Evaluating the Value of Disruption Information for Mitigating Supply Chain Risks

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Abstract
Disruption information creates benefits: with this information, firms can choose better strategies to mitigate supply chain risks. We develop a single product model to quantify the value of disruption information for managing supply chain risks, and to show how this value changes with other parameters (e.g. disruption probabilities).

Keywords: Disruption Information, Disruption Risk Mitigation, Supply Chain Risk Management

Introduction

In Oct, 2012, in the middle of Hurricane Sandy, Walmart successfully managed to open and provided vital goods to local residents (Bhasin 2012). This success has benefited greatly from Walmart's "up-to-the-minute information" through data analysis and close coordination with the Power Company and government agencies (PWC 2013). For instance, Walmart hired a meteorologist to analyze and provide real time weather information to support decision making (PWC 2013).

Both researchers and practitioners acknowledge that disruption information has value and can substantially benefit supply chain risk management. Given the disruption information, researchers believe that firms can be better prepared and choose better strategies to mitigate supply chain risks (Craighead et al. 2007, Kleindorfer and Saad 2005), and that they can enhance their competitive status by immediate response to quickly occupy the market share. For instance, right after the 911 tragedy, there was an increased demand for patriotic commodities. Using its real-time demand tracking and analysis system, Walmart successfully dominated the sales of patriotic commodities by responding quickly to absorb all supply resources (Gerhard et al. 2012). Practitioners also value disruption information as an important way to manage supply chain risks. A recent survey (Accenture 2014) of more than 1000 senior executives from large global companies shows that 60% of leaders will increase risk management related investment by 20% over the next two years. Disruption risk information acquisition, for example through big data analysis, is recognized as one of the important investments for them to make (Accenture 2014, K. Lee 2014, Sanders 2014).

There are several reasons why evaluating the value of disruption information is important. First, understanding the value of disruption information can help supply chain managers make strategic investment decisions (Macdonald et al. 2015). On the one hand, disruption information creates value, but there is cost associated with acquiring this information. So understanding the value of information can help managers make decisions, such as whether to invest and how much to invest. On the other hand, the statement that disruption information creates value is based on the assumption that the information is accurate. In reality, we almost always get imperfect information. Is information with poor accuracy better than no information? Understanding how the value of information changes with the information accuracy is therefore critical. Second, the value of disruption information depends on factors such as disruption frequency, disruption severity, the availability of risk mitigation tools, supply chain design, etc. Understanding how the value of information changes with these factors can support managers' efforts to identify the best risk management strategies. Third, even though the literature shows an increasing interest in evaluating the value of disruption information, none of it builds models based on imperfect information and none of it provides detailed analysis on how the value of information changes with other parameters.

To fulfill these practical needs and to fill the literature gap, we therefore introduce a preliminary supply chain model to provide insight into the following research questions:

- How can we quantify the value of disruption information for mitigating supply chain risks?
- How does the value of information change with other parameters, such as information error, disruption distribution, and the availability of flexible suppliers, etc.?
- What's the tradeoff between the cost of disruption information and supply chain performance?

The remainder of the paper is organized as follows: Section 2 presents a brief review of current literatures. In Section 3, we introduce a preliminary model. In Section 4, we discuss the opportunity for future generalization of the preliminary model.

Literature Review

The study of supply chain disruptions has experienced a recent explosion of interest from researchers and practitioners in the past decade (Kleindorfer and Saad 2005, Snyder et al. 2012, Yang et al. 2008, Craighead et al. 2007). This sharp increase in interest is partly because high-profile disaster events, such as Hurricane Sandy in 2012 and the Tohoku Earthquake in 2011, have brought disruptions into public attention (Snyder et al. 2012), and also partly because the improvement of related analysis techniques has sparked new approaches to support decision making (Accenture 2014, Landwehr and Carley 2014).

