ABSTRACT

MCCOY, JESSICA. The Impact of Internet Disruption to an Information-Sharing Supply Chain. (Under the direction of Russell E. King.)

As more business transactions rely on the internet, a sudden system failure that shuts down the internet could leave companies and factories without the ability to communicate. In this paper we investigate the impact of an information disruption on the expected gain of a single-product two-stage information-sharing supply chain.

A supply chain consisting of a supplier and a retailer can be modeled as a completely observable Markov decision process (MDP) when inventory information is fully shared. The system state space is two-dimensional, composed of the local states (inventory levels) of supply chain members. When information is not fully shared, the system can be modeled as a partially observable Markov decision process (POMDP). Wei *et al.* [19] develop a methodology to determine the value of information in a serial supply chain. The results show that a supplier and retailer who share inventory information dominate a pair which does not share information. This paper considers a supply chain operating at steady state under an optimal information sharing policy (i.e. the expected revenue under that policy is the maximum attainable for that configuration and cost structure).

Suppose that some unexpected event eliminates internet communication between the supplier and the retailer of that supply chain, and the two can no longer share their inventory information. The supplier and the retailer may choose to make decisions based on their optimal “no information sharing” policies until internet communication is reestablished. To model an information disruption and the subsequent recovery, the per-period expected gain can be calculated from the iteration of different information sharing policies using successive approximation techniques first proposed by White [21]. The proposed contingency plan can be simulated and analyzed to study the effects that it has on the expected gain of the supply chain. Experimentation involving the underlying cost structure of the policies can determine which system parameters have the most effect on revenue loss in the event of an information disruption.

In general, increases in the holding cost to the supplier, holding cost to the retailer, the lost sales cost to the retailer, the fixed ordering cost to the supplier, and the unit wholesale cost to the supplier all lead to greater losses of revenue for the supply chain as a whole. Increases in the fixed ordering cost to the supplier and the unit wholesale cost to the supplier primarily drive the revenue loss. Changes in the cost parameters have little effect on the amount of time necessary for a full recovery from an information disruption; the variability of the demand distribution is responsible for the length of the recovery period. In addition, we find that longer information disruptions lead to greater loss for the supply chain.

THE IMPACT OF INTERNET DISRUPTION TO AN INFORMATION-SHARING SUPPLY CHAIN

by
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A thesis submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the Degree of
Master of Science

INDUSTRIAL ENGINEERING

Raleigh, North Carolina

2007

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Biography

Jessica McCoy was born the oldest of Jack and Melanie McCoy's three children. She grew up in Grifton, North Carolina and moved to Durham in 1999 to attend the North Carolina School of Science and Mathematics. After graduating from high school in 2001, Jessica entered the College of Engineering at North Carolina State University. There, she matriculated into Industrial Engineering and chose to double major in Applied Mathematics. During her undergraduate career, she completed a three-term co-op for Philip Morris USA, studied abroad in Peru, Italy, and Brazil, and pursued a minor in each Spanish and Italian Studies. She devoted a significant amount of time to several on-campus organizations, including the NCSU Chapter of Habitat for Humanity, the Caldwell Fellows Program, the University Honors Program, and the University Scholars Program. She began working with Dr. Russell King and Dr. Thom Hodgson in the fall of 2004 as an undergraduate research assistant, and continued to research under them for her thesis.

In August 2006, Jessica entered the NCSU Graduate School to officially begin her M.S. of Industrial Engineering as part of the Accelerated B.S./M.S. program. She was supported by a National Science Foundation Graduate K-12 Fellowship through the College of Engineering's Recognizing Accelerated Math Potential in Underrepresented People (RAMP-UP) program. With this program, she supervised nine undergraduates in their work at two area schools and sustained outreach efforts at those schools.

Jessica looks forward to graduating in August 2007, at which point she will head west to join the Management Science and Engineering Department of Stanford University in pursuit of her doctoral degree. She was awarded both the National Defense Science and Engineering Graduate Fellowship and the National Science Foundation Graduate Research Fellowship for her time at Stanford.

Go Wolfpack!

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1 Introduction and Background

Current issues such as rising fuel costs and shorter product cycles have thrust the study of supply chain and logistics into the spotlight. Competition between rivals is asserted not only through product differences, but also through the speed with which a company can respond to demand and changes in the market and in the supply chains of which that company is part. Due to drastic improvements in technology over the last several decades, the most modern businesses have turned to digital information to communicate data along supply chains. Recent work regarding the value of information to the operation of a supply chain has introduced some of the opportunities inherent in this shift. Wei *et al.* [19] use Markov decision processes (MDPs) to quantify the value of sharing inventory information to various supply chain members. Their work demonstrates that a supply chain without information sharing may operate suboptimally.

