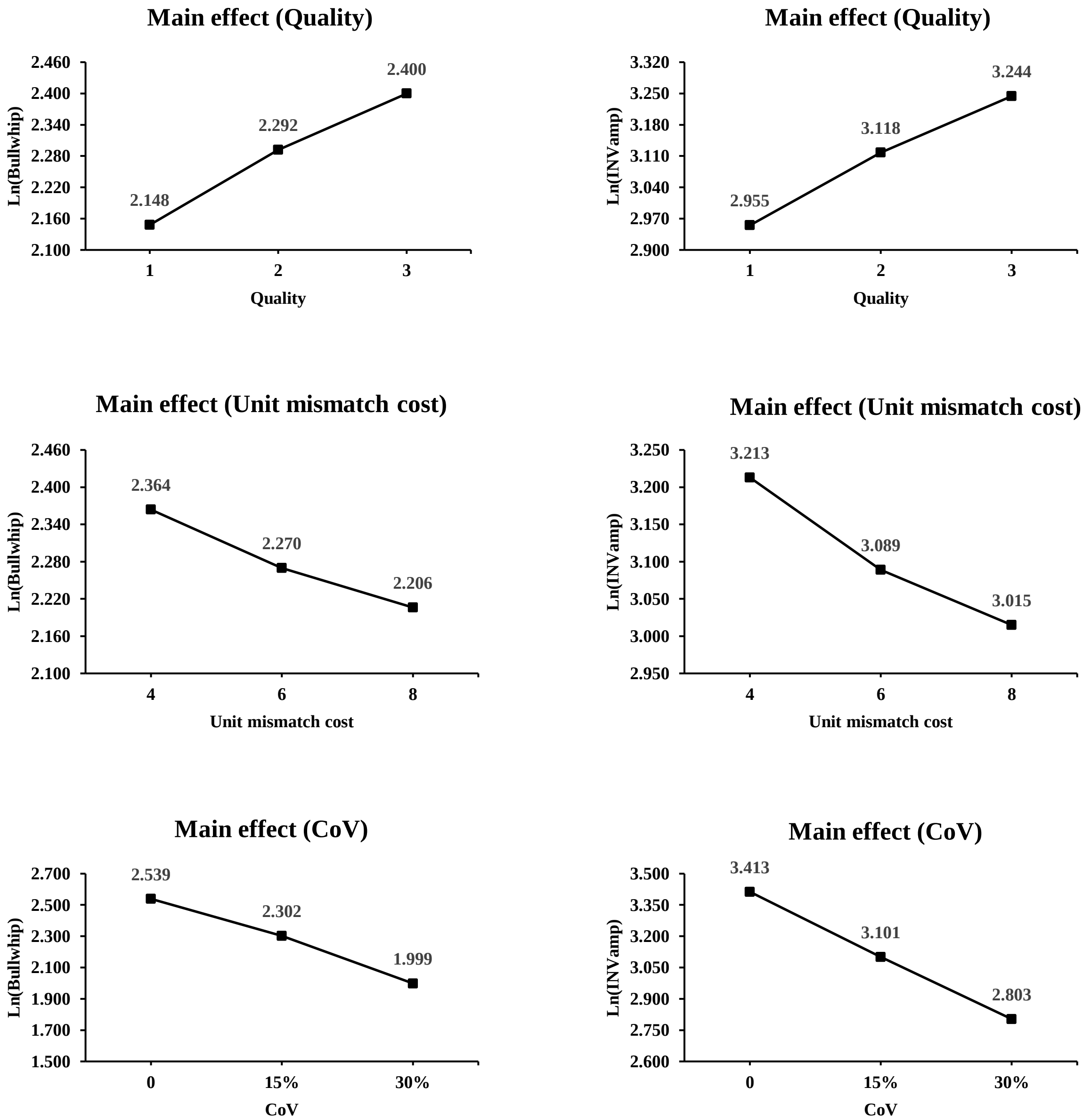
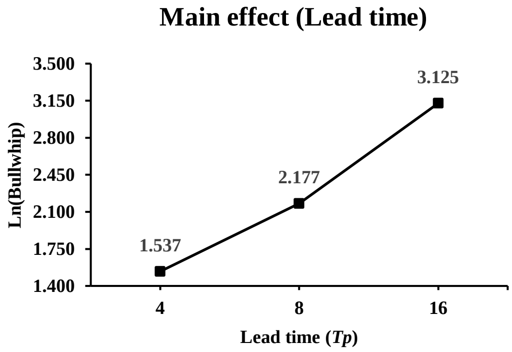


Figure 2. Main effect of using/not using online review

For other variables, the F-values reveal that the lead time variable has the biggest impact on bullwhip and INVamp, followed by the CoV, quality and unit mismatch cost. In Figure 3, the main effects of other variables are presented. For product quality, interesting phenomena can be observed in both bullwhip effect and INVamp. With the increase on product quality, a higher bullwhip effect and INVamp can be observed, indicating that the supply chain dynamic performance is lower. Specifically, compared with the lower quality scenario (i.e. quality = 1), bullwhip is 28.7% higher while INVamp is increased by 33.5% under a higher quality scenario (i.e. quality = 3). Similarly, the bullwhip effect and INVamp increase can also be observed when lead time (T_p) increases. Compared with lead time T_p= 4 case, the case of lead time T_p= 16 can lead average 3.9 times higher bullwhip effect and 12.3 times higher INVamp. The observation of increase on both values induced from longer lead time is consistent with previous literature (e.g. Disney and Towill 2003c; Lee et al. 1997; Chen et al. 2000). On the contrary, for the main effects of the other two variables, when their values decrease, an increase on the bullwhip effect and INVamp is observed. Specifically, compared with the case of unit mismatch cost equal to 8, the bullwhip and INVamp values are 17.1% and 21.9% higher when unit mismatch cost is 4. Similarly, lower CoV of customers can also lead higher bullwhip effect and INVamp. It can be observed bullwhip and INVamp in lower CoV scenario (i.e. CoV = 0) are 71.6% and 84.0% higher than these values in higher CoV scenario (i.e. CoV = 30%).