Along with the traditional interest in supply chain risk management and supply chain design, increased emphasis also has been placed on disruption information, given that it plays an important role in supply chain disruption mitigation and recovery (Craighead et al. 2007;

Kleindorfer and Saad 2005, Saghafian and Van Oyen 2012, Snyder et al. 2012). Craighead et al. (2007) emphasize the importance of warning capability in supply chain disruption. Kleindorfer and Saad (2005) provide a conceptual framework for risk assessment and mitigation of supply chain disruption, where information sharing is an important aspect. Saghafian, and Van Oyen (2012) quantify the value of disruption risk information from suppliers and provide insight into how disruption information increases supply chain resilience.

Evaluating the value of disruption information has been studied using different methodologies. Lee and Tang (2000) quantify the value of demand information sharing between retailers and the suppliers, using a two level supply chain model. Yang et al. (2008) studies how value of risk management strategies change with asymmetric information about supply reliability and the value of symmetric information, using mechanism design theory. Datta and Christopher (2011) investigate the impact of information sharing from large demand uncertainties through simulation. Saghafian and Van Oyen (2012) develop a newsvendor model to quantify the value of disruption risk information, considering a two stage setting with recourse.

The above-mentioned models have two common assumptions: 1) full disruption information can be obtained by one party in supply chain, for example, the supplier, and 2) the disruption is either up or down. However, these assumptions are challenged by the fact that: 1) the full disruption information is hard to obtain or very expensive to obtain, especially if the disruption is caused by natural disaster and terrorism, and 2) in most cases, the disruption only partially influences the material flow along the supply chain, instead of totally shutting it down.

Different from the studies focusing on value of information sharing (Datta and Christopher 2011, Lee and Tang 2000), our study concentrates on evaluating the value of added disruption information. The models examining the value of information sharing are built on the assumption that one party in supply chain has full disruption information, which normally fails to hold in most cases in reality. Our model ignores the effect of asymmetric information inside the supply chain and focuses on the influence of added information.

Modeling Framework

We model a supply chain that consists of one firm, one main supplier, and one flexible supplier. The main supplier is unreliable and is exposed to disruption risks. These disruption risks can be of any kind, including production contingencies, natural disasters, terrorism, etc. We are interested in the influence on the supplier caused by the disruption risk. To model the influence of disruption risk, first we assume there's only one disruption that can happen at one time. If π denotes the actual influence caused by disruption and θ denotes the perceived information of disruption influence, i.e., the estimated disruption influence on the supplier, then the information error can be represented by $\varepsilon = \pi - \theta$. Here we assume $\pi, \theta \epsilon [0,1]$. When $\pi = 0$ then there's actually no disruption influence, and when $\pi = 1$ then the supplier is totally shut down by the disruption. Similarly, $\theta = 0$ means that the firm believes there will be no disruption influence, and $\theta = 1$ means that the firm believes that the main supplier will be totally shut down.

Based on the perceived disruption influence information θ, the firm can estimate the delivery amount from the main supplier. During the disruption time, the firm can also purchase from flexible supplier to mitigate the disruption risk, where the available purchase amount from the flexible supplier is Q. The firm purchases products from suppliers to satisfy demand (D).

Figure 1 depicts this supply chain model. The dashed line box around the main supplier means that how the disruption actually influences on the main supplier is a black box to us and we only care about the extent of the final disruption's influence on the main supplier. For example, the disruption can have an influence either directly on the main supplier or on the transportation path from the main supplier to the firm.

