A Quantitative Model for Analyzing Market Response during Supply Chain Disruptions

Abstract

Supply chain disruptions can lead to firms losing customers and consequently losing profit. We consider a firm facing a supply chain disruption due to which it is unable to deliver products for a certain period of time. When the firm is restored, each customer may choose to return to the firm immediately, with or without backorders, or may purchase from other firms. This chapter develops a quantitative model of the different customer behaviors in such a scenario and analytically interprets the impact of these behaviors on the firm's post-disruption performance. The model is applied to an illustrative example.

Keywords - Supply Chain Risk Management; Supply Chain Disruption; Preparedness; Response; Customer Demand

1. Introduction

Supply chain disruptions have garnered increased attention, both in academia and in practice, since the early 2000s. Modern production methodologies, globalized supply chains, shorter product life cycle, and the emphasis on efficiency have increased the risk faced by many supply chains. Managing the risk facing a supply chain is vital to the success of any company.

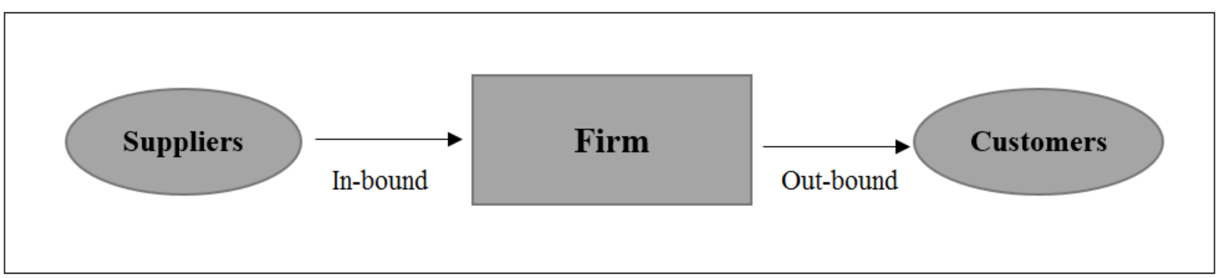

Fig. 1. A simple supply chain model

A supply chain is an integrated system of companies involved in the upstream and downstream flows of products, services, finances, and/or information from a source to a customer (Mentzer et al. 2001). Fig. 1 presents a basic supply chain model from the firm's perspective. A supply chain is characterized by the flow of resources—typically material, information, and money—with the primary purpose of satisfying the needs of a customer, who are the source of revenue for a firm. A supply chain will ideally maximize the total value generated from customers and minimize the cost of meeting consumer demand.

Major disruptions, such as those that occur from natural disasters, terrorist acts, and labor strikes, can interrupt the flow of materials for several firms. Sodhi and Tang (2012) categorized supply chain risk into supply risks, process risks, demand risks, and corporate-level risks. These risks often materialize all together during a major supply chain disruption, and decision makers need to consider all of these risks. Kilubi and Haasis (2015) conducted a systematic literature review on supply chain risk management (SCRM) and identified ten different definitions of SCRM. Lavastre et al. (p. 839, 2012) defined SCRM as "the management of risk that implies both strategic and operational horizons for long-term and short-term assessment." As implied by this definition, decision makers need to consider both the long-term and short-term impacts from a supply chain disruption.

The marketplace or customers can play a significant role in the long-term impacts as their needs, values, and opinions will affect the firm's decisions during the disruption. The volatility of consumer demand is a major form of risk (Jüttner et al. 2003). Firms face a risk of being penalized by their customers if their suppliers default and firms are unable to deliver on their obligations. Assessing how consumers react to such disruptions helps to forecast the long-term profits for the firm and can help it make sound risk management decisions. Modeling consumer behavior is useful not only when a disaster occurs but also to build flexibility within the supply chain as a proactive measure to anticipate such threats and quickly respond.

This chapter presents a probabilistic model to quantify the risk from a severe supply chain disruption with an explicit focus on how consumers or the marketplace's demand for a product should influence a firm's risk management strategies. Many supply chain disruption models assume some type of demand function, which may be constant or random. However, that demand function does not usually change when the disruption occurs, or simple assumptions are made about whether or not customers are willing to wait for a final product. Less research has focused on how the final customers should influence how a firm determines what risk management strategies are appropriate. This chapter models the demand function using a probabilistic approach to customer behavior in a post-disruption scenario. The model assumes that a disruption causes a supplier to default, and a firm is unable to deliver its product to consumers. The market responds with defined probabilities and time delays. The model attempts to measure the extent to which a firm can be penalized due to a default from its supplier and recommends strategies or practices to build resilience to such disruptions.

This chapter is organized as follows: a literature review is given in Section 2. Section 3 presents the mathematical model framework, and Section 4 describes an illustrative example and performs sensitivity analysis. Section 5 concludes the chapter with recommendations, insights, and conclusions drawn from the study.

2. Literature Review

Supply chain management has seen a variety of trends, including Just-in-Time, global sourcing, and outsourcing. These methods are aimed at cutting costs in a firm's supply chain and enabling the firm to compete more effectively. Increasing supply chain efficiency can also make supply chains more vulnerable to disruptions (Christopher 2005). In the race to increase their market share, firms may ignore that their supply chains are susceptible to disruptions.