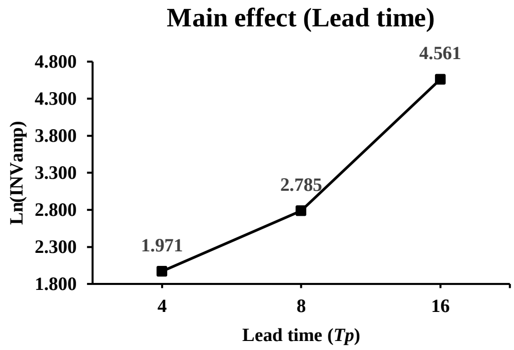
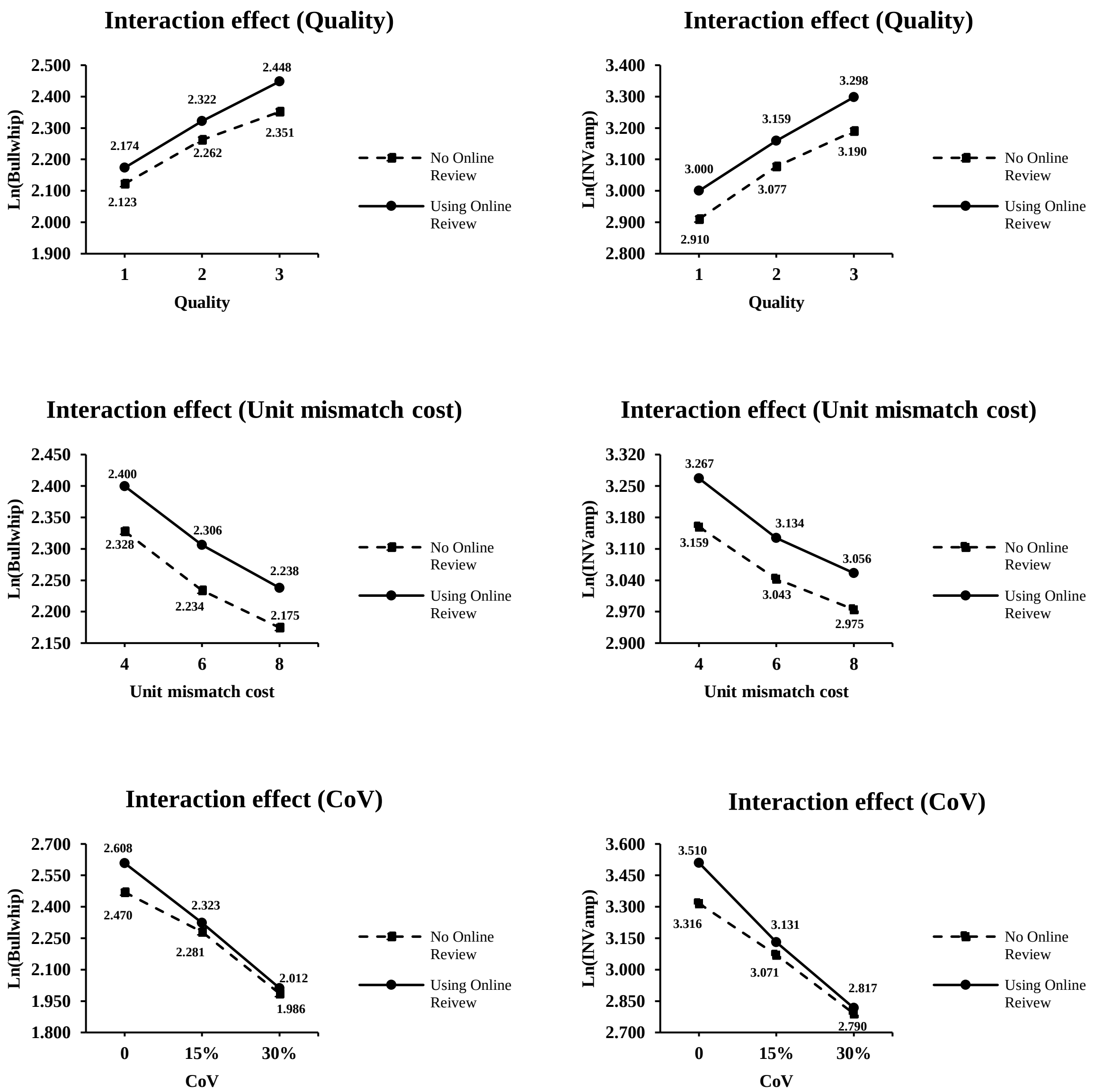


Figure 3. Main effects of other variables

Apart from main effects, the ANOVA results also indicate significant interaction effects between the focal variable (online review) and other variables, presented in Figure 4. Although using online reviews can lead higher bullwhip and INVamp value for supply chain system, such influence can be moderated by other variables. The most important interaction effect, according to the F-value, is generated from lead time and online review interaction. Although bullwhip and INVamp values are always higher when online reviews are used, the adoption of online review will lead to a greater increase in bullwhip and INVamp when the lead time (T_p) is long (i.e. lead time T_p= 16) compared to shorter lead times (i.e. lead time T_p= 4 and 8). Specifically, increases on bullwhip and INVamp led by online review use are 21.0% and 23.0% respectively when T_p is 16, but only 1.2% and 2.8% when T_p is 8 and 0.4% and 4.5% when lead time is 4.

The second important interaction takes place between CoV and online review use. Under such interaction effect, when the volatility of customers is low, which is the case of CoV = 0, the increases on bullwhip and INVamp generated from using online reviews are 14.8% and 21.4% respectively, higher than in the situation of CoV = 15% (4.3% and 6.2%) and when CoV = 30% (2.6% and 2.7%).

