2016

Modeling Disruption in a Fresh Produce Supply Chain

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Design/methodology/approach—This paper develops a mathematical model of a disruption in a fresh produce supply chain and analyzes the relationships among variables.

Findings—The model determines the optimal safety stock as a function of the perishability of the produce, the length of time it takes to find the contamination, the level of demand during the disruption, and the amount of produce that can be rerouted. Applying the model to the 2006 *E. coli* spinach contamination reveals that the drop in customer demand for fresh spinach plays the largest role in Dole losing sales.

Research limitations—The model includes several parameters that may be difficult to estimate. Future models can incorporate uncertainty that is inherent in supply chain disruptions.

Practical implications—The model in this paper can help a supply chain manager explore the trade-offs of different disruption management strategies. For example, a supply chain manager can determine the value of holding additional safety stock versus trying to improve traceability in the supply chain.

Originality/value—This paper quantifies and models insights delivered in the qualitative analyses of fresh produce supply chain disruptions. The theoretical contributions include an analysis of the interaction among safety stock, levels of demand, communication, and traceability parameters in order to help supply chain managers evaluate different strategies to mitigate the effects of contaminated produce.

Disciplines

Industrial Engineering | Operations and Supply Chain Management | Systems Engineering

Comments

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July 27, 2016 This is the author's accepted manuscript to appear in International Journal of Logistics Management.

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Introduction

In recent years, fresh produce contamination has disrupted many fresh produce supply chains (FPSC). According to the Center for Disease Control and Prevention, millions of Americans get sick from contamination in the food supply. For example, hundreds of Chipotle customers got sick from the norovirus in 2015. From 1998 to 2008, a total of 13,352 foodborne outbreaks led to 271,974 illnesses in the United States (Painter *et al.*, 2013), and fresh produce contamination has increasingly been the main cause of these outbreaks (Lynch *et al.*, 2009, Apte, 2010b, Mehmood *et al.*, 2010). Fifty-one percent of the food illnesses in the United States were attributed to plant commodities and 38% of hospitalizations from foodborne illnesses were attributed to produce.

The economic cost of foodborne illness in the United States in 2010 was estimated between US$51 billion and US$78 billion, which includes the economic costs from hospitalizations, lost productivity from consumers being sick, and the value of a statistical life (Scharff, 2012). When contamination occurs in a food industry supply chain (SC), the SC stops producing until the cause of the contamination is discovered and the problem is resolved. The closure of the SC can lead to significant costs in lost business. Table I depicts the costliest food recalls in the United States, and tomatoes and spinach top the list in lost sales at US$250 and US$350 million respectively.

Table I

Organization	Product	Losses (US$ millions)	Year
NA	Spinach	350	2006
NA	Tomatoes	250	2008
Westland/Hallmark	Beef	117	2008
Kellogg	Peanuts	70	2009
ConAgra	Peanut Better	55	2007
Menu Foods	Pet Food	42	2007

Source: McGrath, J., (2009). “10 costly food recalls.” HowStuffWorks.com, March 12. http://money.howstuffworks.com/10-food-recalls.htm June 2, 2016.

In addition to the cost of lost sales, publicly traded firms that announce SC “glitches” (e.g., production or shipping delays) can cause the stock prices of those firms to drop by 10% (Hendricks and Singhal, 2003). Firms that experience SC disruptions have stock returns that are 40% less than those firms who do not have SC disruptions (Hendricks and Singhal, 2005). If these results are true for the fresh produce sector, the cost of food contamination to impacted firms could be quite substantial.

Background

SC management often seeks to make the production and transportation of goods and services more efficient by identifying the drivers of high costs in operations and eliminating waste (Chopra and Meindl, 2007, Pullman, 2012). SC research has increasingly focused on understanding the vulnerabilities within SCs and designing strategies to minimize risk (Rao and Goldsby, 2009, Ghadge *et al.*, 2012, Sanders *et al.*, 2013). A SC can be vulnerable to shortfalls from suppliers, uncertain demand, operational problems such as product contamination, and security or catastrophic risk such as a natural disaster (Lee, 2002, Manuj, 2007). Understanding SCs’ contributions to disaster relief and response is also increasingly important. Practitioners (Eisner, 2007, Fenton, 2008, Nelan, 2008), media, organizational reports, and scholars (Van Wassenhove, 2006, Holguín-Veras *et al.*, 2007, Kovács and Spens, 2007, Apte, 2010a, Çelik *et al.*, 2012) agree that preparation and planning is a significant part of any relief effort. Disasters can be large-scale *natural* disasters (Trunick, 2005, Apte, 2010a, Kovacs and Spens, 2012) or *manmade* disasters that occur *locally* (see, e.g.,Van Wassenhove, 2006, Ergun *et al.*, 2008, Apte, 2010a, Eßig and Tandler, 2010, Tatham *et al.*, 2013). SCs that can respond quickly to disruptions and disasters are better positioned to withstand the disruption and recover quickly (Sheffi, 2005).

Because of the uncertainty in disruptions, decision-making on the run, without apologies, is also necessary (Lee, 2004, Oloruntoba and Gray, 2006, Ergun *et al.*, 2010).

Despite the wealth of mathematical models that address SC risk (Babich *et al.*, 2007, Chang *et al.*, 2015a, Sherwin *et al.*, 2016), disruptions (Snyder *et al.*, 2006, Ivanov *et al.*, 2016, Snyder *et al.*, 2016), and disaster relief (Altay and Green III, 2006, Afshar and Haghani, 2012, Caunhye *et al.*, 2012), mathematical models of food contamination and its impact on agri-supply chains are relatively sparse. The current literature on SC disruptions in the fresh produce sector approaches the problem qualitatively and generally focuses on identifying key factors in these disruptions. For example, Roth *et al.* (2008) argue that traceability, transparency, testability, time, trust, and training are six important concepts for food SC quality, especially when sourcing from China. Apte (2010b) identifies five main factors that drive a SC's vulnerability to a disruption: product type, topological structure of the SC, traceability, communication, and exposure to contamination. Srivastava *et al.* (2015) use interpretive structural modeling to analyze potential SC risks in fresh food retail and performance measures to offer enhanced understanding of the risks and prioritize among risks.

Contribution

It is estimated in humanitarian logistics that one US$ invested in planning and preparing for a disaster saves seven US$ in disaster response (United Nations, 2007, World Meteorological Organization, 2015). This paper is motivated by a desire to quantify the benefits of disruption management strategies so that SC managers can identify a set of good risk management strategies to prepare for such a disruption and evaluate trade-offs in the face of constrained budgets. The frequency of food contamination—annually leading to tens of thousands of hospitalizations in the United States (Scallan *et al.*, 2011, Painter *et al.*, 2013)—and the high costs of these incidents motivate the need for a quantitative methodology of how contamination in a FPSC can disrupt and impact growers and producers. A mathematical model can help SC managers understand how best to manage and react to a disruption in a FPSC.

This paper presents a general mathematical model of a FPSC disruption that incorporates a variety of factors that influence the lost business created by a disruption. The supply chain risk management literature provides mathematical formulas on the optimal amount of inventory under the risk of disruption and compares holding inventory to other strategies such as purchasing from alternate suppliers and rerouting transportation. Snyder *et al.* (2016) offer an extensive literature review on operations research models for SC disruptions due to uncertainty in supply. Tomlin (2006) models inventory strategies for a single-product SC with one reliable supplier and one unreliable supplier. Tomlin (2009) discusses disruption-management strategies such as supplier diversification and contingency sourcing for a SC with two products with short life cycles.

This paper builds on the previous literature by applying these concepts and modeling techniques to contamination in a FPSC. The mathematical model quantifies the qualitative concepts discussed in Apte (2010b) in order to understand how a FPSC may be hurt from contamination and how it can mitigate the consequences of a disruption. Similar to Tomlin (2006), our model is used to find the optimal safety stock for a FPSC but one in which the disruption is caused by contamination as opposed to supplier unreliability. Our model can account for a possible change in sourcing in order to cover demand during a disruption (Tomlin, 2009). The theoretical contributions of this paper include a mathematical analysis of how traceability in the FPSC impacts the ability of a SC manager to find the source of the contamination. The optimal amount of safety stock is described as a function of perishability, demand, the length of time of the contamination, and the amount of produce that can be rerouted. The model is applied to the 2006 outbreak of *E. coli* in spinach to understand how the disruption impacted Dole Fresh Vegetables and what Dole might have been able to do to manage the disruption.