A wide variety of events can disrupt a supply chain, including supply-side difficulties, demand-side variability, operational problems, and large-scale disruptions such as natural disasters (Manuj et al. 2007). Qualitative studies to manage these disruptions recommend excess inventory, additional capacity, redundant suppliers, flexible production and transportation, and dynamic pricing (Sheffi and Rice 2005; Stecke and Kumar 2009). Managing one type of risk may exacerbate another risk, and identifying the best strategy relies on the manager's ability to identify the most crucial risk and understand the trade-offs in SCRM (Chopra and Sodhi 2004). Quantitative studies in SCRM generally model the trade-off between purchasing from alternate suppliers and holding inventory (Tomlin and Wang 2005), or they model the interaction between suppliers and customers (Babich et al. 2007; Xia et al. 2011). MacKenzie et al. (2014) used simulation to model the interactions among supply chain entities where each entity can take different actions such as holding inventory or purchasing from alternate suppliers. Interested readers should refer to Snyder et al. (2016) for an in-depth review of the recent models of supply chain disruptions and disruption management strategies.

Although research has focused on the impacts of supply chain disruptions based on stock returns (Hendricks and Singhal 2005) or based on the economic linkages (MacKenzie et al. 2012), less research has focused on how customers behave during and after a supply chain disruption. Nagurney et al. (2005) examined the impact of unforeseen customer demands on the supply chain, but this research assumes the customer behavior causes the disruption. Ellis et al. (2010) surveyed managers and buyers of materials to study how customers may perceive supply chain risk. Modern supply chain management is very sensitive to customer demand (Nishat Faisal et al. 2006), but examining the relationship between customer demand sensitivity and a manufacturer or retailer during a disruption has not been fully explored. An important exception to this lack of research is the modeling and analysis of consumer behavior following a food contamination (Beach et al. 2008; Arnade et al. 2009).

This chapter seeks to fill the gap in the existing literature by probabilistically modeling customer behavior following a supply chain disruption. Whereas much of the current literature focuses on the interaction between the supplier and the firm, the focus of this chapter is the market response to the disruption and its impact on the firm. The model examines the decisions customers make after the interruption of a firm's service due to a supply chain disruption. Possible customer behaviors are fused within a probabilistic model to assess the expected lost revenue of the firm. A firm can use this forecasted measure of average lost revenue to decide what it should do to prepare and respond to such a disruption in its supply chain.

3. Model

This section presents an overall profile of a supply chain disruption and develops a probabilistic model to focus on the market response to the disruption. A supply chain disruption occurs when a firm’s supplier defaults. A major disruption impacts a firm in distinct phases (Sheffi and Rice

2005). It may take time for the final consumer to be impacted by the supply disruption. If the firm does not have enough inventory or cannot purchase from alternate suppliers, it will not be able to satisfy demand for its goods. Consequently, consumers may choose to purchase from other firms. The consumers' loyalty depends on a number of factors such as their relationship to the product. To get back to standard performance levels, a firm may adopt various response actions such as working at over-capacity levels. If the firm is prepared for such a disruption (e.g., having multiple suppliers or having more inventory), it should be able to respond more effectively (Yu et al. 2009).

3.1 Model Framework

We develop a probabilistic model to quantify the reaction of customers following a supply chain disruption that causes a temporary production shut down. Before the disruption, there are n customers (they could also be retailers) who purchase from a firm in each time period before a disruption. In the base model, we assume the demand equals the number of customers. In other words, every customer buys exactly one product. This assumption is relaxed in Subsection 4.3, which considers varying demands from each customer. An unexpected disruptive event causes one or more of the firm's suppliers to default, and the firm is unable to satisfy any demand beginning at time period $t = 1$. The disruption continues for M time periods, and the firm does not deliver to its n customers for $t = 1, 2, .., M$. The firm recovers from the disruption at $t = M + 1$ and will be able to deliver at its full capacity C orders per time period, where $C \geq n$.

In the post-disruption time period beginning at $t = M + 1$, each customer decides whether or not to return to the firm in each time period $t = M + i$. Note that $i = 1, 2, ...$ since the customer cannot buy from the firm during time periods $t = 1, 2, .., M$. Each customer comes back to the firm with a constant probability p in each time period. The value of p depends upon the type of product as well as the firm's response actions such as qualifying alternate suppliers and making up for lost production by running at maximum capacity. If a customer decides not to return to the firm at a particular time period, the model assumes that it will return to the firm in the next period with the same probability p. Once a customer returns to the firm, it will continue to purchase from the firm in all future time periods.

If a customer buys from the firm at time $t = M + i$, it will return with one of the following behaviors:

1. Customers can return right away without backorders at time $t = M + 1$. This category of customers might have used inventory from safety stock, not used the product, or purchased the product from other firms during the time periods 1 through M.
2. Customers who come back immediately and have backorders.
3. Customers who do not return immediately but return later to the firm with no backorders.