Lee *et al.* [11] describe the sources of and costs associated with the bullwhip effect in supply chains. Fuller *et al.* [6] estimate that 25-33% of the annual grocery industry is tied up in excess inventory exacerbated by the bullwhip effect. Sharing inventory information is critical in diminishing the distortion of information that increases as one moves further from the final point of sale in a supply chain. The policy adopted for an information-sharing chain reduces costs and therefore raises the profit of involved members. This paper investigates the effects of a disruption to the flow of information on such a supply chain, which is heavily dependent on real-time information sharing.

When studying the effects of supply chain disruptions and the merits of different risk management strategies, much work has been done on production disruptions (for example, the loss of the production of a supplier due to a natural disaster). Tomlin [18] compares risk management strategies in the case of a production failure by natural causes; he references the fire that paralyzed chip production for a Philips plant and sent shock waves through the cell phone manufacturing industry [10]. A series of economic reforms in Eastern Europe changed the communication structure between dairy farmers and processors, and a case study of the situation in Moldova concluded that the supply chain disruption resulted in a "market failure" [7]. Bartholomew [1] describes more recent supply chain catastrophes and asserts that, due to ever-leaner operations, supply chains have become “more unwieldy to manage.” Blackhurst *et al.* [2] agree: “the trend towards customer response time, increased agility and lower inventory levels, in essence, increase the potential negative impact of a disruption.”

Reduction in safety stock across supply chains is not the only modern trend that increases the consequences of a major disturbance. Widespread technological vulnerabilities such as the Y2K problem as well as heightened security due to 9/11 have greatly affected contingency policies across the board. One researcher estimates additional annual logistics costs due to new security regulations in the United States alone at $65 billion [4]. In light of increased probability of a production or transportation disruption, organizations should prepare contingency plans to employ until recovery. Unfortunately, as little as 5-25% of Fortune 500 companies have such policies in place to implement in the case of crisis [14].

To recover more quickly from a disruption – either in demand or supply – communication with the other members of the supply chain is critical [12], [15], [17]. In today’s world, “communications is essential in bringing about action,” and “without communications support, a manufacturer could not operate” [13]. The sharing of inventory data has been shown to be advantageous not only in the day-to-day operation of a supply chain, but is also crucial in rapid recovery in the event of a production disruption. However, disruptions in a supply chain are not limited to production. As more and more business transactions occur with strong reliance on the internet, a sudden system failure that reduces or even eliminates internet communication would cripple many organizations. A massive power outage or the criminal elimination of the router infrastructure could leave businesses and factories unable to communicate. The consequences of a sudden loss of information on the ordering or production policy and therefore on the expected profit of a supply chain are addressed in this paper, as well as the length of the recovery period once information communication is reestablished.

As in previous work, the system here can be modeled as a Markov decision process with restricted observations (ROMDP) which is a special case of a partially observable Markov decision process (POMDP). Wei *et al.* [20] develop a computationally efficient technique for supply chain problems, using work by Serin and Kulkarni [16] as a basis for understanding MDPs with observability constraints. This allows larger and more realistic problems to be analyzed over what can be studied with existing computing methods. By iterating efficiently through the state space to reach optimality using the methods elaborated by Davis *et al.* [5] and Wei *et al.* [20], the transition probabilities matrix and steady-state probabilities for the whole supply chain can be generated for both the full and no information sharing models. These matrices can be used to model a supply chain operating in steady state under an information sharing policy, an information disruption to that supply chain, and subsequent recovery when internet communication is reestablished. Figure 1 illustrates these three phases:

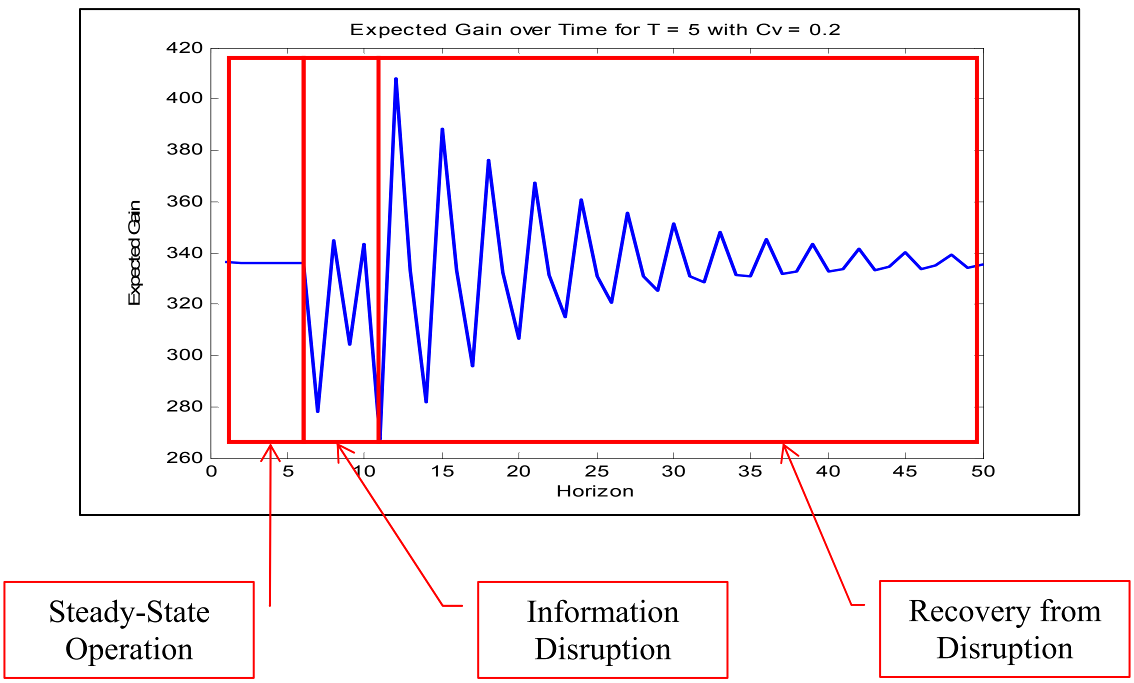

Figure 1: Expected gain of an information-sharing supply chain before, during, and after a five-period information disruption.

During an information disruption, the optimal control policy for the no information sharing case is applied. State probabilities are determined using this control policy starting with the steady state probabilities of the full information sharing model to reflect decision making. The no information sharing transition matrix is applied iteratively to create new state probabilities to simulate the contingency plan. By calculating the expected gain at each step, the effects that an information disruption has on the profit of the system can be analyzed. The procedure is reversed to simulate the return of internet; that is, the optimal policy for the full information sharing model is applied starting with the most recent state probabilities from the disruption phase until steady state is reached again.

2 Methodology

As a system with a definable state space and set of probabilistic transitions, a two-stage supply chain can be modeled as an MDP. The one-step, transition probability matrix **P** records the probability of transitioning from one state to another over one transition or period, for all combinations of states. For a completely ergodic MDP, the probability of transitioning into a state is the same regardless of the initial system state. The transition matrix is used to calculate the state probabilities $\boldsymbol{\pi}$; for a completely ergodic process,

$$\boldsymbol{\pi} = \boldsymbol{\pi} \cdot \mathbf{P} \tag{1}$$

In addition, there may be some reward or cost associated with transitioning from one state to another; the expected rewards for the next transition for each state are tabulated in the matrix **q**. The gain g of a supply chain in steady state can be calculated in vector form using these expected rewards as

$$g = \boldsymbol{\pi} \cdot \mathbf{q} \tag{2}$$

where $\boldsymbol{\pi}$ is the vector of steady state probabilities, and **q** is the vector of expected immediate rewards for all states. The notation used here is borrowed from Howard [9].

For a simple two-stage system with only one alternative for any given state, **P** is a two-dimensional matrix and $\boldsymbol{\pi}$ and **q** are vectors. Element p_{ij} is the probability of transitioning from state i to state j, π_i is the steady state probability associated with state i, and q_i is the expected one period reward of state i. The dimensions of **P** and **q** increase accordingly when multiple alternatives are considered for each state; p_{ij}^k and q_i^k are defined as before for i and j, under alternative k. The two-phase method described in Howard [9] cycles between the value-determination operation and the policy-improvement routine and results in an optimal policy for the system. Since the state space is composed of inventory levels, an optimal policy dictates the best decision (order/production quantities) to be made at any given state; for example, "when the retailer's inventory is 3 units and the supplier's inventory is 5 units, the retailer should order 2 units and the supplier should order 1 unit."