The paper is structured as follows: we review the literature on the vulnerability and disruptions in FPSCs and discuss how our paper combines the qualitative and quantitative approaches. Following the literature review, we present a network model of a contamination in a FPSC and differentiate between contaminations at a source versus contamination at an intermediate node. In the section following methodology we discuss some of the implications of the model and the interplay of different factors and model parameters. We illustrate our developed model with an illustration showing how it can be used for an organization such as Dole Fresh Vegetables to recognize the likely impact of a disruption and mitigation of the same by preparing and planning. The data in this case study is based on information published after the actual disruption in September 2006. Concluding remarks with managerial implications for managing the risk of a potential disruption appear in the final section.

Literature review

This paper combines SC risk management with food SCs, specifically FPSCs. Consequently, this literature review examines some of the key findings in SC risk management and disruption management before discussing the unique structure of FPSCs and potential risks and contamination in these SCs. SC risk management focuses on understanding the vulnerabilities in the SC (Wagner and Bode, 2006, Diabat *et al.*, 2012, Simchi-Levi *et al.*, 2015, König and Spinler, 2016), the likelihood of risks (Sanchez-Rodrigues *et al.*, 2010, Vilko *et al.*, 2014, Gualandris and Kalchscmidt, 2015), the consequences if something goes wrong

(Craighead *et al.*, 2007, MacKenzie *et al.*, 2014), and how SCs can respond or recover to those disruptions (Sheffi, 2005, Tang, 2006, Chang *et al.*, 2015b). Even if a SC focuses on minimizing its vulnerabilities, disruptions can still occur, and SC managers need to think about how to manage a disruption if it occurs. Disruption management generally refers to actions taken during and after a disruption occurs (Yu and Qi, 2004). Disruption management strategies may include using backup suppliers (Tomlin, 2006, Hopp *et al.*, 2008), rescheduling production (Bean *et al.*, 1991, Adhyitya *et al.*, 2007), moving production to other machines (Lee *et al.*, 2006), moving production to alternate facilities (MacKenzie *et al.*, 2014), and transporting goods by different modes (MacKenzie *et al.*, 2012). This paper examines some of these disruption management strategies within the context of contamination in a FPSC, such as using inventory (i.e., safety stock), increasing production at non-contaminated nodes, and rerouting transportation.

Before examining the risks that FPSCs face, we explore the unique structure of FPSCs. FPSCs are different from traditional manufacturing SCs because of the multitude of growers, the risk of contamination, and the perishability of product. Readers can find an excellent review by Ahumada and Villalobos (2009) of planning and operational models for agricultural products. Producers and distributors need to consider the freshness of the product when making decisions about prices and the amount of quantity to produce (Cai *et al.*, 2010). Mathematical models for FPSCs incorporate the value of preserving perishable commodities (Ahumada and Villalobos, 2011a), different demand functions (Balkhi and Benkherouf, 2004, Deng *et al.*, 2007), the impact of time-varying demand on lost sales and purchase costs (Dye *et al.*, 2006), and inventory, replenishment, and through-put policies (Thron *et al.*, 2007). A case study for melons and sweet corn discusses strategies to design a FPSC such as the responsiveness and efficiency of the SC (Blackburn and Scudder, 2009). Ahumada and Villalobos (2011b) develop an integrated tactical planning model for a FPSC to incorporate product decay in addition to traditional factors such as price estimation and resource availability.

Although FPSCs can be vulnerable to similar types of disruptions as other SCs, FPSCs are also vulnerable to food contamination, which can close the entire SC until the source of the contamination is found and the problem is resolved. If a contamination is announced, consumers may also stop eating that product and substitute other produce for the contaminated produce (Arnade *et al.*, 2011). Although not specifically a FPSC, Elmsalmi and Hachicha (2013) initially identify 62 risk variables for a food pastry SC and discuss the sourcing risks. Identifying the source of contamination and ensuring that other sources are not contaminated can be challenging to food inspectors (Manning *et al.*, 2006). Safety concerns can be managed by product traceability to allow the SC to identify the source of contamination more quickly (Wilson and Clarke, 1998, Folinas *et al.*, 2006, Roth *et al.*, 2008). Alfaro and Rábade (2009) illustrate through a Spanish vegetable industry case study that traceability in addition to guaranteeing food safety can provide qualitative and quantitative advantages at different stages of the SC. The safety of the food (Roth *et al.*, 2008), the information about food safety (Yee *et al.*, 2005), and consumers' perceptions (Wilson and Clarke, 1998) influence each other to determine the impact of contamination. Other factors contributing to SC risk in the food retail industry include perishability, lack of supply visibility, production variability, transportation breakdowns, and the unavailability of suppliers (Apte, 2010b, Pullman and Wu, 2012, Srivastava *et al.*, 2015).

Despite the wealth of operational models that examine how FPSCs manage, transport, and sell fresh produce, a mathematical model of how a FPSC reacts to a food contamination in terms of planning for lost production, level of safety stock, and identifying and quantifying some of the parameters has yet to be published. The majority of research exploring a FPSC's vulnerability to food contamination is qualitative (e.g., Roth *et al.*, 2008, Apte, 2010b).

This paper uses the SC disruption management literature (Yu and Qi, 2004; Tomlin, 2006; MacKenzie *et al.*, 2014), as described earlier, to present a disruption management model for a FPSC. The model is informed by prior qualitative studies on the vulnerability in a FPSC. Apte (2010b) investigates factors that contribute to the vulnerability of a FPSC and identifies product type, the topological structure of the SC, the SC's exposure to contamination, traceability of the product, and communication as key contributors to the SC's vulnerability. This paper incorporates these factors into a mathematical model of a FPSC. The analysis based on the model explains how these factors relate to each other and contribute to the vulnerability and the ability of the SC to recover from a contamination. The paper examines the interaction between safety stock and levels of demand, communication, and traceability parameters in order to help SC managers evaluate different strategies to mitigate the effects of contaminated produce. The major implication of this paper is the potential of the model to help SC managers evaluate trade-offs of risk mitigation strategies in face of restricted budgets for managing risks of possible disruption.

Research methodology

The use of quantitative methods to address planning for a FPSC is well founded within the current literature (Ahumada and Villalobos, 2009, Zhang and Wilhelm, 2011, Shukla and Jharkharia, 2013, Wishon *et al.*, 2015). The objective of this research is to help a SC manager explore the trade-offs of different disruption management strategies. To accomplish this we need a methodology that will examine the interaction between safety stock and levels of demand, communication, and traceability. This translates to the need to determine the optimal safety stock as a function of the perishability of the produce, the length of time it takes to find the contamination, demand during the disruption, and the amount of produce that can be rerouted. A mathematical model can quantify elements that make a FPSC vulnerable to disruptions and the benefits of different disruption management strategies.

Overview of the Model

Contamination in a FPSC can be discovered by any of the internal or external players anywhere in the process. Our assumption is that contamination has been discovered at a final demand point. However, this does not mean it has occurred at that point. Figure 1 shows the decision-making process for the SC in which the first step is discovering the original source of the contamination. If the contamination occurs in a distribution node, such as a warehouse or a retailer, the SC will use a combination of rerouting the produce and using the safety stock to avoid lost sales. Although we assume the SC has safety stock, the safety stock is also perishable. If contamination occurs at a producing node such as on the farm, the SC will seek to mitigate the disruption by using safety stock and seeing if other nodes can produce more. We detail each of these steps by presenting the mathematical model that corresponds to Figure 1.