The probability q represents the conditional probability that the customer who comes back immediately at $t = M + 1$ will require backorders for $t = 1, 2, .., M$. In other words, given the customer has returned to the firm, the probability that he or she will have backorders is q. The revenue from backorders is accounted for at $t = M + 1$ since backorders are taken only in that time period. We assume that customers who wait longer to return do not have backorders (behavior number 3). The initial model assumes the firm can satisfy all the backorders. This could be because the firm is able to monitor activity and make plans to increase capacity to satisfy backorders. If q is small, the firm can be reasonably confident the backorders will not exceed its capacity. Since this assumption may not be realistic, Subsection 3.3 discusses how the model might change if a capacity constraint limits the number of backorders the firm can accept. Even if the lack of a capacity constraint may not be realistic, modeling the situation without this constraint generates useful insights into the potential benefits of increasing capacity after reopening.

3.2 Calculating the Firm's Post-Impact Revenue

The revenue at time periods $t = 1, 2, .., M$ is zero since the firm is not delivering any product to its customers. The total expected revenue after the firm reopens is calculated by estimating the number of customers who decide to buy from the firm at each period after it reopens at $t = M + 1$. Let X_t be the number of customers who decide to come back and purchase from the firm at time t. $X_t = 0$ for $t = 1,2, .., M$

For $t = M + 1, M + 2, ...$ each of the n customers returns with a constant probability p and X_t follows a binomial distribution.

At $t = M + 1$, $$X_{M+1} \sim Binom(n, p)$$ $$with\ E[X_{M+1}] = np$$

At $t = M + 2$, $$X_{M+2} \sim Binom(n - X_{M+1}, p)$$ $$with\ E[X_{M+2}] = np(1 - p)$$

At $t = M + 3$, $\quad X_{M+3} \sim Binom(n - X_{M+1} - X_{M+2}, p)$

$$with\ E[X_{M+3}] = np(1-p)^2$$

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At $t = M + i$, $\quad X_{M+i} \sim Binom\left(n - \sum_{j=1}^{i-1} X_{M+j}\ , p\right)$

$$\text{with } E[X_{M+i}] = np(1-p)^{i-1}$$

Since the model assumes that a customer who returns to the firm will continue to purchase from the firm in subsequent periods, the expected number of customers who purchase from the firm at $t = M + i$ is:

$$np\left(1 + (1-p) + (1-p)^2 + (1-p)^3 + \cdots + (1-p)^{(i-1)}\right)$$
$$= np\left(\frac{1 - (1-p)^i}{1 - (1-p)}\right)$$
$$= n\left(1 - (1-p)^i\right)$$

Since customers that return at $t = M + 1$ may return with backorders, the number of orders for the firm may exceed the number of customers X_{M+1}. The number of customers who return with backorders is represented by the random variable Z. The model assumes that backorders are placed only once at time $t = M + 1$ and $Z \sim Binom(X_{M+1}, q)$.

Although it makes intuitive sense to assume that customers who did not return to the firm immediately satisfied their demand during the shutdown period, $t = 1, 2, .., M$, from another firm, a further extension to this model may consider situations where customers who do not return immediately but return later to the firm also places backorders. In that case Z would need to be indexed by time t.

Since each customer orders exactly 1 product in each time period, a customer who returns with backorders is assumed to have M backorders (one backorder for each period that the firm was closed). Thus, the total number of orders at time $M + 1$ is $M * Z + X_{M+1}$. Using the expected number of customers from the above results and the conditional probability of placing a backorder, we calculate the expected number of orders at $t = M + 1$:

$$= \begin{pmatrix} \text{Expected number of} \\ \text{customers who return} \\ \text{with backorders} \end{pmatrix} * \begin{pmatrix} \text{Backorder} \\ \text{quantity} \\ \text{per customer} \\ + \\ \text{Regular order} \\ \text{quantity per} \\ \text{customer} \end{pmatrix} + \begin{pmatrix} \text{Expected number of} \\ \text{customers who return} \\ \text{without backorders} \end{pmatrix} * \begin{pmatrix} \text{Regular order} \\ \text{quantity per} \\ \text{customer} \end{pmatrix}$$

$$= (np * q) * (M + 1) + np * (1 - q) * 1$$

$$= np(qM + q + 1 - q)$$

$$= np(qM + 1)$$

The expected cumulative orders at time $t = M + i$ for $i > 1$ equals $n\,(1 - (1 - p)^i)$, which is equivalent to the expected cumulative number of customers who have returned by time $t = M + i$.

If the firm's per-unit selling price is c, we calculate R_t the lost revenue at time t:

$$R_t = \begin{cases} cn & \text{if } t = 1,2,..,M \\ c(n - X_{M+1} - Z) & \text{if } t = M + 1 \\ c\left(n - \sum_{i=1}^{t} X_{M+i}\right) & \text{if } t = M + 2, M + 3, \dots \end{cases}$$

The expected lost revenue at time t is denoted as $\bar{R}_t$.

3.3 Production Capacity Considerations

In the proposed model, it is important to look at the production capacity of the firm, especially at time $t = M + 1$, when backorders may be received. The number of orders $M * Z + X_{M+1}$ must not exceed the available capacity C. If $M * Z + X_{M+1} > C$, the excess orders will be carried forward to the next time period, $t = M + 2$, but capacity restrictions require that $M * Z + X_{M+1} + X_{M+2} \leq 2C$.