Work done by Wei *et al.* [19] determines the optimal policies for a series of information-sharing models, including a model where the supplier and the retailer share information (the information sharing model) as well as a model where the supplier and retailer *do not* share inventory information (the no information sharing model). The information sharing model can be solved as a centralized MDP where a central observer can see the states of both the retailer and the supplier. The no information sharing model is decentralized and must be solved iteratively; alternately, either the supplier's policy or the retailer's policy is fixed and the other entity's policy is optimized. From analysis of their five two-stage models, Wei *et al.* [19] conclude that sharing information is beneficial to the expected gain of the supply chain, and that information flowing contrary to the flow of material is equivalently profitable to a full two-way information sharing model.

Wei *et al.* [19] use Howard's two-phase method as the basis for their heuristic. Howard's method solves simultaneous equations in two phases (value determination and policy improvement; equations 3 and 4, respectively) to reach an optimal control policy:

$$g + v_i = q_i + \sum_{j=1}^{N} p_{ij} \cdot v_j \qquad \forall i = 1,\ldots,N \tag{3}$$

$$\max_k \left\{ q_i^{\,k} + \sum_{j=1}^{N} p_{ij}^{\,k} \cdot v_j \right\} \quad \forall i = 1,\ldots,N \tag{4}$$

where v_i is the reward of starting the process in state i. In the value determination operation (equation 3), the transition probabilities **P** and the expected immediate rewards **q** are used to solve the set of n linear equations for v_i and g. The value determination operation must be applied to a policy, either an initial policy (e.g., a vector of ones) or the policy resultant from the previous iteration of the policy improvement routine. Using the solution set of v_i from the value determination procedure, the policy improvement routine is applied to find the policy that maximizes the expected reward (equation 4). This policy is returned to the value determination phase; optimality is guaranteed when each phase is allowed to converge.

The simultaneous equations approach is a powerful modeling tool, but falls short computationally when the state space is large. White [21] builds on Howard's techniques with the introduction of the successive approximations method to improve computational efficiency for large-scale problems. To combat roundoff error inherent in problems with long horizons, White proposes that the absolute rewards be scaled relative to an arbitrarily-chosen v_i:

$$
\begin{aligned}
&V_i(n) = \max_k \left\{ q_i^k + \sum_{j=1}^{N} p_{ij}^k \cdot v_j(n-1) \right\} \\
&g(n) = V_N(n) \\
&v_i(n) = V_i(n) - g(n) \qquad\qquad i = 1, 2, \ldots N
\end{aligned}
$$

where V_i is the absolute reward and v_i is the relative reward (scaled arbitrarily by V_N) of starting the process in state i with n periods left to go in the horizon; the above equations assume the existence of $\mathbf{V}(n\text{-}1)$ and $g(n\text{-}1)$.

Hodgson and Koehler [8] apply cheap iterations to a value-determination operation to approximate the steady state v_i before applying a policy optimization phase (instead of optimizing every period as in White's method). Using a restricted number of iterations instead of iterating until convergence reduces computational time needed to calculate the relative rewards, but may require more cycles to reach the optimal policy.

Wei *et al.* [19] use Markov decision processes and the methodology developed by Howard [9], White [21], and Hodgson and Koehler [8] to model supply chains that utilize several levels of information sharing. As a system with MDP characteristics (i.e., a definable state space and set of probabilistic transitions) where all information is available to a single viewer, a full information sharing supply chain can be modeled as a completely observable MDP with a central omniscient decision maker. Wei *et al.* [19] apply their solution methodology to this model in order to find the ordering policies of the supplier and retailer which maximize the revenue of the supply chain. Supply chain profits gained from sharing inventory information can be split between members via negotiations.

The case of a supply chain which does not share information is more complex, and Wei *et al.* [20] employ a decentralized restricted observation Markov decision process (DEC-ROMDP) to accommodate multiple decision makers (in this case, the supplier and the retailer) in the absence of full observability. Their model alternates between the policies of the supplier and retailer, fixing one and optimizing the other until both converge to policies that maximize net supply chain revenue. The DEC-ROMDP is a subset of the restricted observation Markov decision process (ROMDP) developed by Davis *et al.* [5] for a two-stage supply chain where the retailer follows a fixed policy (e.g., a (Q,r) policy with given parameters) and the only supplier's policy need be determined.