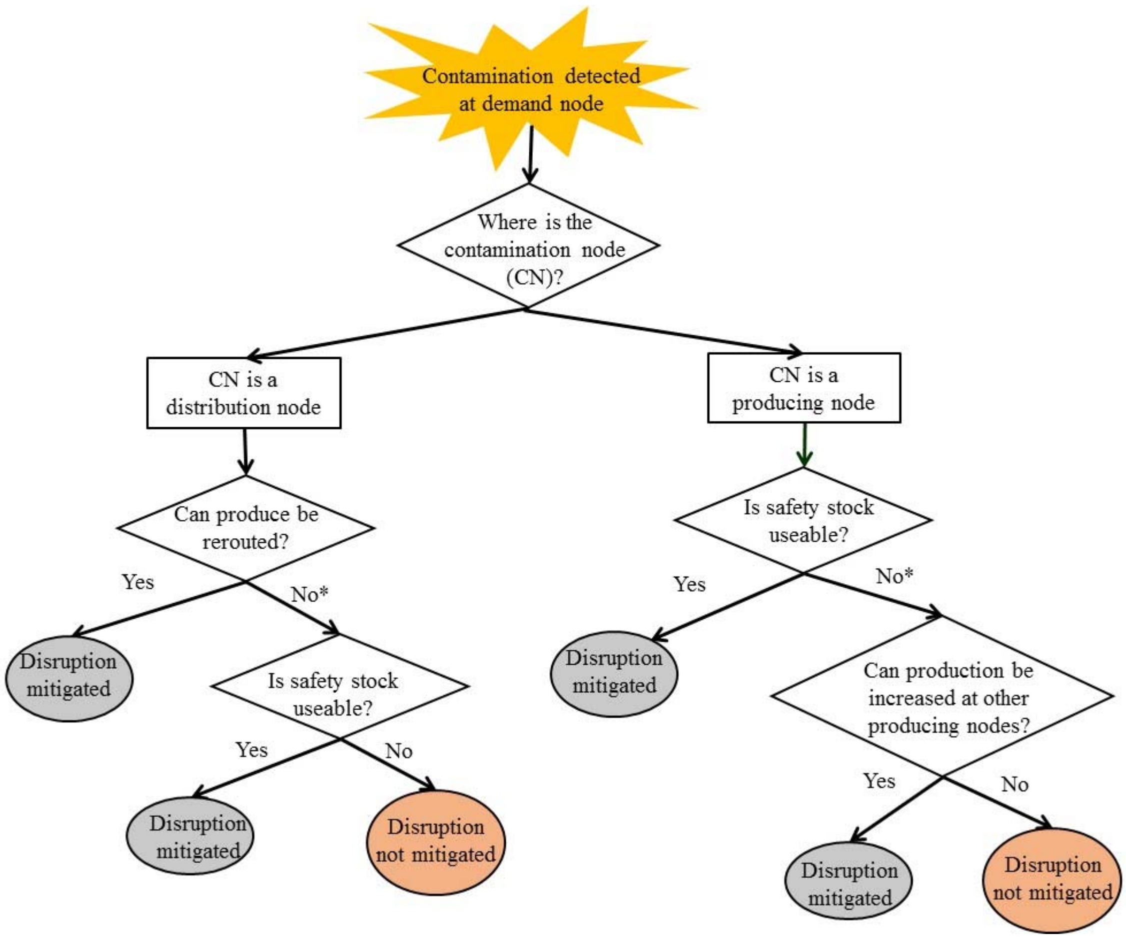

Figure 1

Model development

Table II depicts the notation used in the SC model. A FPSC is a dynamic SC where once contamination is detected decisions have to be made quickly. The model development therefore freezes the timeline in equilibrium where, before disruption, the total amount produced by the SC equals the total demand, $Q = D$. The assumption of an equilibrium state is common in SC models (e.g., Xiao and Qi, 2008, Qiang *et al.*, 2009). The supposition allows us to understand and measure the impacts of a SC disruption which suddenly thrusts the SC into disequilibrium. Table III lists the key assumptions in this mathematical model.

Table II

$N =$	Number of nodes in SC
$q_{ij} =$	Amount of produce moving from node i to node j before disruption
$q_{ij}^{*} =$	Amount of produce moving from node i to node j during disruption
$\mu_{ij} =$	Maximum amount of produce that can move from node i to node j
$r =$	Source node
$t =$	Sink node
$Q =$	Total amount produced by SC before disruption
$Q^{*} =$	Total amount that can be delivered during disruption if there is no additional production (does not include safety stock)
$Q^{**} =$	Total amount that can be delivered during disruption if there is additional production
$d_i =$	Amount of produce for demand node i before disruption
$d_i^{*} =$	Amount of produce for demand node i during disruption
$D =$	Total amount demanded before disruption
$D^{*} =$	Total amount demanded during disruption
$s =$	Safety stock that can be used in case of a disruption
$t_s =$	Length of time until safety stock perishes
$T_1 =$	Length of time to find source of contamination
$T_2 =$	Length of time for contaminated node to recover
$w =$	Warehouse node

Table III

Key model assumptions
Demand equals supply before disruption
Nothing is produced until the source of contamination is discovered
Nothing is produced in the contaminated node or can flow through the contaminated node until the node is declared safe
SC first attempts to meet demand by rerouting production and using safety stock
The safety stock cannot be used beyond its expiration date

Similar to Nagurney (2006), we view the SC as a network of suppliers and distributors. The network model for a FPSC (Ahumada and Villalobos, 2011a, Yu and Nagurney, 2013) provides a theoretical construct in order to determine the flow of fresh produce through the SC which allows us to compare the flow under normal circumstances to the flow during a disruption or contamination. For example, as will be discussed further in the case study, Dole Fresh Vegetables sources from a multitude of farmers and operates 3 salad packaging plants. These packaging plants deliver to distribution centers and retailers throughout North America. The network model translates mathematically to one production node r where product "flows" to each of the producing nodes (e.g., farmers), and we can assume there is one sink node t to which all the product that is demanded from the final consumers flows (Figure 2). The total demand equals the sum demanded by all the demand nodes. This is equivalent to the total amount that flows to node t: $D = \sum_{i=demand\ node} d_i = \sum_{i=1}^{N} q_{it}$ where d_i is the amount demanded at demand node i, q_{ij} is the amount that is transported from node i to node j, $q_{ij} = 0$ if no arrow connects nodes i and j, and N is the total number of nodes in the SC. The total amount produced equals the sum produced by each of the producing nodes or the amount of product that flows from node r: $Q = \sum_{i=1}^{N} q_{ri}$. We also assume there is some safety stock s that is held. The safety stock can be divided so that several nodes hold safety stock.

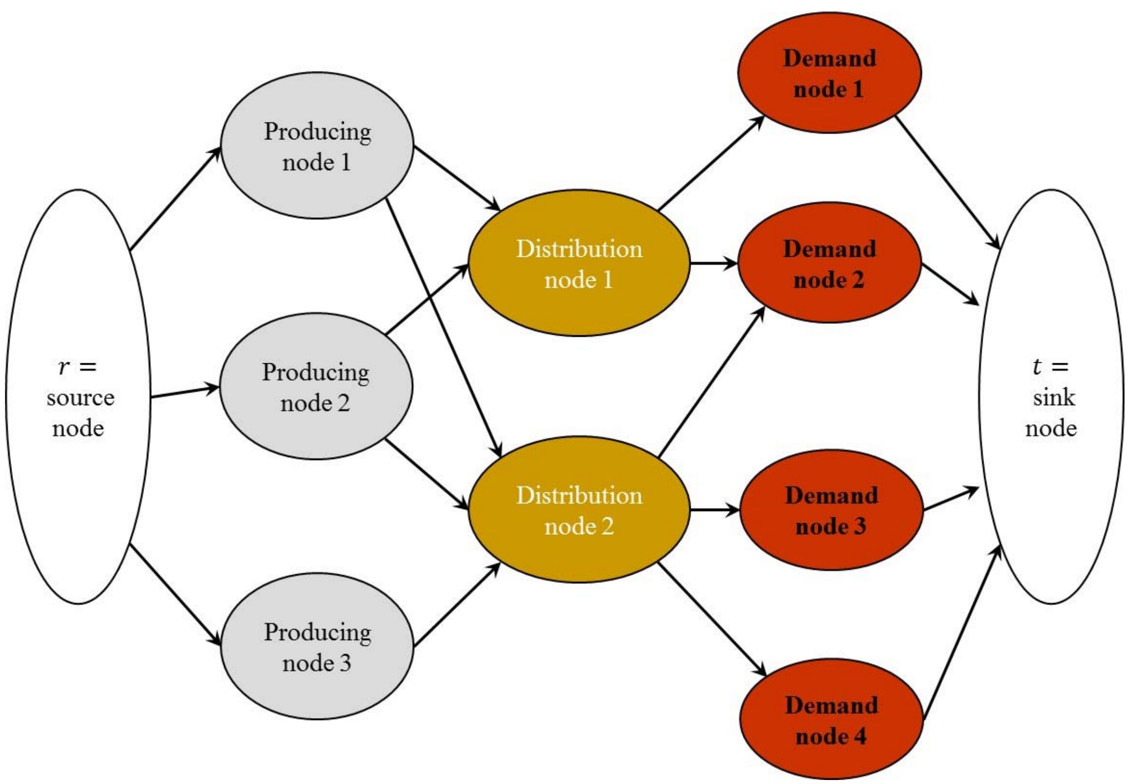

Figure 2

When contaminated produce is discovered, we assume it takes time T_1 to discover the source of the contamination, which can be a difficult and lengthy task (Pullman and Wu, 2012). T_1 reflects the traceability of the SC. Historic data suggests that FPSC is shut down till the source of contamination is discovered. Hence it is plausible that in order to mitigate the situation the entire SC is shut down during the time it takes to find the source of the contamination. Therefore, the lost production during T_1 is

$$\boldsymbol{T_1 Q}. \tag{1}$$

After the contaminated node is discovered, we assume that node is closed, and it takes time T_2 to fix the problem and reopen that node. A node is closed if the production at or distributed through that node is halted based on the type of the node.