Third, although relatively less significant compared with the first two interaction effects, product quality can also moderate the online review's influence on dynamic performance. From Figure 4, when product quality is higher (i.e. quality = 3), the increases of bullwhip and INVamp led by online review use are 10.2% and 11.4%, respectively, which are not considerably higher than these values in the quality = 2 situation (6.2% and 8.5%) and in the quality = 1 situation (5.2% and 9.4%).



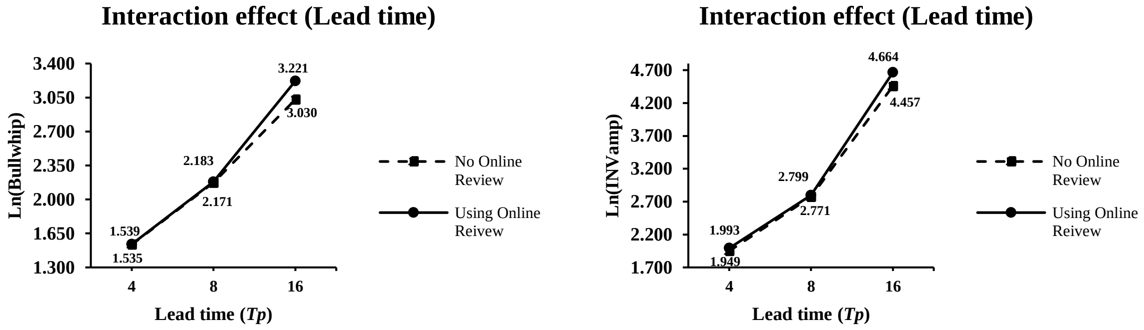


Figure 4. Interaction effects between online review and other variables

Finally, unit mismatch costs can also moderate the influence of online review on bullwhip and INVamp, but such influence seems also less significant than the moderating effects from lead time and CoV. The increases led by online review use in bullwhip and INVamp in the case of unit mismatch cost = 4 are 7.5% and 11.4%. Such increases on both measures are quite close to these in higher unit mismatch cost situation which are 7.5% and 9.5% for unit mismatch cost = 6, as well as 6.5% and 8.4% for unit mismatch cost = 8, respectively.

5. Discussion

Our results show that overall, the bullwhip effect and INVamp will be higher when online reviews are used in supply chain, and the percentages of increase are 7.3% and 9.7% for bullwhip effect and INVamp on average. Although the average increase for both measures is not dramatic, in some cases, such as where long lead time exists, the increase for both can be higher than 20%. In addition, such an increase can be amplified from the downstream retailers to upstream manufacturers. As observed by previous literature (Dejonckheere et al., 2004), dynamic effects within a supply chain with four echelons can see an increase from downstream to upstream significantly, which generates a significant cost impact (Metters, 1997). In this case, adopting an online review system may significantly influence the bullwhip and INVamp of upstream companies. This finding enriches literature in supply chain dynamics and enables a better understanding of supply chain dynamics in the e-commerce context, paving the way for further supply chain optimisation and performance improvement.

The interaction effects indicate that companies selling products with long lead time and low customer volatility can suffer significantly more bullwhip and INVamp increase from adopting online reviews. The results here indicate the need for companies to invest in decreasing the lead time if they intend to adopt online reviews. In addition, the interaction effect between customer volatility and online review use suggests that products with strong seasonality will probably suffer less impact of dynamic performance change from online review adoption. Therefore, retailers selling products with a smooth demand pattern may need to pay more attention to the influence on the bullwhip and INVamp induced from adopting online review systems.

Finally, the main effects from other variables also provide insights on research and practice. Although they are not the focus of this paper, we found that higher product quality and lead time can lead to higher bullwhip and INVamp values, while higher unit mismatch cost and customer volatility can lead lower values of both measures. These results endorse the need for lead time reduction. Further, given that higher quality can raise bullwhip and INVamp, with quality being defined as the net quality (real product quality less price), this may suggest companies adopting a high price strategy can lower bullwhip and INVamp, because the higher price essentially decreases product net quality. Of course, as price increases can also decrease customer demand, such a pricing decision should be made under the consideration of all possible influences. Meanwhile, companies need to be aware that products with higher customer volatility (e.g. strongly seasonal products) or higher unit mismatch cost (e.g. niche products) can have lower bullwhip and INVamp, which can support companies to make more rational decisions like capacity planning and budget allocation.

In practice, from the main and interaction effects in ANOVA results, managers need to reflect on the implications arising from the increased bullwhip and INVamp online reviews can bring. Companies need more flexible production and warehouse management practices such as building flexible production lines, transportation schedules as well as warehouse resourcing. Moreover, as the amplification of bullwhip is also observed through supply chains more widely, under online review adoption companies should promote the supply chain collaboration through practices such as adopting vendor-managed replenishment or promoting demand information sharing (Cannella & Ciancimino, 2008). Put it simply, supply chain flexibility and collaboration should be focused more when online reviews are adopted.

6. Model limitations and extension

As the model developed is for exploratory purposes, it still has limitations. In outlining these, we also suggest potential extensions to the modelling that may be explored in the future.

6.1 Competition

In our model, we only considered one retailer in the market. To extend the model, one direction is to consider competition between retailers. A simple and straightforward extension can be made based on Li and Hitt (2010) and Kwark, Chen and Raghunathan (2014), where two competing retailers, namely retailer 1 and retailer 2, are assumed in the market, selling product 1 and product 2 which are assumed as imperfect substitutes. The substitute model here can cover many commonly seen cases in practice. For example, two competing retailers sell similar products with the same function but different vertical attributes (e.g. different colours). In addition, it can also cover the case that two competing retailers source the identical product from the same manufacturer and sell to customers, but customers have different loyalty to each retailer. This can be seen with large, competing retailers on their own platforms, or by smaller retailers using a common platform like Amazon.