For the models where information is not fully shared, the state of the system is not known precisely at any given point in time. Whereas in a completely observable model, a supplier's policy might be different for any combination of the supplier and retailer inventory levels, if the retailer's inventory level is unknown to the supplier then the supplier's policy is wholly dependent on the supplier's own inventory. Similarly, if the inventory level of the supplier is unknown to the retailer, then the retailer's ordering policy relies only on the retailer's own inventory level. Consider the following example of a system where the supplier and retailer each have capacity 2:

Supplier's Inventory \ Retailer's Inventory	0	1	2
0	k_1	k_2	k_3
1	k_4	k_5	k_6
2	k_7	k_8	k_9

(a)

Supplier's Inventory \ Retailer's Inventory	0	1	2
0	k_1	k_1	k_1
1	k_2	k_2	k_2
2	k_3	k_3	k_3

(b)

Supplier's Inventory \ Retailer's Inventory	0	1	2
0	k_1	k_2	k_3
1	k_1	k_2	k_3
2	k_1	k_2	k_3

(c)

Figure 2: Illustration of state groups

In a completely observable scenario, the supplier and retailer each have a policy as tabulated in (a) where the order quantity k_i depends on both inventory levels. If the supplier does not have access to the retailer's inventory level, her policy would resemble (b) where the policy only depends on the supplier's inventory level. Similarly, if the retailer does not have access to the supplier's inventory level, her policy would resemble (c) where the policy only depends on the retailer's inventory level. The lack of full observability reduces the state space into state groups; a supply chain member's policy must be consistent across the groups.

Instead of applying Howard's policy improvement routine (equation 4) to optimize the policy for all states, Wei *et al.* [20] find the set of alternatives k that maximizes the gain for all state groups G through the following equation:

$$\max_{k} \sum_{i \in G(j)} \pi_i \left\{ q_i^{\,k} + \sum_{j=1}^{N} P_{ij}^{\,k} \cdot v_j \right\} \tag{5}$$

The global optimality guaranteed under Howard's assumed conditions and methods cannot be guaranteed under the relaxation for state groups.

To find the steady-state characteristics of both information sharing models, Wei *et al.* [19] apply Hodgson and Koehler's methodology to Howard's two-phase procedure. The system cycles back and forth between the two phases until the same policy is obtained twice in a row and the cumulative change in the relative values v_j over all states j, is small (or until the differences between a policy and the previous policy are below a small defined limit, to account for loss of precision due to roundoff error). Because of the state group relaxation, the solution can only be guaranteed to be a local optimum. Wei *et al.* [20] apply a series of perturbations to the solution reached by the two-phase cycle to further improve upon the successive approximations methods. Improved solutions are sought by slighting changing and rescaling the steady state probabilities or by substituting a sub-optimal policy for the best policy (e.g., the second-best policy) in the policy improvement phase, and then applying the two-phase routine to the newly perturbed system. The perturbations potentially allow the system to move away from one local maximum to a better local maximum. Wei *et al.* [20]

find that a combination of small perturbations on the policy and on the steady state probabilities of a system yields solutions with higher net revenues for the supply chain.

Wei *et al.* [19] define a set of parameters (e.g., inventory capacity, holding costs, and customer demand) derived from experience with the apparel retail industry for their experimental designs. By applying their methods to that set of parameters, the defining matrices and policies of an information sharing policy and of a no information sharing policy for the chain can be calculated. This output – steady state probabilities, transition probability matrices, expected immediate reward matrices, and policies – is in turn used for the investigation at hand.

Suppose a two-stage supply chain has adopted the optimal information sharing policy and is operating at the expected gain according to that policy. Some unexpected and potentially catastrophic event eliminates internet communication between the supplier and the retailer and the entities are unable to share their respective inventory information. At the loss of internet communication, the supplier and the retailer may choose to implement the optimal no-information-sharing policy immediately as the primary contingency plan; this policy is associated with the maximum expected revenue for the supply chain as a whole when no information is shared between the supplier and retailer. This paper models and analyzes just such an occurrence.