When contaminated produce is discovered, demand may or may not decrease at the demand nodes because consumers are nervous about eating the produce. Thus, $d_i^* \leq d_i$ where d_i^* is the demand at final demand node i during the disruption. Total demand during the disruption is $D^* = \sum_{i=demand\ node} d_i^*$. The loss of demand is a function of how the SC communicates the problem to the final consumers, the amount of trust the consumers have in the SC, and the essentialness of the product. If the product is essential, meaning that consumers buy the product to satisfy basic needs, demand generally may not decrease much, if at all (Apte, 2010b). Estimating this loss in demand and how a firm can attempt to influence customers to return can be daunting, but several studies (e.g., Richards and Patterson, 1999, Verbeke and Ward, 2001, Zhang *et al.*, 2012) have modeled demand changes resulting from past food contaminations and quantified the substitution effect and the impact of both negative and positive media stories on demand. The analysis from these historic cases can be used to estimate demand fluctuations for a future contamination. The case study in this paper models a spinach contamination in which the demand for fresh spinach took almost two years to fully recover (Arnade *et al.*, 2009).

Contamination at Distribution Node

As depicted in Figure 1, the disruption management alternatives differ if the contaminated node is a distribution node or producing node. Thus, the model differs for these two scenarios. If the contaminated node is a distribution node—which we define as any node that does not produce—the producing nodes should not need to increase their production. We assume the SC will attempt to meet demand D^* through a combination of rerouting transportation to bypass the contaminated node and using safety stock.

The amount of produce generated through the SC during the disruption, Q^*, can be determined by solving the maximum-flow network optimization problem (P) of the restructured network given a closed distribution node. Let q_{ij}^* be the amount of produce transported from node i to node j during the disruption. Let μ_{ij} be the capacity of each arc from node i to node j. When distribution node i is closed $\mu_{ij} = 0$ and $\mu_{ki} = 0$.

$$Q^* = \text{maximize} \quad \textstyle\sum_{i=1}^{N} q_{it}^* \tag{2}$$

$$\text{subject to} \quad \sum_{j=1}^{N} q_{ij}^* - \sum_{k=1}^{N} q_{ki}^* = 0 \quad \text{for } i = 1, \dots, N \tag{3}$$

$$0 \le q_{ij}^* \le \mu_{ij} \qquad \text{for } i, j = 1, \dots, N \text{ and } j = t \tag{4}$$

$$q_{ri}^* \le q_{ri} \qquad \text{for } i = 1, \dots, N \tag{5}$$

The objective function (2) maximizes the total produce transported during the disruption. Constraints (3) and (4) are for flow balance and capacity, respectively. Constraint (5) describes our assumption that if production does not increase when a distribution node is closed, then the new production q_{ri}^* at each producing node is less than or equal to q_{ri}, which is what was produced before the contamination. Production might decrease, or at least be held as inventory at the producing node, during the disruption because demand decreases or rerouting production is infeasible. Each $\mu_{it} = d_i^*$ (the amount demanded by node i after the disruption). The intermediate μ_{ij} may be determined by transportation constraints or the amount of produce that one node is able to ship through another node.

If it is infeasible to reroute all production, then Q^* may be less than D^*. For example, in Figure 2, if distribution node 1 is closed because of contamination, the SC is unable to deliver produce to demand node 1 since no arc connects the distribution node 2 and demand node 1. Demand node 1 may be geographically too distant and separated from distribution node 2, the fresh produce could spoil due to lengthy transportation (Xiao and Chen, 2012), or the SC may not have enough transportation capacity. But if the SC can transport produce from each distribution node to each demand node (unlike in Figure 2), an arc should connect each distribution and demand node.

If $Q^* < D^*$ because of an inability to reroute produce, safety stock may be used to fill the gap. Even if all of the product from the producing nodes can be rerouted, safety stock may still be used because the contaminated produce at the distribution node would likely be destroyed. We assume that s is the amount of safety stock that can be used during the disruption. If some of the safety stock is held at the contaminated node, it would likely be destroyed, which makes s less than what the SC may have had before the disruption. If all of the safety stock is at the contaminated node, the SC may not have any safety stock during this disruption.

The length of time that the safety stock lasts before it perishes is determined by t_s. If $t_s < T_1$ the safety stock perishes before the SC reopens. The amount of lost production using safety stock and rerouting transportation is

$$\left(\min\left\{(t_s - T_1)^+, \left(\frac{s}{D^* - Q^*}\right), T_2\right\}\right)(Q - D^*), \tag{6}$$

where T_2 is the length of time until the contaminated node is functioning.

The safety stock can be exhausted either because it perishes due to t_s or because all of it is used. The expression $\frac{s}{D^*-Q^*}$ determines how long the safety stock will last before all of it is used. If the safety stock lasts beyond the recovery time of contaminated node, $\frac{s}{D^*-Q^*} > T_2$, and the time till safety stock perishes is longer than locating the source of contamination and recovery of that node, $t_s > T_1 + T_2$, then the disruption ends before the safety stock is depleted or perishes. Consequently, if $D^* < Q$, the losses only occur due to the SC being closed for T_1 time and a possible decrease in demand.

If the safety stock perishes or is used up before the contaminated node recovers, the lost production can be expressed as

$$\left(T_2 - \min\left\{(t_s - T_1)^+, \left(\frac{s}{D^* - Q^*}\right)\right\}\right)^+ (Q - Q^*). \tag{7}$$

The total amount of lost production compared to the production before the disruption when the contaminated node is a distribution node is the sum of Equations (1), (6), and (7).

Contamination at Production Node

If the contaminated node is a producing node, the SC may not be able to produce as much as it was producing before the disruption. We assume the SC uses safety stock before any other nodes increase their production. Given that the application for our model is fresh produce, increasing production may be very difficult and/or take a very long time. Even with safety stock, it may be necessary to reroute transportation, and the optimization problem in (P) should be solved but with the inclusion that node i is closed, which is represented by:

$$q^*_{ri} = 0\,. \tag{8}$$

Equation (6) can then be used to calculate the lost production with the use of safety stock.

Producing nodes that are not closed may be able to increase their production to make up for some of the lost capacity of the closed node. If these nodes can increase their production, we can calculate Q^{**} the amount of produce that can be delivered to the final consumers if nodes can produce more during a disruption through the following maximum-flow network problem, (P'):

$$Q^{**} = \text{maximize} \quad \sum_{i=1}^{N} q^*_{it} \tag{9}$$

$$\text{subject to} \quad \sum_{j=1}^{N} q^*_{ij} - \sum_{k=1}^{N} q^*_{ki} = 0 \quad \text{for } i = 1, \dots, N \tag{10}$$

$$0 \leq q^*_{ij} \leq \mu_{ij} \qquad \text{for } i, j = 1, \dots, N,\ i = r, \text{ and } j = t \tag{11}$$

The optimization problem in (P') is identical to (P) except that the producing nodes are constrained by μ_{rj} rather than q_{rj}, where μ_{rj} represents the maximum amount that node j can produce.

If the safety stock perishes or is used up before the contaminated node recovers and the SC can increase its production, the lost production can be expressed as

$$\left(T_2 - \min\left\{(t_s - T_1)^+, \left(\frac{S}{D^* - Q^*}\right)\right\}\right)^+ (Q - Q^{**}). \tag{12}$$

Equation (12) differs from Equation (7) because the lost production is determined by the difference between Q and Q^{**} rather than the difference between Q and Q^*. The total amount of lost production when the contaminated node is a producing node is the sum of Equations (1), (6), and (12).

In addition to discussing the consequences of two distinct situations of contamination at a distribution or at a production node through the model, other insights the model offers are the interplay of various parameters. These relationships lend themselves to careful planning on the manager's part.

Model insights

The trade-offs faced by a SC manger based on the different strategies such as rerouting the produce or whether to use safety stock are derived using the models. However, different situations such as whether the contamination exists at the source node or distribution node lead to further insights such as interactions among drivers of the disruptions parametrized here such as traceability, safety stock, demand, and perishability of the FPSC.

Traceability of product

An important element for the SC to recover quickly is to find the source of contamination as fast as possible, traceability. Failure to do so results in loss of revenue for the growers and suffering of the consumers. Traceability mitigates the losses resulting from contamination through prompt corrective action and by sharing information about unaffected nodes in the SC (Wilson and Clarke, 1998, Roth *et al.*, 2008, Apte, 2010b).