Under such settings, we can first consider both retailers have identical pricing and service policy. The real quality of both products is assumed as the same, but customers have different preference on each product (Kwark et al., 2014). The real quality is denoted as q_1 and q_2 for product 1 and 2, which can only be realised after purchase. After getting fulfilled, the customer realised utility for each product can be formed as $U_{it}^{r1} = q_1 - \beta x_{it}$ for product 1 and $U_{it}^{r2} = q_2 - \beta(1 - x_{it})$ for product 2 (Li & Hitt 2010). For those customers who are willing to post reviews, U_{it}^{r1} or U_{it}^{r2} as well as Equation (3) can generate ratings if online reviews are adopted by retailers.

To model the customer choice before purchase, the expected quality is needed to form the model. Following Li and Hitt (2010), the expected quality for each product is denoted as q_1^e and q_2^e and is assumed as equal (i.e. $q_1^e = q_2^e$). Such assumption is reasonable because products are functionally substitutable or sourced from the same manufacturer, and both retailers have the same pricing and service policy. Therefore, customers can generate their expected utility for each product as $U_{it}^{e1} = q_1^e - \beta x_{it}$ and $U_{it}^{e2} = q_2^e - \beta(1 - x_{it})$. For demonstrative purposes, we suppose retailer 1 adopts online reviews while retailer 2 not, and then customers can generate the expected utility under the influence of online rating for product 1 as U_{it}^{er1}. Through comparing U_{it}^{er1} with U_{it}^{e2}, customers will decide which product to buy. To illustrate this case, we propose the customer choice between product 1 and product 2 in Figure 5.

Further, we can consider the competition of retailers on their pricing and service policy (e.g. warranty). As we consider q_1 and q_2 as the 'net quality' in customer utility sense, such competition can also lead different realised utility of buying the product. In other words, although the product's material quality is the same, the 'net quality' of product 1 and product 2 can be different under distinct pricing and service policies. For example, a lower price and/or longer warranty time can lead higher customer utility and thus higher net quality. Therefore, we can reasonably assume q_1 is not necessarily equal to q_2. In addition, as the pricing and service policy can be inspected before purchase, customers can form unequal expected quality q_1^e and q_2^e for product 1 and product 2 under the influence of different policies.

The above discussion models the customer side. For the supply side modelling, Equations (8) to (12) can be directly applied to this competition model without any change. Both retailers' replenishment and fulfilment processes still employ the IOBPCS framework. By doing this, our proposed model adds supply chain elements in competition under the influence of online reviews, and considers the situation of customer comparisons between products as well as the influence of product stock-outs on customer switching behaviour.

A flowchart is presented in Figure 5 to clearly demonstrate the whole process of supply chain competition under the influence of online reviews. As there are two retailers, the decisions on adopting online reviews can generate four possible scenarios, namely both retailers adopting online reviews, neither having reviews, and only one retailer using online reviews. For clarity, the simulation flowchart in Figure 5 only reflects the case that retailer 1 uses online reviews while retailer 2 does not, but the other mentioned situations are also possible. Similar to the notation in our basic model, we notate $\bar{R}_t^1$ is the average rating of product 1 in period t, while U_{it}^{score1} is the utility generated from $\bar{R}_t^1$ based on Equation (6). U_{it}^{er1} is the expect utility for product 1 under the influence of online rating based on U_{it}^{score1} and U_{it}^{e1} using Equation (7). R_{it}^1 here is each customer i's rating for product 1. It is also possible that the two retailers order from different suppliers.