Similarly, the firm can estimate and forecast the production capacity levels for future time periods. Depending on the willingness of customers to wait for the backorder delivery, the firm needs to prioritize production with the goal of meeting customer needs. If customers are likely to be lost in case of a late delivery, the firm will have to consider whether it can temporarily increase its production capacity or other alternatives to meet the spike in demand due to backorders.

4. Illustrative Example

This model can be applied to several situations. For example, a consumer-product manufacturing firm could face a supply chain disruption forcing it to shut down production. The firm's customers could react in different ways. One, a retailer who uses inventory during this period may come back to the firm immediately with backorders to replace its inventory. Two, a retailer who temporarily switches to another supplier may decide to come back when the firm starts producing again. Three, a retailer who switches to another supplier may decide not to come back when the firm starts producing again. The latter retailer may come back at a later stage depending on the firm's performance. By estimating the probability that the retailer takes any of these actions, the model can account for each of these scenarios.

4.1 Lost revenue with backorders

We illustrate the application of this model to a scenario in which a firm experiences a supply disruption and must stop production for $M = 4$ periods. Table 1 provides values for the parameters in this example.

Table 1. Parameters

	Symbol	Value
Number of customers or demand per period	n	100
Per unit selling price in dollars	c	1000
Probability with which customers return in each period	p	0.15
Conditional probability of backorder requirement	q	0.50
Duration of the disruption in periods	M	4

The average value and standard deviation of lost revenue at each time period were obtained via 10,000 simulations of the supply chain disruption model for customer reactions using the parameters in Table 1. Since the firm is unable to produce during $t = 1,2,..,M$, the lost revenue at each time period equals the total revenue per period at undisrupted production rates. Because some of the lost revenue in the first M periods may be recaptured via backorders, the lost revenue may not actually be completely lost. In the model, this is accounted for at $t = M + 1$.

Since the binomial distribution can be approximated by the normal distribution, we calculate 90% probability intervals for the lost revenue $\bar{R}_t \pm 1.64S_t$, where $\bar{R}_t$ is the average lost revenue and S_t

is the standard deviation for time period t. The results are illustrated in Fig. 2. The expected lost revenue reduces to less than 1% of the total pre-disruption revenue after $t = 34$, and the revenue from sales is almost completely restored to pre-disruption levels. If each time period is a week, the firm returns to its full performance in approximately 8 months.

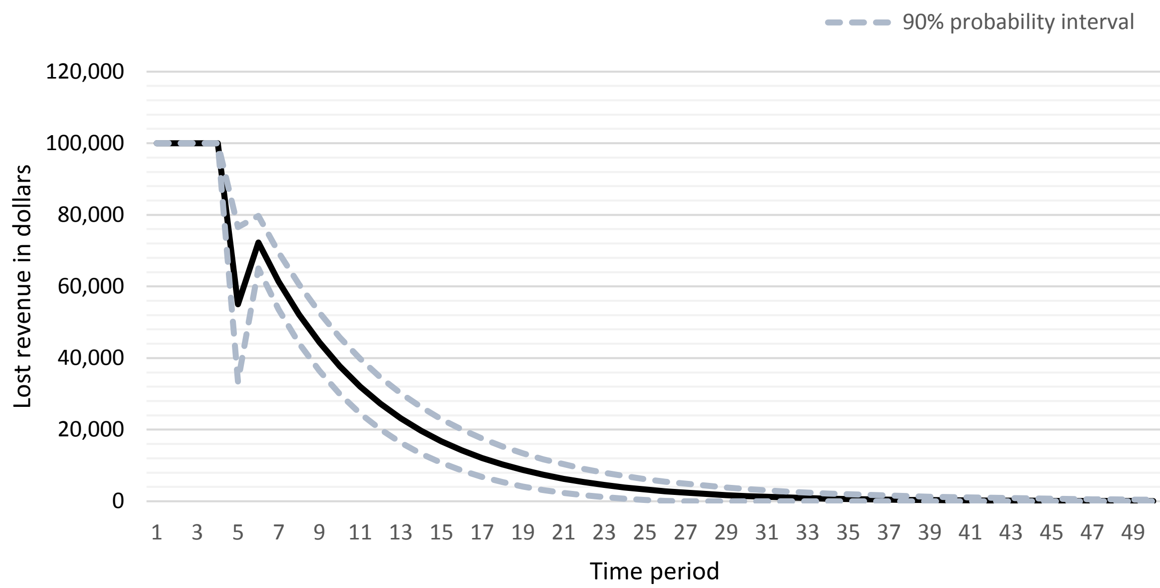

Fig. 2. The firm's expected lost revenue per period from the supply chain disruption.