The model parameterizes traceability through T_1. Given that contaminated product is first discovered at a final demand node, T_1 might be determined by the probability p that a node is the source of the contamination given that the contamination was found at a specific demand node. T_1 and p could follow a reciprocal relationship:

$$\boldsymbol{T_1} \propto \frac{(\mathbf{1}-\boldsymbol{p})}{\boldsymbol{p}}. \tag{13}$$

If $p = 0$, the SC expects that the node will not be contaminated. This implies that the time it takes the SC to find that contaminated node is infinite. If $p = 1$, the SC knows immediately that the node is contaminated.

The key here is whether the grower has visibility into the SC. Based on the type of network, size, market reach and resource availability, the growers may or may not have access to technology that can lead to visibility. Some large growers considered high-tech growers such as Fresh Express, Dole, or Taylor Farms do have this access. If the SC has high-tech growers with good visibility in its SC, the time to discover the contaminated node will be small even if the initial probability of a contaminated node is small. If the SC is composed of low-tech growers without much visibility into the SC—a lack of traceability—the time it takes to identify the contaminated node will decrease as the probability increases, but the time decreases more slowly than under the situation with good traceability.

Figure 3 displays three curves each of which follows the proportion in Equation (13). Although all three curves depict a reciprocal relationship between T_1 and p, the curvature differs among the three curves. The curvature, or how quickly T_1 decreases as p increases, reflects the ability of a SC to trace the source of the contamination. A SC manager can use this functional relationship and Figure 3 to identify the curve that best mirrors the ability of the SC to trace product and provide visibility. From there, the manager could estimate prior to a disruption the time the SC would be closed while investigators try to find the source of contamination.

The time to find the source of contamination can depend on many factors in addition to the prior probability that a node or a SC is contaminated. In the United States, when a contamination occurs, the FDA launches an investigation to determine the source of the contamination. The FDA will use the number of people who are sick and the geographical dispersion of these illnesses in order to begin to identify the brand of the contaminated produce, the SC distribution, and the lot numbers that are contaminated. Laboratory tests and epidemiological information are critical for the FDA to arrive at conclusions and release information about the source of the contamination. Ultimately, we can think of the length of time to find the contamination or to verify that certain nodes are free of contamination as a function of all these factors.

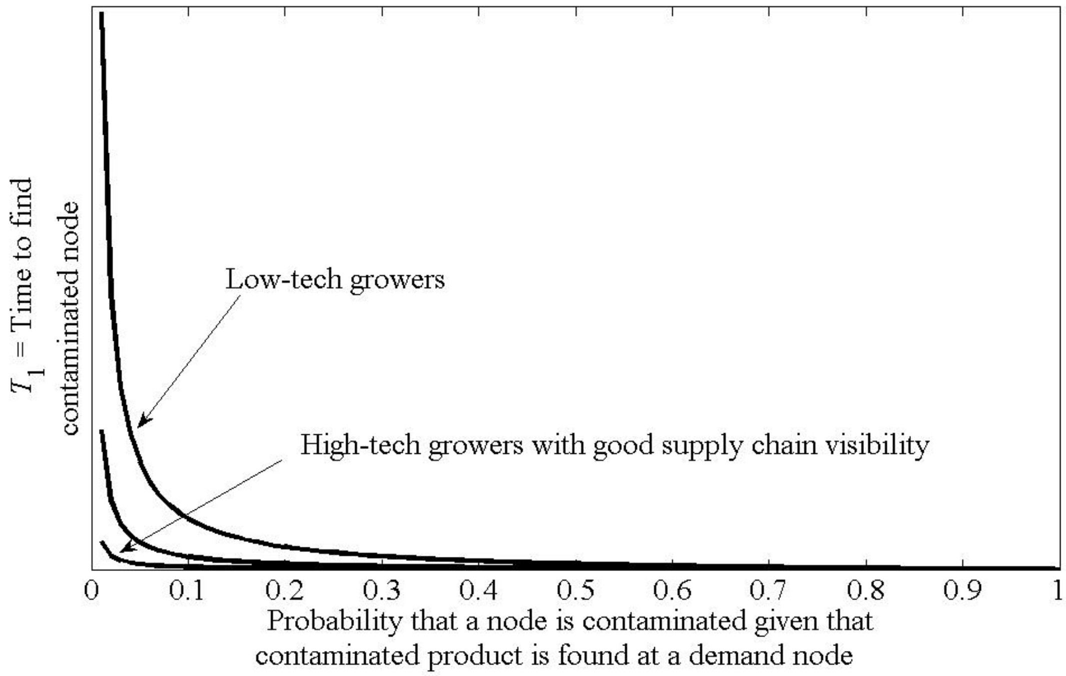

Figure 3

The probability p that a node is contaminated given that contaminated produce was discovered at a specific demand node may depend on the complexity of the SC as well as on how well the SC has previously determined and measured the risks of contamination at each node. If many nodes handled produce that was delivered to the demand node and many different producers could have supplied the product, the chances that any one node is contaminated are probably smaller. Thus it may take a long time to find the contaminated node. If only one or a few producers delivered product to that demand node and if only one or a few distribution nodes handled the product, the chances that a node is contaminated given that the demand node had contaminated produce are fairly large. In other words, the ability of the SC to find the contaminated node may depend on the structure of the SC.

Interaction of safety stock with other parameters

Safety stock and demand: Understanding the benefits gained from better communication and holding safety stock may be important in determining the proper risk management strategy. Better communication and more trust means that demand during the disruption will not drop as much, or mathematically that D^* will be closer to D, the demand before the disruption. Figures 4 and 5 display the contour lines for lost production given different values for D^*, demand during the disruption, and s for different types of contamination nodes. Contour lines closer to the northeast part of the chart represent less production lost. Figure 4 represents a case where the contaminated node is a distribution node, and Figure 5 depicts the situation where a producing node is contaminated.

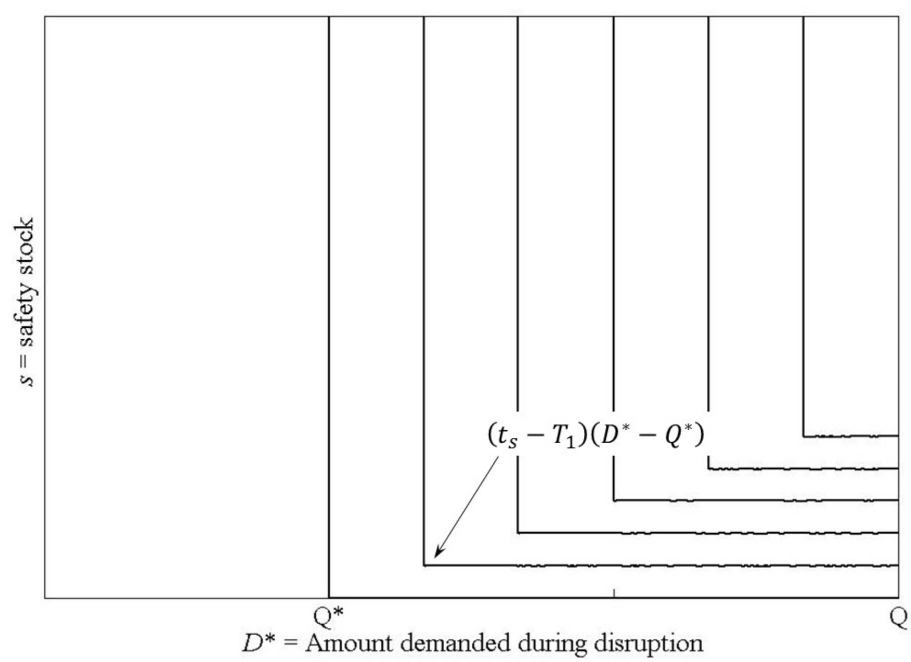

Figure 4

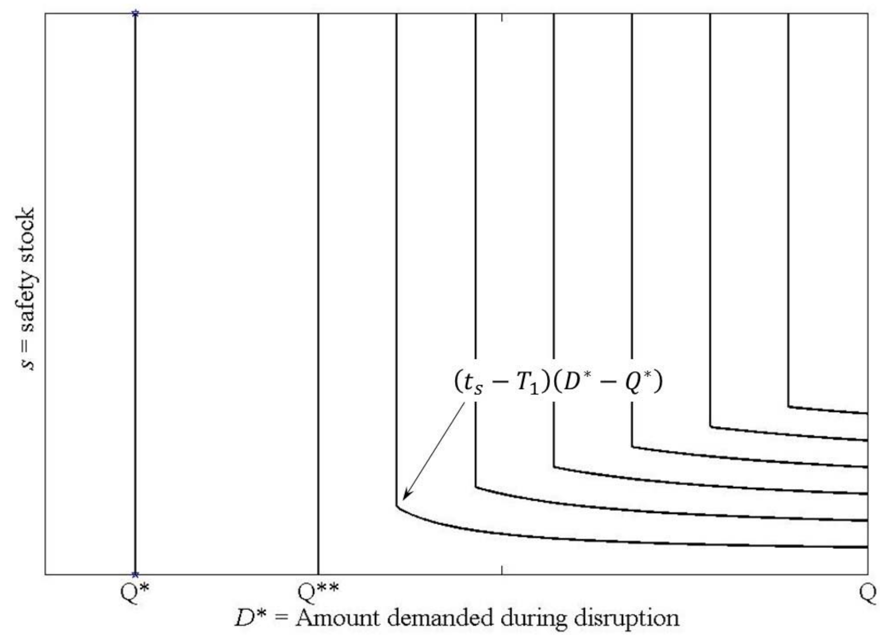

Figure 5

For both situations, if $Q^* = D^*$, the producer can produce at least as much as what is demanded and does not need to rely on inventory to meet demand. This suggests that producers that do not build trust with their consumers or follow good communication practices about the risks may not be helping themselves by holding safety stock.