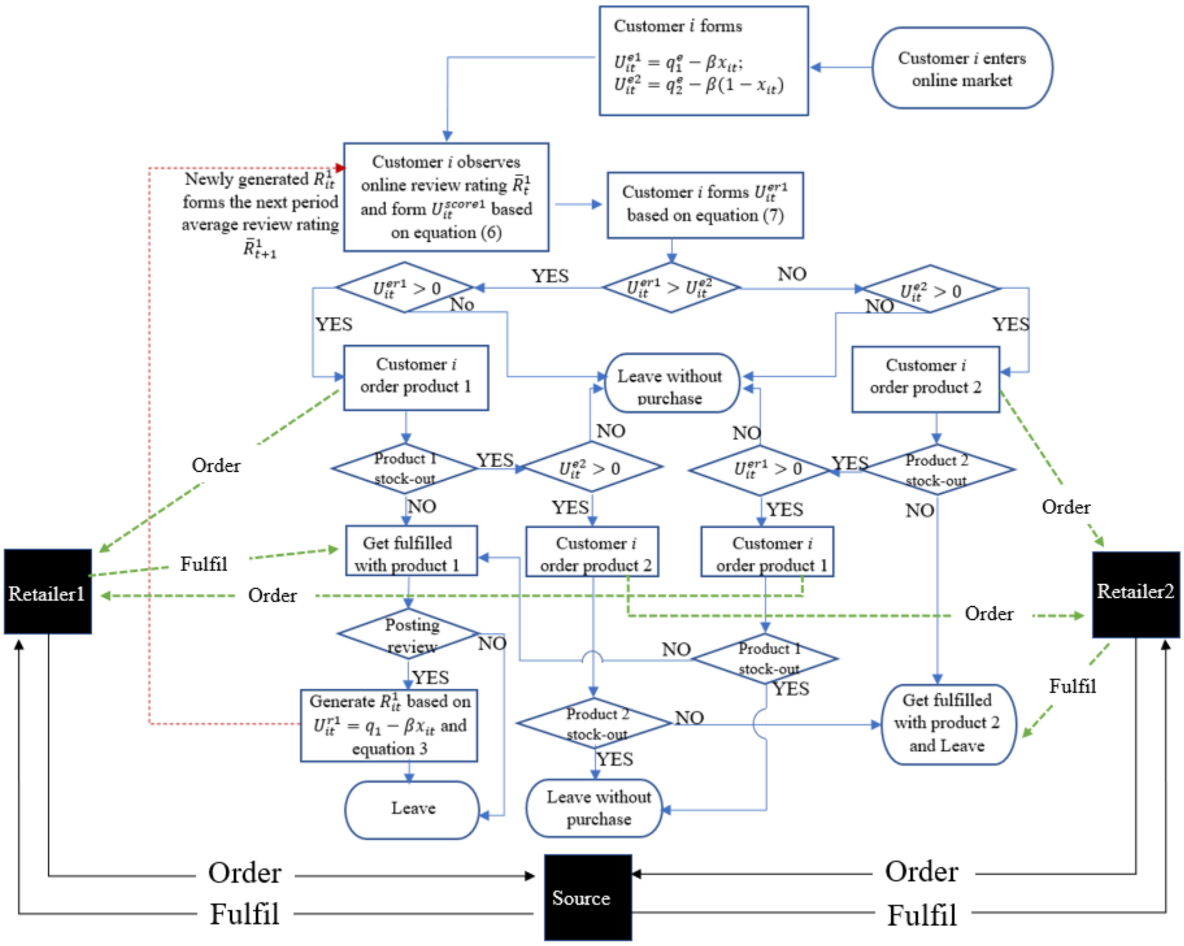


Figure 5. Simulation flowchart for online review influence on competing retailers

6.2 Dual sourcing

Another possible extension sees a common retailer source products from two suppliers, which is essentially a dual sourcing problem. Sourcing products from two or multiple suppliers can mitigate the disadvantages of singe source, such as instability supply (Wang, Gilland & Tomlin, 2010) or supply constraints (Zhang et al., 2012).

Although previous literature discusses many aspects of the dual sourcing problem, such as the cost, lead time, and capacity of different suppliers, we focus on the product quality of different suppliers from the perspective of online review adoption in supply chain. More specifically, we consider the retailer's decision making on online review adoption when facing two suppliers who supply a single type of products with different quality levels. The problems of different supply quality have been explored in some research (e.g. Liu, Li & Lai, 2004; Wagner, Gürbüz & Parlar, 2019), but not from an online review perspective. The quality of supplier 1 (i.e. q_H) is higher than supplier 2 (i.e. q_L) due to, for example, greater investment in manufacturing technology. Although the product quality information is known to the retailer, it is unknown to the customers until they buy and are fulfilled. In other words, before purchasing the products, customers will think the products are all the same, and they will still form expected quality, q^e. Under such setting, q^e is not necessarily equal to q_H or q_L.

Consistent with our base model, as customer expected quality before purchase is still q^e, a customer will order the product when his/her expected utility is greater than 0. If the online review system is adopted, a rating $\bar{R}_t$ will be accessible and will influence the customer expected utility as well. Therefore, all the decision behaviours before purchase are completely the same as our base model decision process. However, in this extension, the difference is the generation of $\bar{R}_t$. For those who ordered and get fulfilled by the products, they will generate the real utility as $U_{it}^H = q_H - \beta x_{it}$ if fulfilled by the higher quality product and as $U_{it}^L = q_L - \beta x_{it}$ if fulfilled by the lower quality product. With no online review system, the model is the same as our base model. However, if an online review system is adopted, customers will rate the product based on a mix of U_{it}^H and U_{it}^L. Although $\bar{R}_t$ is still generated based on equation (5), the rating information is not based on the real product quality as there are essentially two quality levels involved.

For the supply side, the retailer order, $O_t^{(h)}$, is generated still based on equation (12). However, as there are two suppliers, a retailer will place orders to both suppliers. Based on previous research (Glock, 2012), we assume there will be $\rho O_t^{(h)}$ to supplier 1 and $(1-\rho)O_t^{(h)}$ to supplier 2 with $0 < \rho < 1$. We draw the flowchart about this extension below in Figure 6, and future research should investigate the interaction effect between online review adoption and product quality (q_H and q_L) as well as the proportion of orders to supplier 1 (i.e. ρ).

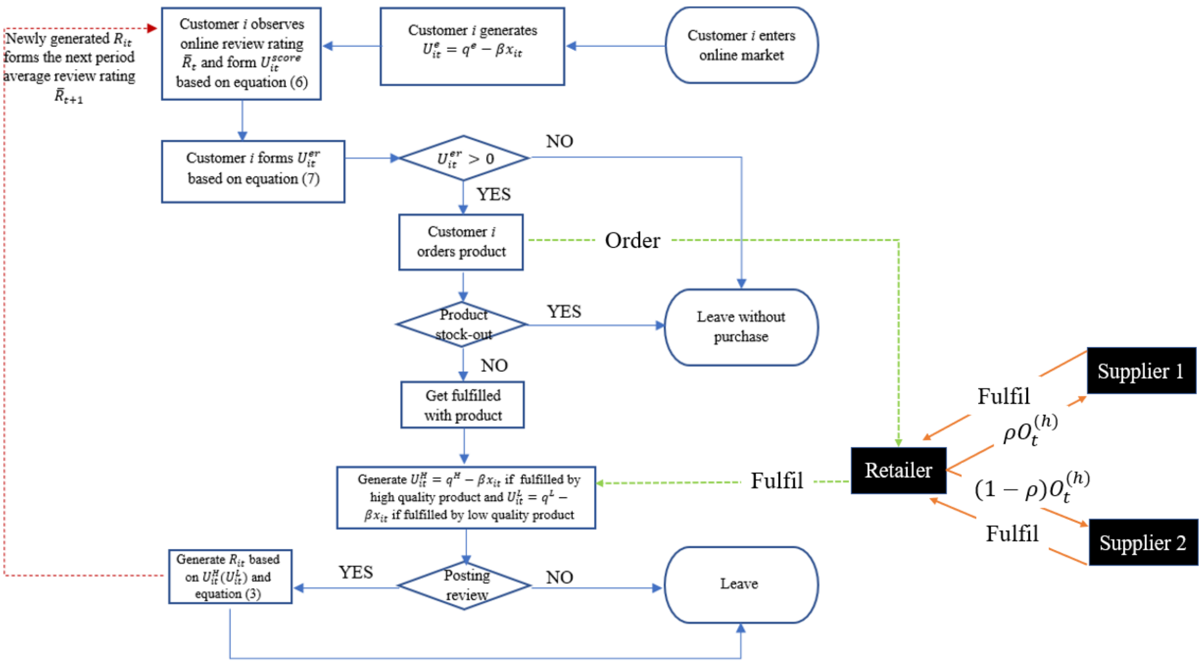


Figure 6. Simulation flowchart for online review influence on dual sourcing supply chain