As depicted by the probability interval, there is a 5% probability the lost revenue will be less than $1,000 within 24 periods and a 5% probability the lost revenue will be greater than $1,000 for at least 42 time periods. The expected lost revenue is at its maximum value for the first four periods, which is equal to the total pre-disruption revenue per period and then drops from $100,000 to $55,000. The downward spike in the expected lost revenue is due to the backorders. The lost revenue at $t = 5$ has a 5% probability of being as low as $33,444, which would occur if many customers return with backorders. If very few customers return with backorders, the lost revenue could be $76,556, which is the 95% upper bound for lost revenue in that time period. At time $t = 6$, the expected lost revenue increases to $72,250 and then gradually decreases over time as the firm recovers from the disruption.

4.2 Lost revenue without backorders

Certain disruptions may not allow for backorders. For instance, a restaurant could be closed for a period of time because of food poisoning, and when it reopens, backorders are not realistic because the delivered product is a service that cannot be backordered. We can assign $q = 0$ in the simulation model to reflect such a situation. Fig. 3 illustrates this scenario without backorders. Here, the expected cumulative lost revenue is higher because of the lack of backorders.

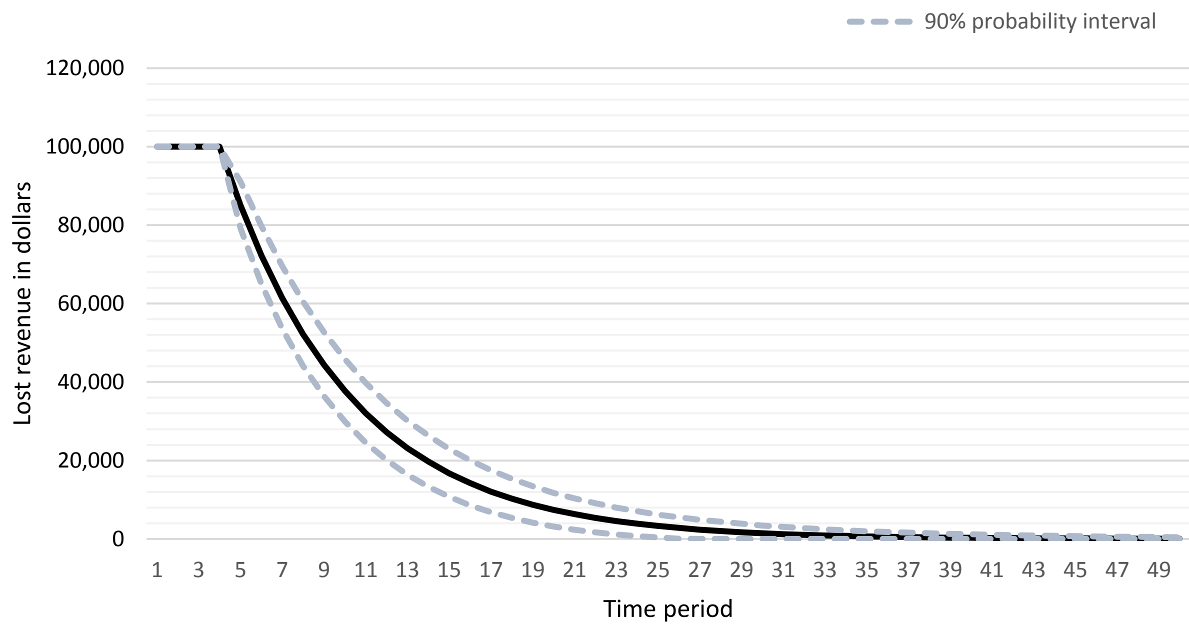

Fig. 3. The firm's expected lost revenue without backorders.

4.3 Customers with varying demand

The assumption that each customer buys exactly one product may not be valid. This sub-section extends the simulation model to accommodate varying demands from the firm's customers. The demand from customer l is n_l where $l = 1, 2, \ldots, n$. We assume each n_l follows a discrete uniform distribution between 1 and 5, i.e., $n_l \sim U(1, 5)$. Backorders are ignored for simplicity. Parameters from Table 1 along with a simulation of $n_l \sim U(1, 5)$ were used in the model with varying demand from different customers to run 1,000 simulations. The results are illustrated in Fig. 4.

The maximum total expected lost revenue is much higher than the previous cases because the total initial demand is more than in the previous cases. The shape of recovery is very similar to the model in section 4.1 because each customer returns with the same probability. The expected lost revenue reduces to less than 1% of the total pre-disruption revenue after time period 25. This is comparable to the results from the model in sections 4.1 and 4.2. The results might look different if customers returned with different probabilities. For example, perhaps customers with more demand from the firm might be more likely to return because it may be more difficult for these customers to get all of their demand satisfied from the firm's competitors.