If the contaminated node is a distribution node, it is optimal to choose $s = (t_s - T_1)(D^* - Q^*)$, which occurs at the "elbow" point in Figure 4. If $s > (t_s - T_1)(D^* - Q^*)$, more safety stock is available than what can be used because demand has dropped and/or a lot of production can be rerouted. If $s < (t_s - T_1)(D^* - Q^*)$, the producer does not have enough product to satisfy demand. For a given D^*, increasing the safety stock increases sales during the disruption in a linear manner until $s = (t_s - T_1)(D^* - Q^*)$ is reached.

If the contaminated node is a producing node, it is still optimal to select $s = (t_s - T_1)(D^* - Q^*)$, the elbow point in Figure 5. If $s > (t_s - T_1)(D^* - Q^*)$, more safety stock is available than what can be used because demand has dropped too much. If $s < (t_s - T_1)(D^* - Q^*)$ and $Q^{**} = D^*$, the other nodes can increase their production to Q^{**} and meet all the demand once the safety stock is depleted. If $s < (t_s - T_1)(D^* - Q^*)$ and $Q^{**} < D^*$, the SC does not have enough produce to meet demand. In this last case the SC's performance could be improved if more safety stock were available. Table IV summarizes these results for safety stock for the two types of nodes.

Table IV

Contaminated node	Condition for safety stock	Consequence
Distribution node	$s = (t_s - T_1)(D^* - Q^*)$	Optimal
	$s > (t_s - T_1)(D^* - Q^*)$	Wasted safety stock
	$s < (t_s - T_1)(D^* - Q^*)$	Not enough produce to meet demand
Producing node	$s = (t_s - T_1)(D^* - Q^*)$	Optimal
	$s > (t_s - T_1)(D^* - Q^*)$	Wasted safety stock
	$s < (t_s - T_1)(D^* - Q^*)$ and $Q^{**} = D^*$	Safety stock and additional production can meet demand
	$s < (t_s - T_1)(D^* - Q^*)$ and $Q^{**} < D^*$	Not enough produce to meet demand

Safety stock and perishability: The interaction of safety stock and the perishability of the product as represented by t_s reveals a similar story to safety stock and demand (or communication) during the disruption. Figure 6 depicts contour lines for production lost during the disruption where contour lines in the southwestern direction represent less production lost. The shape of the contour lines remains the same whether or not the contaminated node is a distribution or producing node. The elbow point occurs when $s = (t_s - T_1)(D^* - Q^*)$. It is not optimal to have more safety stock than what the perishability of the product allows.

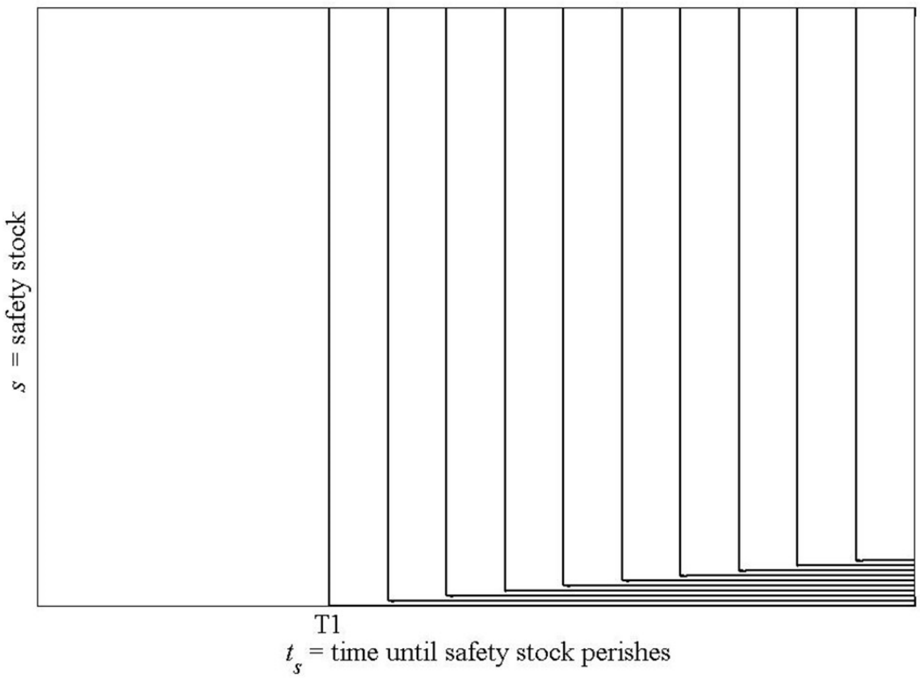

Figure 6

In the next section we illustrate our model using a case study and offer some insight into how the model can benefit a FPSC in case of a disruption due to contamination.

Case study

The case study is meant to demonstrate how the model can be used as a tool for an organization such as Dole Fresh Vegetables to understand and quantify the plausible impact of a disruption. The model can be used for the purpose of understanding the aftereffects of a disruption and analyzing “what-if” scenarios (i.e., what might happen if contaminated product is found in a FPSC). The case study is a real-world application of how the model can be used. The data in this case study is based on information published after *E. coli* was discovered in bagged spinach in September 2006.

Applying the model to this real-world example requires some modifications to the general model presented in the paper. The case study is based on a real contamination in which demand and supply change over time. We apply the model at each day during the disruption, and if the SC produces more than demand in the current day, the additional supply becomes inventory for the next day. Although the model investigates each type of node in the FPSC, the case study concentrates on three processing facilities of Dole Fresh Vegetables and uses a broad customer demand function.

Background

In September 2006, *E. coli* was found in Dole Fresh Vegetables' bagged spinach, and the source of the contamination was eventually traced back to Natural Selection Foods, a supplier for Dole. This case study depicts how the FPSC model could be applied to an outbreak of contaminated spinach in Dole's SC.

Dole Fresh Vegetables purchased vegetables from 38 independent growers in California, 10 in Arizona, 2 in Ohio, 1 in Florida, and 1 in Canada, and Dole operated 3 salad packaging plants in 2006: 1 in California, 1 in Arizona, and 1 in Ohio (Dole Food Company Inc., 2007, Lobeck, 2010). Florida and Canada do not grow much spinach (Roman, 2012, Economic Research Service, 2015), and it appears unlikely that they are part of Dole's spinach SC. For ease of illustration we choose an instance where Dole has a total of 50 spinach producing nodes (located in California, Arizona, and Ohio), and each farmer sends its spinach to the processing plant located in the same state.

The United States produced 605 million pounds of fresh spinach in 2006, and bagged spinach accounts for about 75-90% of the fresh spinach supply (National Agricultural Statistics Service, 2015). Dole's market share of the ready-to-eat salad market was 34% (Dole Food

Company Inc., 2007), so we estimate that Dole supplied (605)x(0.8)x(0.34) = 164.6 million pounds of bagged spinach in 2006.

Although daily demand and supply has variation in reality, for simplicity, the daily demand and supply is constant before disruption. The model estimates that Dole produces 164.6 / 365 = 0.451 million (or 451,000) pounds of bagged spinach each day. Based on the capacities and distribution of the growers, we also estimate that each grower supplies the same amount of spinach, so the California facility daily produces 343,000 pounds, the Arizona facility produces 90,000 pounds, and the Ohio facility produces 18,000 pounds of bagged spinach.

Events

On September 14, 2006, the FDA advised that consumers should not eat bagged spinach, and the advisory was extended to fresh spinach the following day. No fresh or bagged spinach was available for the next 5 days, and $T_1 = 5$ in this application. After the FDA announced that some spinach was safe to eat, spinach from California was not available for an additional 10 days. On September 29, the FDA announced that spinach on the shelf was safe to eat (Akkad, 2006, Ostrom, 2006).