6.3 Product Return

A further model extension could include product returns. To model this process, we need to make several adjustments. We can assume the product real quality is not fixed but a random variable q_{it} for each customer i in period t, and it could follow a normal distribution as $q_{it} \sim N(u_q, \sigma_q^2)$ (Hu et al., 2017). q^e is still the quality estimation. If we assume $u_q = q^e$, the estimation can be regarded as a correct estimation on the mean of q_{it}, as otherwise it is a biased estimation. The customer's real utility U_{it}^{r} will turn to $U_{it}^{r} = q_{it} - \beta x_{it}$, and it will be used to rate the product based on Equation (3). To model customer return decisions, we follow Anderson, Hansen and Simester (2009) and assume the customer's cost of returning a product is $W > 0$. W can be the delivery fee paid by the customers to return the product to the retailer, or the time and effort spent on the return process such as re-packaging. When $U_{it}^{r} < -W$, the customer will choose to return the product, otherwise this customer will keep the product. Finally, we can evaluate the purchase decisions. When online reviews are adopted, the expected purchase of customer i in period t under the influence of online reviews will be U_{it}^{er} based on Equation (7). As customers have no information about the real utility (i.e. U_{it}^{r}) before purchase, they can only use U_{it}^{er} to estimate it. If $U_{it}^{er} > 0$, this customer will expect the post-purchase utility greater than 0, meaning that he/she will not expect a product return as W is always greater than 0. However, if $U_{it}^{er} < 0$, there can be two scenarios if this customer still buys this product. On the one hand, if $-W < U_{it}^{er} < 0$, this customer will expect to keep the product, gaining utility as $U_{it}^{er} < 0$. On the other hand, if $U_{it}^{er} < -W < 0$, this customer will expect to return the product, gaining utility as $-W < 0$. This is because after customer returns the product, they gain nothing but incur the cost of product return. In both scenarios, the customer will expect a negative utility for purchasing the product if $U_{it}^{er} < 0$. Therefore, if a customer is rational, they will only buy the product if $U_{it}^{er} > 0$ when considering the product return cost before purchase. Similarly, if online reviews are not used, a customer will buy the product only if $U_{it}^{e} > 0$.

For the supply chain side, to adapt our original model to product return, the retailer ordering process needs to be adjusted. We here assume that customers in period t who do not keep their product will return the product immediately, and the returned product can be received by the retailer in the next period $t + 1$. The returned product is assumed to be no difference from the new product and can be re-sold to new customers directly, and thus all supply chain side equations from (8) to (11) hold. In future research, such an assumption can be relaxed by considering the remanufacturing processes (Tang & Naim, 2004). Now, different from the original model, the returned product can be used to fulfil customers and, following Zhou and Disney (2006), Cannella, Bruccoleri and Framinan (2016) and Turrisi, Bruccoleri and Cannella (2013), the order policy in Equation (12) is changed to:

$$O_t^{(h)} = MAX\left(0, (L+1) * \widehat{D}_t^{(h)} - I_t^{(h)} - WIP_t^{(h)} - RT_t^{(h)}\right) \tag{15}$$

where $RT_t^{(h)}$ is the returned product received in period $t > 1$ and

$$RT_t^{(h)} = \sum_{i=1}^{n_{t-1}^{(h)}} \tau\left(U_{i(t-1)}^r + W\right), where\ \tau(a) = \begin{cases} 1, & a < 0 \\ 0, & else \end{cases} \tag{16}$$

It should be noted that such an ordering process is just one of the possible replenishment policies for product return, and there exist other policies which can be adapted in our model based on different assumptions (see Tang & Naim, 2004; Turrisi et al., 2013). Addressing differing ordering process in online review influenced supply chain can thus be an interesting future direction. To better demonstrate this return model, we present a flowchart in Figure 7. If online reviews are not used, the purchasing decision criterion turns to $U_{it}^e > 0$.