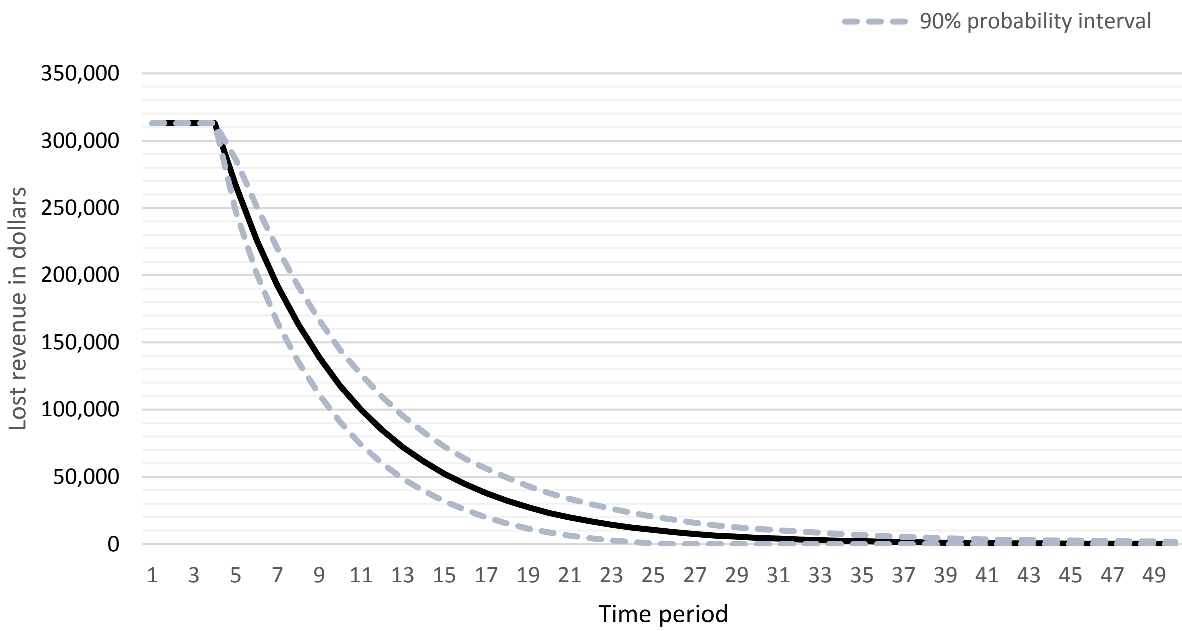

Fig. 4. The firm's expected lost revenue with varying demand from customers

4.4 Risk management insights

A firm can use this model to understand how parameters impact the firm's expected lost revenue. The results discussed are highly sensitive to the value of p. As illustrated in Fig. 5, the firm recovers more quickly when the probability with which customers are gained back in each period is larger. This makes intuitive sense since firms with loyal customers tend to recover faster. We observe that the downward spike at time $t = M + 1$ is directly correlated with p. At $t = M + 1$, the cumulative expected number of orders including the backorders is directly proportional to the probability of customers buying from the firm at a given time period after the disruption.

The expected lost revenue in time period $t = 5$ is negative when $p = 0.4$. This negative value represents revenue greater than $100,000 in that period, a trend that continues as the value of p increases. Such situations may require the firm to work at overcapacity immediately after reopening to meet the sudden increase in demand, which is an integral part of the firm's recovery process (Sheffi and Rice 2005). This provides an important insight to the firm's management that in case of a production shut down, it may need to be prepared to temporarily increase its production capacity after reopening. The model also helps to estimate the maximum production the firm would need in order to meet the demand.

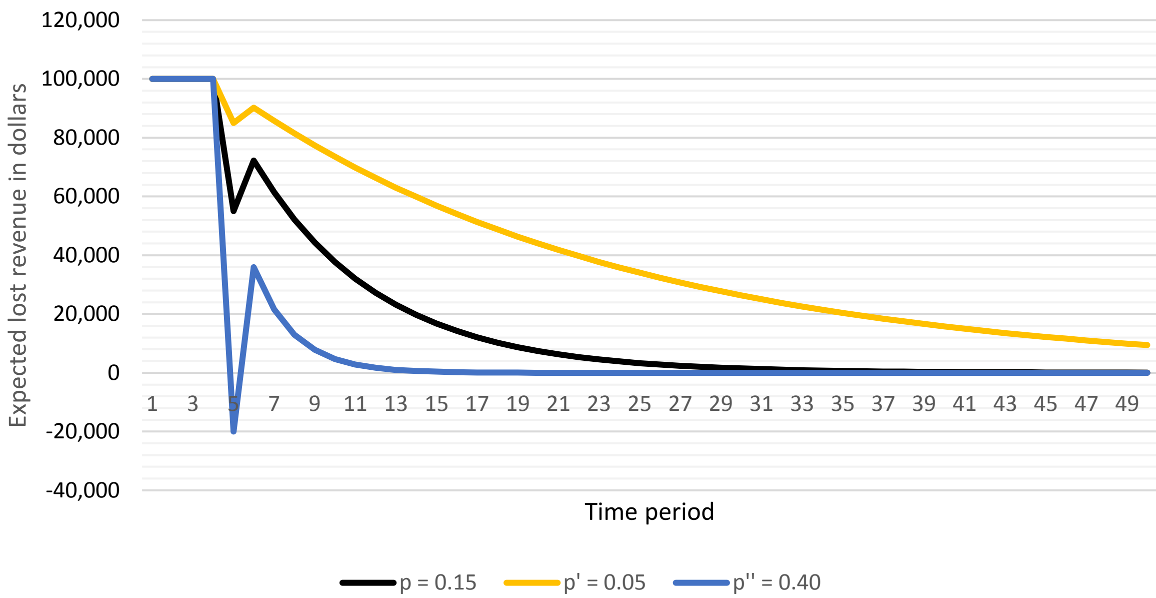

Fig. 5. Sensitivity of expected lost revenue to p.