Based on these timelines, the original advisory was issued on day 0 and no bagged spinach was sold through day 4. Because spinach only stays fresh for about two days (Sawyer, 2013), any safety stock that Dole had before the contamination was spoiled by the time Dole could start selling spinach again. On day 5, bagged spinach from Dole's Ohio and Arizona facilities can be sold, which is only 24% of Dole's total production capacity. On day 16, Dole begins to sell spinach from its California facility.

However, demand for bagged spinach dropped drastically due to the *E. coli* outbreak and took more than a year to fully recover. Arnade *et al.* (2009) estimate that 3 weeks after the outbreak, demand for bagged spinach was 37% of what it would have been without the disruption; in 26 weeks demand was 83%; and in 68 weeks demand was only 90%. We can regress these data points to a logarithmic function $D^{*}(\delta) = 18.2 * \log(1 + 0.363\delta)$ to calculate the daily percentage of pre-disruption demand where δ is the number of days after the first FDA advisory (Figure 7).

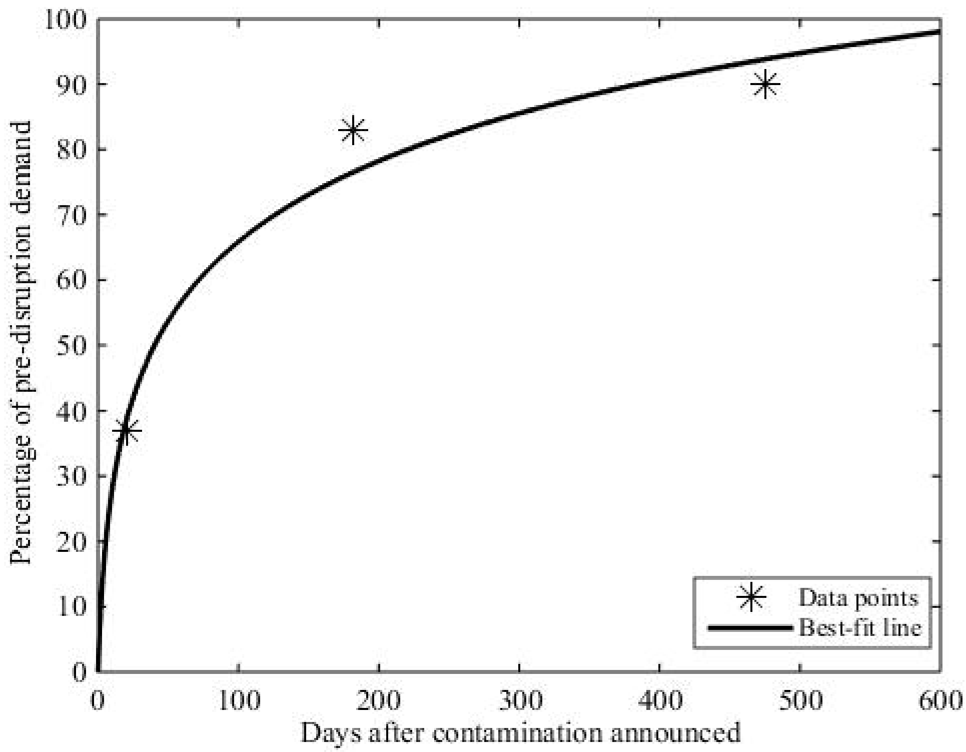

Figure 7

Analysis

We use this demand function and multiply it by 451,000 (Dole's pre-disruption supply) as the daily demand for Dole's bagged spinach from the initial disruption onward. Unlike the mathematical model that assumes a static demand, the demand for bagged spinach after disruption changes over time. Each day has a different demand, and Dole would like to produce enough to meet that demand. Figure 8a depicts the daily demand and the demand that Dole can satisfy for 600 days after the FDA's original announcement, and Figure 8b displays the first 20 days in order to highlight the differences between the demand and supply in the initial weeks.

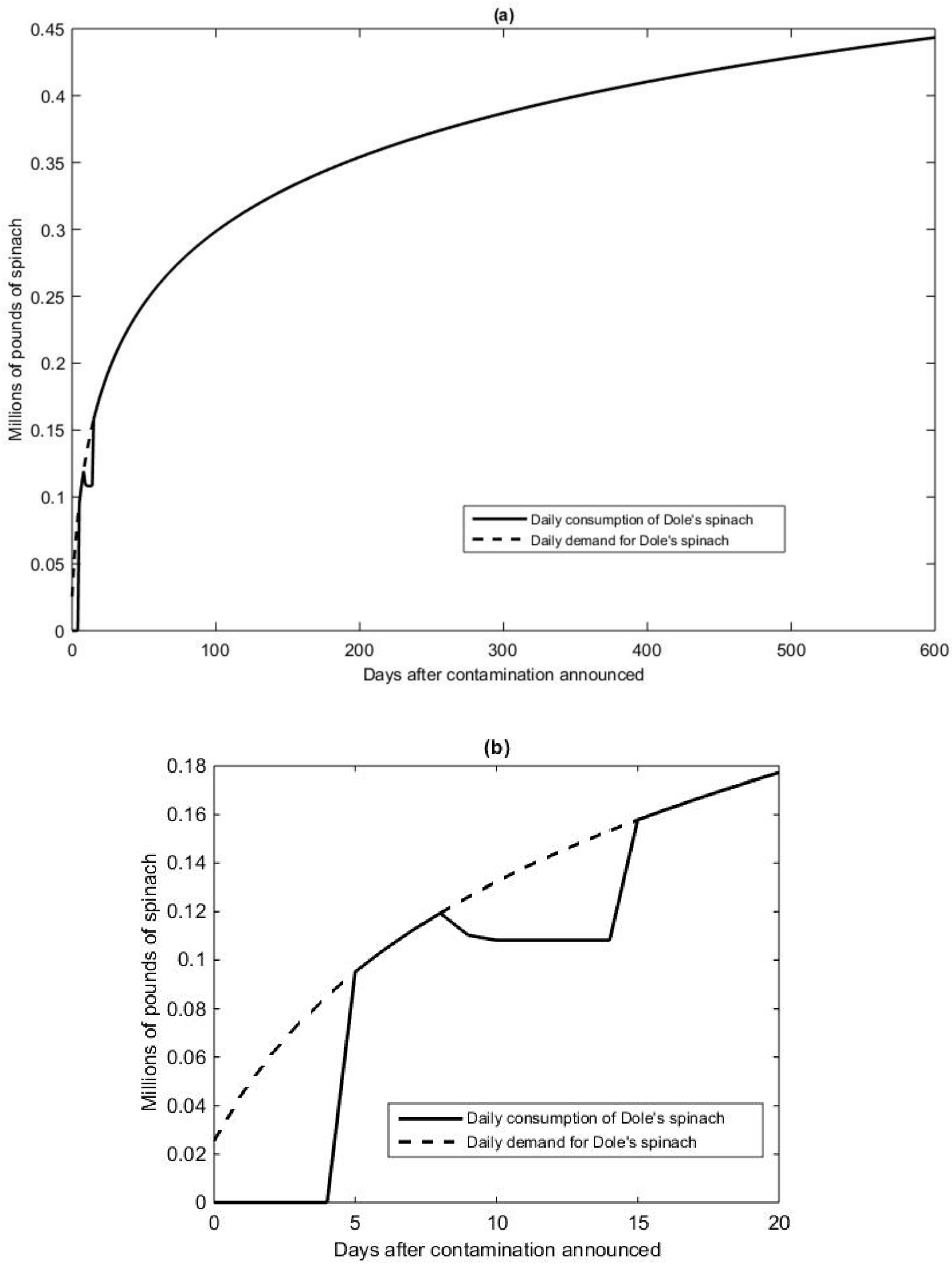

Figure 8

As can be seen from the figures, Dole can meet the daily demand for its bagged spinach beginning with day 15. Demand exceeds Dole's production during the first 4 days after the contamination announcement and 9-14 days after the announcement. During the first 4 days after the announcement, the model assumes that Dole does not sell any spinach because the FDA has not declared spinach is safe to eat. Beginning on day 5, Dole is able to sell spinach produced from its Arizona and Ohio salad processing facilities but not from its California facility. Because the model assumes that demand for bagged spinach continues to rise, Dole is able to meet the demand for its spinach through these two facilities from 5-8 days after the contamination announcement. However, from 9-14 days after the contamination announcement, demand is greater than what Dole can produce. Beginning on day 15, the FDA announced that spinach from California was safe, and Dole can sell bagged spinach processed at its California facility. At this point, Dole can produce 451,000 pounds of spinach a day, but demand never reaches that high during the two years after the contamination.