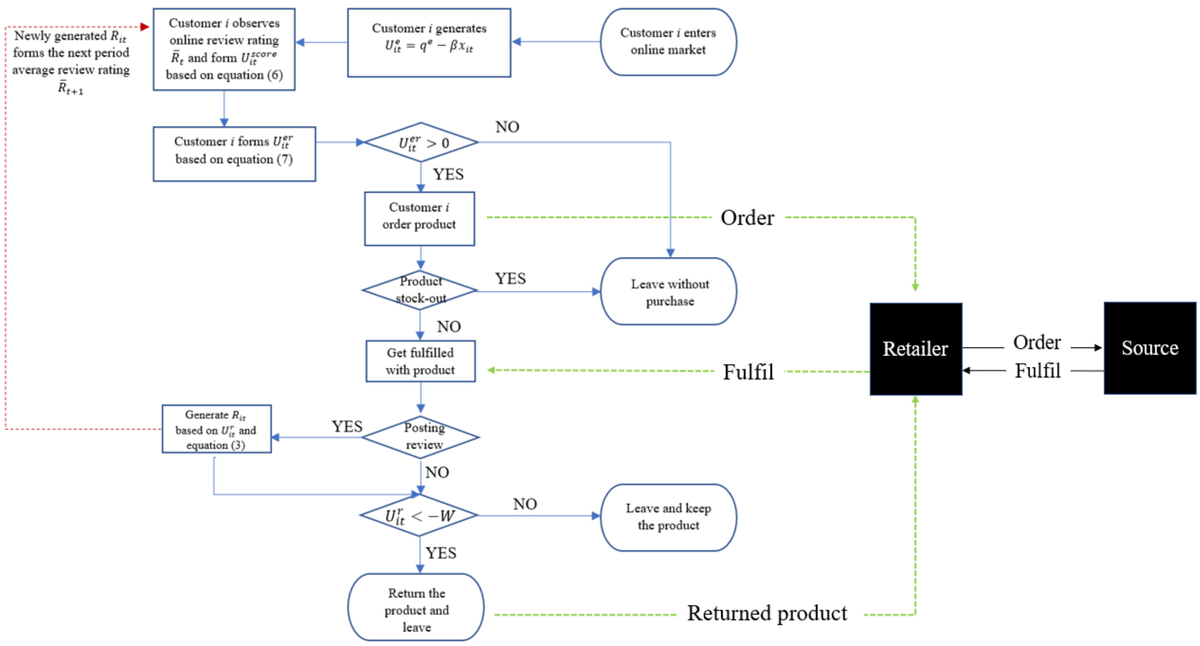


Figure 7. Supply chain with online reviews and product return

6.4 Online review quality and manipulation.

In our model we assume customers give an honest opinion in the reviews that they post. However, this is not always the case. It is possible that reviews are strategically manipulated, including promotional or fake reviews posted by companies to attract customers (Dellarocas, 2006; Mayzlin, Dover & Chevalier, 2014). To add online review manipulation behaviour to our original model, we consider two types of customers, namely 'normal' customers and 'recruited' customers. Normal customers are the customers in our original model, but the recruited customers are paid by companies to generate good reviews for the product. Normal customers make purchase decisions based on U_{it}^{er}, while recruited customers will always purchase the product if there is no stock-out condition. After purchasing and getting fulfilled, normal customers will post their rating based on their real utility U_{it}^{r} as well as Equation (3), while recruited customers will always post 5-star. As there is no need to consider the recruited customers utility before and after purchase, this model essentially only focuses on normal customers. The original model formulation is otherwise unchanged, as only the online review process is affected.

6.5 Other possible extensions

Apart from the above extensions, some other interesting directions may also be worth exploring. First, we currently assume the delivery time is the same for every customer. However, it is not necessarily true in practice. Some customers may experience longer delivery time than others. To relax our assumption, delivery time can be modelled as a random variable and vary for each customer. Previous research suggested that shorter delivery time can attract more customers (e.g. Shen, Xu & Guo, 2020; So, 2000). Therefore, customers with shorter delivery time may gain higher utility of purchasing the product, and they may be willing to give a higher rating in online reviews, which in turn influences the future customer purchase choice. Through modelling the delivery time into customers' utility as well as online review generation process, deeper insights can be obtained on the interaction between online reviews and supply chains.

Second, we assume in each scenario that the lead time is not a random distribution, but a fixed number as 4, 8, or 16 periods long. Our assumption is consistent with previous literature (e.g. Dejonckheere et al., 2004), and keeps our model simple in its exploratory stage. However, existing research also suggests that if lead time is considered as a random distribution, not only its mean value may influence supply chain dynamics, but also its variance level (e.g. Chatfield & Pritchard, 2013). Therefore, it could be interesting to consider lead time as a random variable and examine both its mean and variance effect in supply chain dynamics through which new insights can be expected to add to existing research by considering online review influence.

Third, we only consider the dynamics of a single echelon supply chain. Although we observed the increased bullwhip and INVamp of the retailer under the influence of online reviews, we do not examine the multi-echelon supply chain case. In other words, the results only suggest the information mismatch and misprocessing between market and retailer's operations under online reviews. How supply chain dynamic performance influenced by online reviews can be transmitted from retailer to upstream companies remains unclear. Previous research shows examining the dynamic performance in multi-echelon supply chain can offer valuable and systematic insights (Cannella, Barbosa-Póvoa, Framinan & Relvas, 2013), and significant amplification of bullwhip effect is observed through supply chain from downstream to upstream (Dejonckheere et al., 2004). Therefore, to further understand the online review influence on supply chain dynamics, extending the model into a multi-echelon supply chain is promising.

Finally, we only use supply chain dynamics to evaluate the performance, which means we evaluate the online review value from a company perspective. However, online review value should be evaluated from customer perspective to check how the adoption of it can bring customer surplus and welfare (e.g. Li & Hitt, 2008; Zhang, Li, Cheng & Lai, 2018). Therefore, an interesting extension can be creating a compound performance indicator combining customer welfare and supply chain efficiency to evaluate the influence of online reviews in supply chains.

7. Conclusions

To conclude, this paper explores the influence of adopting online reviews on supply chain dynamics through simulation experiments. The results show that overall, adopting online reviews will bring higher bullwhip effect and INVamp in the supply chain on average, but such influence will be moderated by product quality, product unit mismatch cost, lead time, and customer volatility. As shown in the literature review , this paper represents the first exploration into the influence of online reviews on supply chain dynamics.

This paper has several research contributions. First, online reviews are identified as an influential factor of bullwhip and INVamp. Different from the most of previous literature in this area, our model assumed customers are heterogenous in the process of product ordering. Although such modelling methods are commonly seen in the marketing and economic fields (e.g. Li & Hitt, 2008; Hu et al., 2017), it is less common in supply chain dynamics research where customers are often assumed to be homogeneous. As such, this paper also contributes to the simulation-based research in the 'operations-marketing interface' (Tang, 2010). In addition, our paper extends the well-established family of IOBPCS models to online review aspect. As the IOBPCS model is flexible in modelling different types of supply chain, interested researchers can also build further work by integrating our model with other IOBPCS variations (Lin et al., 2017). Finally, we identify further adaptations to our model for different scenarios including market competition, dual sourcing, product return, and review manipulations, building a general modelling framework for future research in this topic.

This paper also contributes to practice. We find that adopting online reviews in the supply chain can bring higher bullwhip effect and INVamp and, in some scenarios discussed above, such influence can be significant. Previous research has highlighted the harmfulness of high bullwhip and INVamp, such as cost increases (Metters, 1997; Cannella et al., 2018), a decrease in service level (Bayraktar et al., 2020), and supply chain inefficiency (Cannella et al., 2013). Therefore, our work reveals a 'dark side' of online review adoption to inform managers. However, the purpose of this paper is not to persuade managers and companies to give up online reviews directly, but to raise awareness of their impact, and they are advised to build flexibility and collaboration capabilities to cope with these drawbacks. Undoubtedly, the advantages of online reviews are significant. Through providing customers with more transparent information, online reviews help improve purchase satisfaction, leading to higher corporate reputation, better customer relationship (Huang, Potter & Eyers, 2020) and quicker service recovery (Gu & Ye, 2014).