A similar trend can be observed with the sensitivity analysis on q, as illustrated in Fig. 6. The time of recovery remains the same since p is constant. This is also an important insight since firms need to think about the likelihood that their customers will place backorders. Accordingly, they can devise suitable production plans.

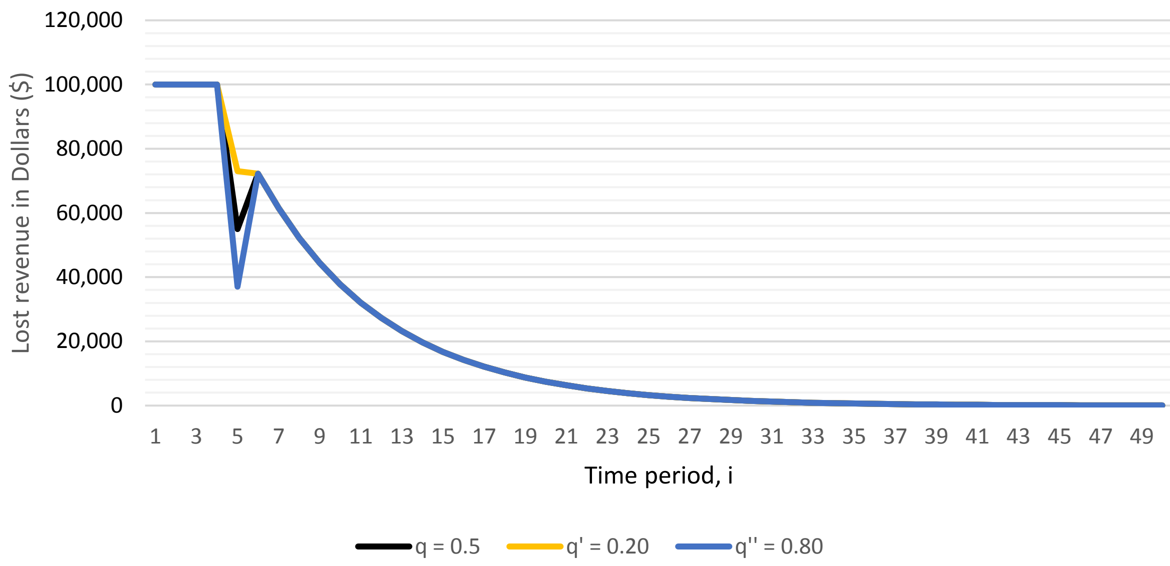

Fig. 6. Sensitivity of expected lost revenue to q.

Firms can prepare for disruptions by using this quantitative model to estimate the potential loss in revenue due to a shutdown of operations from a supply chain disruption. Moreover, the model can be used to evaluate whether preparation strategies are economical. Investments to reduce the chances of a supply chain disruption itself may not be practical or economically reasonable. In such cases, firms can use the expected lost revenue from the model to decide whether or not investments to reduce the risk of a disruption are cost effective. Preparedness measures can help reduce the probability of a disruption and/or allow the firm to regain more of its revenue following a disruption. Even if the disruption cannot be avoided, preparedness measures could reduce the shutdown length M. It is logical to assume that the probability of customers returning depends on M. Decision makers can make decisions about investing in preparedness measures based on understanding how much revenue will be lost if the disruption occurs as well as the chances of the disruption itself.

For example, the cumulative expected lost revenue in the illustrative example is $536,667. A risk-neutral firm should spend at most $536,667 in preparing for this type of disruption and should spend much less once the probability of a disruption is considered. Investing in risk reduction strategies such as inventory or an additional supplier could reduce the time the firm is closed. The chances of customers returning immediately to the firm are higher if the firm is not closed as long. This would increase the probability p and reduce the cumulative expected lost revenue. In the example, increasing the value of p from 0.15 to 0.2 decreases the total expected lost revenue from \$536,667 to \$360,000. Strategies that could reduce p from 0.15 to 0.2 are economically wise if these strategies cost less than \$176,667, assuming an extremely high probability of disruption.

5. Conclusions

This chapter proposes a model to quantitatively represent the way customers or the marketplace reacts to a supply chain disruption. The model is used to identify the impact of such an event on the firm's revenue. From the firm's perspective, the total expected lost revenue is a measure of the impact of the supply chain disruption and can be analyzed to draw useful insights to manage the risk of such an event.

The results obtained from applying the model serves as an illustration of the usefulness of the model. The simulation of the customer response model allows the firm to anticipate how customers might react to a supply chain disruption. The model can inform decision making to manage the risks of a supply chain disruption. Insights from the model can reveal how a disruption can affect the firm's revenue depending on the customers' decisions and the time a firm takes to recover to its pre-disruption revenue levels. Sensitivity analysis on the model parameters reveals how the probability at which customers return to the firm impacts the recovery time. Firms that expect most of its customers to return with backorders may need to temporarily increase production capacity. Management can use the cumulative expected lost revenue projections to evaluate investments aimed at increasing the firm's resilience to supply chain disruptions.