Observations

We make the following observations if Dole Fresh Vegetables had access to this model before the disruption. The safety stock only lasts two days; therefore, having additional inventory at the beginning of the disruption does not benefit Dole as the inventory of spinach expires before Dole is able to sell its spinach again. If Dole were able increase its production in the Ohio and Arizona facilities that were not affected by the contamination during the two days prior to the announcement that some spinach was safe to eat (day 5), then Dole could have used that inventory to fill demand during the 9-14 days following the initial disruption, as shown in Figure 9. In this case, $Q^* + s \geq D^*$ for each day during days 5-14 where Q^* is the daily production from Dole's Arizona and Ohio facilities, D^* is the daily demand, and s is the daily inventory that Dole would be able to build up and keep replenished. The only demand that Dole would not be able satisfy is during the first 4 days after the disruption, which is represented by T_1 in the model.

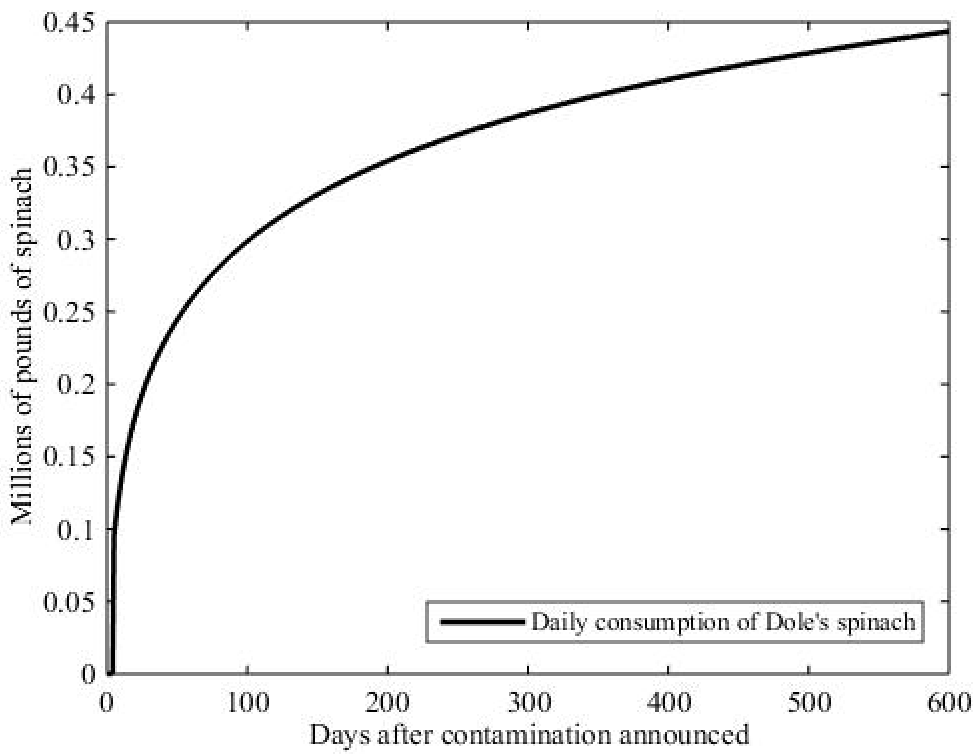

Figure 9

This case study shows how critical the demand function is in determining the amount of spinach that Dole could sell. If demand for bagged spinach had remained constant during the entire time—perhaps by more successful communication that spinach was safe—Dole could have sold 0 pounds of bagged spinach from 0-4 days, 108,000 pounds from 5-14 days, and 451,000 pounds from 15 days and more.

Conclusion

The FPSC model presented herein includes the different elements in a SC that increase or decrease vulnerability to a contamination. The model incorporates different disruption management strategies such as rerouting production, using safety stock, and increasing production based on the existing SC disruption models to determine safety stock for fresh produce. The suppliers in our models have certain unreliability due to contamination of the product that forces possible supplier modification. We contribute to the theory by developing mathematical formulas for many qualitative aspects that determine the extent of the impact of a contamination, including visibility within the SC, communication to customers, the perishability of the produce, the amount of safety stock, and the SC's structure. Specifically valuable is the understanding of the traceability of the contaminated produce that is modeled by the length of time the SC is completely shut down while the search for the source of the contamination is underway. We model the effect of communication and the essentialness of the product through the demand for the produce during the disruption.

The model developed here and insights offered through the resulting interaction between safety stock and various parameters can help SC managers quantify the benefits of different disruption management strategies to mitigate the impacts of contaminated produce. An SC manager can estimate how much safety stock would be needed based on different situations. Having the right amount of safety stock if production is lost may be critical to mitigating the disruption in the FPSC. The model determines the optimal safety stock $s = (t_s - T_1)(D^* - Q^*)$ in such a case. Calculating the optimal amount of safety stock follows the strong academic and practical tradition of calculating the optimal amount of inventory within a production system. If demand drops due to a contamination, the SC may be able to satisfy demand without relying on safety stock (i.e., $Q^* \geq D^*$), in which case having more safety stock does not produce any benefits. Similarly, a SC that succeeds in keeping demand high during a disruption may not be able to take advantage of it if safety stock is unavailable and produce cannot be rerouted to non-contaminated nodes. The safety stock could also expire while the SC is trying to find the source of the contamination. The right amount of safety stock depends on the perishability of the produce, the length of time it takes to find the contamination, the level of demand during the disruption, and the amount of produce that can be rerouted based on the model.

We apply the model to the 2006 *E. coli* contamination in the spinach supply for Dole Fresh Vegetables. The primary lesson learned from this application is that the drop in customer demand and its gradual increase play the biggest role in Dole's lost sales. One observation that can be made based on the timeline of FDA announcements, their known processes, and affected spinach sales is that if Dole were able to forecast when FDA announced that spinach was safe to eat, it could have increased its production and avoided some lost sales. Such planning will depend on protocol established with FDA.

SC managers have limited budgets to manage the risk of potential disruptions and must consider the trade-offs between different disruption management strategies. This model can help a SC manager explore those trade-offs by quantifying the benefits of different strategies. Although the case study focuses on a historical contamination, the application is more important as an illustration of how Dole can use the model to prepare for a future contamination. We believe that if the model is utilized over time with known data, Dole can estimate how the contamination will affect demand and which production facilities will be closed and use the model to quantify lost sales and lost production. For example, what is the benefit during a disruption of holding additional safety stock versus adding an alternate distribution node? In the case study, holding more safety stock was not beneficial because the FDA did not announce that bagged spinach was safe to eat until after the safety stock perished. The model can help answer questions like this one so that a SC manager can understand the extent to which each strategy can limit production losses for the SC. Careful risk management should also consider the cost of each strategy, and the costs of the different strategies can be examined with the benefits as quantified by the model in order to determine the most cost-effective set of strategies.

The model deals with perishability and disruption due to contamination. However, this model can be extended to several instances. One such instance is the vaccine SC. Vaccines are perishable. They are used in disaster response routinely where disruptions, internal (contamination) and external (destruction of infrastructure) to the chain are common. The production may have considerable lead time due to supply issues or significant delay originating from obsolescence of the vaccine due to mutating bacteria. Another example is the blood or plasma SC.

As with all models, the FPSC disruption has certain limitations due to assumptions. The data used in the case study fails to reflect day-to-day variability. But the case study provides an example of how the model can be used to help a FPSC plan for a disruption. Other factors, such as the inclination of consumers towards designating the product type of the contaminated produce as non-essential or essential, have their roots in behavioral operations management. However, we have held off from incorporating these enhancements for future augmentations of our model. Our purpose for refraining from these intricacies is to maintain the focus, simplicity, and understanding of the first model of its kind in this research. The paper discusses “what-if” scenarios derived from plausible situations. This renders analysis as lessons learned with certain assumptions.

Characterizing the risk of a FPSC disruption also involves analyzing the uncertainty in a disruption, and all of the model parameters could be uncertain before contamination is discovered. Being able to quickly trace the source of the contamination can help reduce that uncertainty, but uncertainty may still exist about how demand can change during the disruption, how much produce can actually be rerouted, whether the safety stock will be contaminated, and whether producers can increase their output. Future work can incorporate that uncertainty into this model by allowing the model parameters to follow probability distributions and calculating either a full probability distribution over production losses or the expected value.

As one of the first attempts to uncover drivers of lost production, the model offers a useful tool for FPSC managers to plan for disruption due to contamination. According to the practitioners and scholars alike, planning for disasters is a better strategy for mitigation. The research discussed in this paper is one such planning tool in the toolbox of the SC managers.

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