Appendix 1. Notations

Notations for main model	Description
U_{it}^{e}	expected utility before purchase of i^{th} customer in period t without the influence of online review
q^{e}	customers' expected product quality before purchase
p	product price (normalised to 0)
β	unit mismatch cost
x_{it}	mismatch degree on product of i^{th} customer in period t
U_{it}^{r}	real utility after purchase of i^{th} customer in period t
q	product real quality (assumed to be equal to q^{e})
R_{it}	product rating by i^{th} customer in period t
$\overline{R_t}$	average product rating in period t (which is shown in the online review system)
n_t^{r}	number of customers posting rating in period t
U_{it}^{er}	expected utility before purchase of i^{th} customer in period t under the influence of online review
U_{it}^{score}	expected utility before purchase of i^{th} customer in period t generated from the average product rating in online review system
θ_{it}	relative weights put on U_{it}^{score} when i^{th} customer in period t generates U_{it}^{er}
T_p	physical distribution lead time
L	system lead time ($T_p + 1$)
α	simple exponential smoothing parameter
D_t^{a}	customers vising the e-commerce platform in period t
$D_t^{(h)}$	customers who decide to buy the product in period t, where $h = N$ for no online review while $h = R$ for using online review
$n_t^{(h)}$	customers who decide to buy the product and are fulfilled by the retailers in period t, where $h = N$ for no online review while $h = R$ for using online review
φ_{it}	indicator of posting review; 1 means posting review while 0 means not posting review

$I_t^{(h)}$	retailer's available inventory on hand in period t, where $h = N$ for no online review while $h = R$ for using online review
$O_t^{(h)}$	retailer's order placed to its supplier in period t, where $h = N$ for no online review while $h = R$ for using online review
$WIP_t^{(h)}$	retailer's work-in-process in period t, where $h = N$ for no online review while $h = R$ for using online review
$\widehat{D}_t^{(h)}$	retailer's forecast for the future period generated in period t, $h = N$ for no online review while $h = R$ for using online review

Notation for extended models	**Description**
q_1	real quality for product 1
q_2	real quality for product 2
U_{it}^{r1}	real utility of i^{th} customer in period t after purchase product 1
U_{it}^{r2}	real utility of i^{th} customer in period t after purchase product 2
q_1^e	customers' expected quality for product 1 before purchase
q_2^e	customers' expected quality for product 2 before purchase
U_{it}^{e1}	expected utility of i^{th} customer in period t without the influence of online review before purchasing product 1
U_{it}^{e2}	expected utility of i^{th} customer in period t without the influence of online review before purchasing product 2
U_{it}^{er1}	expected utility of i^{th} customer in period t under the influence of online review before purchasing product 1
$\bar{R}_t^1$	average rating in online reviews in for product 1 in period t
U_{it}^{score1}	expected utility of i^{th} customer in period t before purchasing product 1 which is generated from the average product rating in online review system
R_{it}^1	product rating by i^{th} customer in period t for product 1
q^H	real quality of product from supplier 1 (high product quality)
q^L	real quality of product from supplier 2 (low product quality)
ρ	proportion of ordering products from supplier 1
U_{it}^H	real utility of i^{th} customer in period t fulfilled by supplier 1

U_{it}^{L}	real utility of i^{th} customer in period t fulfilled by supplier 2
W	cost for returning a product
$RT^{(h)}$	the number of returned products received in period t, where $h = N$ for no review while $h = R$ for using online reviews

Appendix 2. The influence of different distributions of customer weights on rating score

In the model, a uniform distribution $U(0,1)$ is chosen to model the weights placed by customers on the online rating score. For robustness, here we test a normal distribution and triangular distribution. To be compatible with $U(0,1)$, whose mean is 0.5, we choose $N(0.5, 0.1^2)$ and $Triangular\ (0,1,0.5)$. As all three distributions have a mean value equal to 0.5, which means that on average, customers equally believe their own expectation and online review information (i.e. rating). However, as a further test, we vary the parameters of the normal and triangular distributions with mean/mode values of 0.3 (less reliance on reviews) and 0.7 (more reliance on reviews). Table A2 compares the bullwhip and INVamp in all scenarios.

Table A2. Bullwhip and INVamp value comparison based on different weight distributions

	No online review	Online review adopted		
		$\theta_i \sim U(0,1)$	$\theta_i \sim N(\mu, 0.1^2)$	$\theta_i \sim Triangular(0,1,m)$
$Ln(Bullwhip)$	2.245	2.315	2.285 ($\mu = 0.3$) 2.313 ($\mu = 0.5$) 2.372 ($\mu = 0.7$)	2.308 ($m = 0.3$) 2.313 ($m = 0.5$) 2.334 ($m = 0.7$)
$Ln(INVamp)$	3.059	3.152	3.106 ($\mu = 0.3$) 3.140 ($\mu = 0.5$) 3.222 ($\mu = 0.7$)	3.135 ($m = 0.3$) 3.145 ($m = 0.5$) 3.166 ($m = 0.7$)

Remark: as the weights can only range from 0 to 1, the normal distribution is truncated by bounding the value from 0 to 1.

It can be clearly seen from Table A2 that our finding holds no matter what kind of distribution is assumed. This is because when online review is adopted, the logarithmic bullwhip values are always higher than 2.245 (i.e. bullwhip value without online review), and INVamp values higher than 3.059 (i.e. INVamp value without online reivew). Also, it can be observed that when the mean of three distributions is 0.5, their bullwhip/INVamp values are very close. With the mean of customer weight distribution increases, both bullwhip and INVamp increase. The reason is a higher mean value leads more weight on online review ratings in the purchase decision process.

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