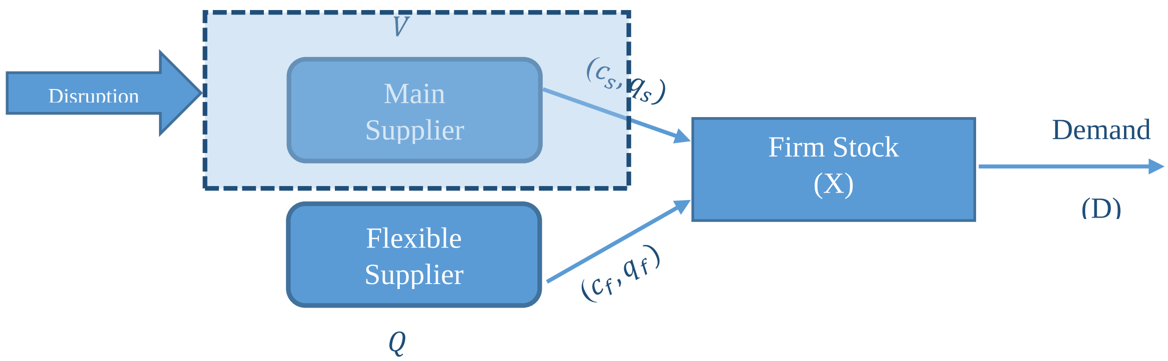

Figure 1: Supply Chain Model

Figure 2 shows the sequence of events in the decision process, and we will discuss the detailed process below.

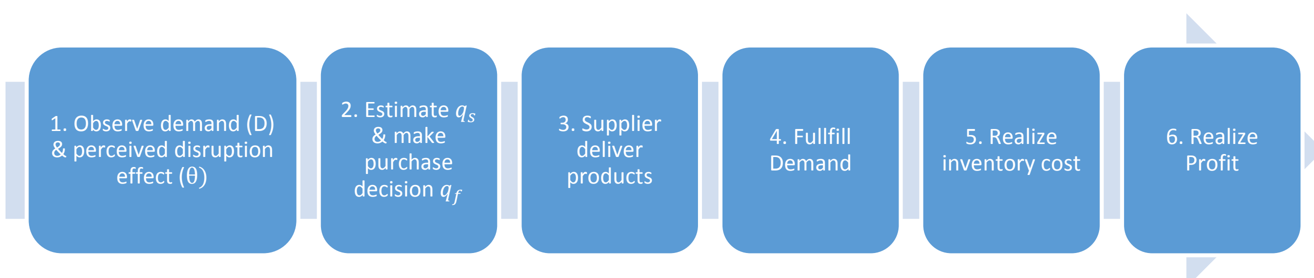

Figure 2: decision process sequence

At the beginning, the firm can observe demand (D) and the perceived disruption influence information θ, which is an estimation of π, the actual disruption influence on the main supplier.

At the second step, the firm can calculate the *estimated* delivery amount from the main supplier $q_s = (1 - \theta) * V$ and can make the purchase decision q_f from the nonlinear programming model below. The optimal solution of this model is denoted as q_f^*. Here c_s represents the unit purchasing cost from the main supplier and c_f represents the unit purchasing cost from flexible supplier. r is the unit selling price, h is the unit inventory holding cost and p is the unit penalty cost of unsatisfied demand.

Nonlinear Programming Model (3.1)

Decision Variable:
q_f: Order amount from flexible supplier during disruption time

Parameters:
θ: perceived disruption influence on the main supplier, $\theta \epsilon [0,1]$.
π: actual disruption influence on the main supplier, $\pi \epsilon [0,1]$.
ε: information error, $\varepsilon = \pi - \theta$.
q_s: the estimated delivery amount from the main supplier, $q_s = (1-\theta) * V$.
c_s: the unit purchasing cost from the main supplier.
c_f: the unit purchasing cost from the flexible supplier.
r: the unit selling price.
h: the unit inventory holding cost.
p: the unit penalty cost of unsatisfied demand.
V: the contracted amount from the main supplier.
Q: the available purchase amount from the flexible supplier.
$Profit_\theta$: the estimated profit given the disruption influence information θ.
$Profit(\theta)$: the actual profit realized when given the disruption influence information θ.
$Profit_0$: the actual profit realized when there's no disruption influence information given.