The proposed model could be developed further by relaxing some of the assumptions. For instance, customers may return with different probabilities or probabilities that change over time. Further extensions to this research can include the development of a decision-making framework to utilize the mathematical model to determine the most effective risk management decisions during a supply chain disruption. Another extension is to model the probability of a supply chain disruption along with the total expected lost revenue to make sound management decisions regarding investments in preparedness measures. An optimization model that minimizes the lost revenue during the disruption periods can also serve as a future extension to this chapter.

6. References

Arnade, C., Calvin, L., & Kuchler, F. (2009). Consumer response to a food safety shock: the 2006 food-borne illness outbreak of E. coli O157: H7 linked to spinach. Applied Economic Perspectives and Policy, 31(4), 734-750.

Babich, V., Burnetas, A. N., & Ritchken, P. H. (2007). Competition and diversification effects in supply chains with supplier default risk. Manufacturing & Service Operations Management, 9(2), 123-146.

Beach, R. H., Kuchler, F., Leibtag, E. S., & Zhen, C. (2008). The Effects of Avian Influenza News on Consumer Purchasing Behavior: A Case Study of Italian Consumers' Retail Purchases (No. 56477). United States Department of Agriculture, Economic Research Service.

Chopra, S., & Sodhi, M. S. (2004). Managing risk to avoid supply-chain breakdown. MIT Sloan Management Review, 46(1), 53.

Christopher, M. (2005). Logistics and Supply Chain Management: Creating Value-Adding Networks (3rd ed.). Harlow, England: Pearson Education.

Ellis, S. C., Henry, R. M., & Shockley, J. (2010). Buyer perceptions of supply disruption risk: A behavioral view and empirical assessment. Journal of Operations Management, 28(1), 34-46.

Hendricks, K. B., & Singhal, V. R. (2005). Association between supply chain glitches and operating performance. Management Science, 51(5), 695-711.

Jüttner, U., Peck, H., & Christopher, M. (2003). Supply chain risk management: Outlining an agenda for future research. International Journal of Logistics: Research and Applications, 6(4), 197-210.

Kilubi, I., & Haasis, H. D. (2015). Supply chain risk management enablers: A framework development through systematic review of the literature from 2000 to 2015. International Journal of Business Science & Applied Management, 10(1), 35-54.

Lavastre, O., Gunasekaran, A., & Spalanzani, A. (2012). Supply chain risk management in

French companies. Decision Support Systems, 52(4), 828-838.

MacKenzie, C. A., Barker, K., & Santos, J. R. (2014). Modeling a severe supply chain disruption and post-disaster decision making with application to the Japanese earthquake and tsunami. IIE Transactions, 46(12), 1243-1260.

MacKenzie, C. A., Santos, J. R., & Barker, K. (2012). Measuring changes in international production from a disruption: Case study of the Japanese earthquake and tsunami. International Journal of Production Economics, 138(2), 293-302.

Manuj, I., Dittmann, P., & Gaudenzi, B. (2007). Risk management. In J. T. Mentzer, M. B. Myers, & T. P. Stank (Eds.), Handbook of Global Supply Chain Management (pp. 319-336). Thousand Oaks, Calif.: Sage Publications.

Mentzer, J. T., DeWitt, W., Keebler, J. S., Min, S., Nix, N. W., Smith, C. D., & Zacharia, Z. G. (2001). Defining supply chain management. Journal of Business Logistics, 22(2), 1-25.

Nagurney, A., Cruz, J., Dong, J., & Zhang, D. (2005). Supply chain networks, electronic commerce, and supply side and demand side risk. European Journal of Operational Research, 164(1), 120-142.

Nishat Faisal, M., Banwet, D. K., & Shankar, R. (2006). Mapping supply chains on risk and customer sensitivity dimensions. Industrial Management & Data Systems, 106(6), 878-895.

Sheffi, Y., & Rice Jr, J. B. (2005). A supply chain view of the resilient enterprise. MIT Sloan Management Review, 47(1), 41.

Snyder, L. V., Atan, Z., Peng, P., Rong, Y., Schmitt, A. J., & Sinsoysal, B. (2016). OR/MS models for supply chain disruptions: A review. IIE Transactions, 48(2), 89-109.

Sodhi, M. S., & Tang, C. S. (2012). Managing Supply Chain Risk. New York: Springer Science & Business Media.

Stecke, K. E., & Kumar, S. (2009). Sources of supply chain disruptions, factors that breed vulnerability, and mitigating strategies. Journal of Marketing Channels, 16(3), 193-226.

Tomlin, B., & Wang, Y. (2005). On the value of mix flexibility and dual sourcing in unreliable newsvendor networks. Manufacturing & Service Operations Management, 7(1), 37-57.

Xia, Y., Ramachandran, K., & Gurnani, H. (2011). Sharing demand and supply risk in a supply chain. IIE Transactions, 43(6), 451-469.

Yu, H., Zeng, A. Z., & Zhao, L. (2009). Single or dual sourcing: Decision-making in the presence of supply chain disruption risks. Omega, 37(4), 788-800.