Objective Function:

$$\max Profit_\theta = Revenue_\theta - Inventory\ Holding\ Cost_\theta - Shortage\ Cost_\theta - Ordering\ Cost_\theta$$

$$Revenue_\theta = r * min\{D, q_s + q_f\} \tag{1}$$

$$Inventory\ Holding\ Cost_\theta = h * [q_s + q_f - D]^+ \tag{2}$$

$$Shortage\ Cost_\theta = p * [-q_s - q_f + D]^+ \tag{3}$$

$$Ordering\ Cost_\theta = c_s * (1-\theta) * V + c_f * q_f \tag{4}$$

Constraints:

$$q_f \leq Q \tag{5}$$

$$\theta \epsilon [0,1] \tag{6}$$

$$q_f \geq 0 \tag{7}$$

At the third step, given (θ, π) and the contracted delivery amount from main supplier V, the actual delivery from the main supplier is given by q_s', which can be calculated as below. The firm thus actually gets q_s' from main supplier and q_f^* from the flexible supplier.

$$q_s' = (1-\pi) * V = (1-\theta-\varepsilon) * V \tag{8}$$

At the fourth step, the firm attempts to fulfill the demand. The actual amount fulfilled is

$$min\{D, q_s' + q_f^*\} \tag{9}$$

At the fifth step, the firm realizes either the inventory cost or the shortage cost, as given in (2) and (3).

At the last step, the firm realizes the actual profit $Profit(\theta)$ given the perceived disruption influence information θ:

$$Profit(\theta) = Revenue - Inventory\ Holding\ Cost - Shortage\ Cost - \ Ordering\ Cost$$
$$= r * min\{D, q_s' + q_f^*\} - h * [q_s' + q_f^* - D]^+ - p * [-q_s' - q_f^* + D]^+ - c_s * q_s' - c_f * q_f^*$$

(10)

In the situation that the firm has no information about the disruption influence, the firm makes the purchase decision assuming there's no disruption influence. Because even though the influence of disruption can be large, the disruption is a rare event. So it makes sense that the firm assume there's no disruption, then no disruption influence, given no information about the disruption influence. Therefore, the optimal purchase amount from the flexible supplier q_f^0 given no disruption influence information can be obtained through solving the nonlinear programming model (3.1) when $\theta = 1$, and the corresponding profit given no disruption influence is:

$$Profit_0 = Revenue - Inventory\ Holding\ Cost - Shortage\ Cost - Ordering\ Cost$$
$$= r * min\{D, q_s^0 + q_f^0\} - h * [q_s^0 + q_f^0 - D]^+ - p * [-q_s^0 - q_f^0 + D]^+ - c_s * q_s^0 - c_f * q_f^0$$

(11)

q_s^0 is the actual purchase amount from main supplier without disruption influence information

$$q_s^0 = (1 - \pi) * V \tag{12}$$

Therefore, we can derive the value of information θ from below formula:

$$VI_\theta = Profit(\theta) - Profit_0 \tag{13}$$

Implications

This preliminary model can be easily expanded in two ways to address more complex research questions:

First, we can study the influence of warning time and information quality through changing the available purchase amount from flexible supplier Q. Q can be substituted by $Q(\tau)$, $Q(\varepsilon)$ or $Q(\tau, \varepsilon)$, which respectively represents that the available purchase amount depends on the warning time before the disruption τ, the information error ε, or both. Normally, we would expect $Q(\tau)$ to increase with τ, because if firms can get more timely advanced information, then they can be better prepared and have more available flexible supply. If we look at ε as a measure of information quality, then we can model the idea that better information can provide better preparation by assuming that $Q(\varepsilon)$ is increasing with the absolute value of ε ($|\varepsilon|$). Because the influence of $Q(\tau, \varepsilon)$ is more complex, analyzing its behavior will require making assumptions based on the questions we want to pursue.

Second, we can compare the influence of different type of disruptions through changing the actual disruption information π. Oke and Gopalakrishnan (2009) summarize three categories of disruption risk: high-likelihood & low-impact (eg, operational disruptions, demand variation), medium-likehood & medium-impact (eg, loss key supplier, ecomonic) and low-likehood & high-impact (eg, natural disaster). By further adjusting this preliminary model to vary the probability of occurrence $p(\pi)$ and the disruption severity π, we can also measure the value of disruption information in different situations.

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