2.1 Model Assumptions

Consider a two-stage supply chain consisting of a supplier and a retailer; the supplier here is thought of as having her own upstream supplier. Without loss of generality, the model could be a production model where the supplier is a manufacturer who produces goods to be passed on to the retailer. For the purposes of this investigation, the supply chain is focused on a single product and is operating over an infinite horizon. The supplier and retailer are both limited in their order quantities by inventory capacity and have a series of costs associated with operation such as inventory holding costs, penalty or lost sales costs, and ordering costs (fixed and variable). The per-period event sequence for each member is detailed as follows:

- **Supplier**: The supplier's inventory holding cost is incurred at the beginning of the period based on inventory held at that time. The supplier may choose to place an order such that she does not exceed her own capacity; the upstream supplier is perfect and both fixed and variable ordering costs are incurred. After ordering decisions have been made, the supplier receives the order from the retailer and ships product from current inventory. If the retailer's order quantity exceeds the supplier's on-hand inventory, unmet demand is lost. At the end of the period, the supplier's newly-arrived shipment is added to on-hand inventory.

- **Retailer**: The retailer's inventory holding cost is incurred at the beginning of the period based on inventory held at that time. The retailer may choose to place an order such that she does not exceed her own capacity, but that order will only be filled to the extent that the supplier has sufficient inventory. Over the course of the period, the retailer experiences demand and meets that demand as possible. If demand occurs in excess of the inventory held at the retailer, the retailer incurs a stock out cost as lost demand is not backordered. If applicable, the retailer receives a shipment from the supplier at the end of the period (resultant from any previously-placed order).

The event sequences and parameters values are important assumptions in the development of the cost structure, which is delineated more clearly in the following section. These assumptions are used to construct the parameters of the MDP models such as the transition probability matrix and the expected immediate rewards vector. The aforementioned methodology is, in turn, applied to these MDP parameters to maximize the performance of the supply chain through the optimization of supplier and retailer ordering policies.

2.2 Model Parameters

The notation here is borrowed from Wei *et al*. [19]; they define the following parameters:

x: A member of the supply chain; either the supplier (s) or the retailer (r).

c_x: The inventory capacity for supply chain member x.

w_x: The unit purchase (wholesale) cost for supply chain member x.

h_x: The unit holding cost per period for supply chain member x.

f_x: The fixed cost per order for supply chain member x.

l_x: The unit lost sales cost for supply chain member x.

i_x: The inventory level of supply chain member x; $i_x = 0,1,\ldots,c_x$.

k_x: The order quantity placed by supply chain member x.

V: The unit selling price to the customer.

D: The random variable representing customer demand. It is assumed that the demand each period is independently and identically distributed and is in the range $[0, c_r]$. The value d represents a particular instance of this random variable.

N: The length of the horizon under evaluation.

T: The length of information disruption.

Of the above cost parameters, some are considered internal costs of the supply chain (i.e., those that result from transactions between the retailer and the supplier) and do not factor into the expected gain calculations. Specifically, the unit lost sales cost to the supplier (l_s), the fixed order cost for the retailer (f_r), and the unit purchase cost for the retailer (w_r) are assumed to be zero for the purposes of calculating expected gain for the whole supply chain.

The state space for the MDP models is two-dimensional; system state i corresponds to local states (i_s, i_r) where i_s is the supplier's inventory level and i_r is the retailer's inventory level. State i = (i_s, i_r) transitions to state j = (j_s, j_r) where

$$\begin{aligned} j_s &= \max\left(i_s - k_r, 0\right) + k_s \\ j_r &= \max\left(i_r - d, 0\right) + \min\left(i_s, k_r\right) \end{aligned}$$

If the system is in state i, experiences demand d, and the supplier and retailer follow policies (k_s, k_r), the immediate reward for each the supplier and the retailer can be calculated as

$$\begin{aligned} q_s(d) &= -\left[h_s \cdot i_s + w_s \cdot k_s + f_s \cdot \min\left(k_s, 1\right)\right] \\ q_r(d) &= v \cdot \min\left(d, i_r\right) - \left[l_r \cdot \max\left(d - i_r, 0\right) + h_r \cdot i_r\right] \end{aligned}$$

The immediate reward for the supply chain as a whole is the sum of the two, and the expected immediate reward out of state i is calculated using the probability mass function of the demand distribution:

$$q_i = \sum_{d=0}^{c_r} p_D\left(d\right)\cdot\left(q_s(d)+q_r(d)\right) \quad \forall i$$

These expected immediate rewards are then used in conjunction with the state probabilities $\boldsymbol{\pi}$ to determine period gain for the supply chain as will be addressed in section 2.3. To analyze the effects that specific parameters (e.g., the holding cost of the supplier) have on the gain, $\mathbf{q}$ can be partitioned into parts associated with the different parameters and then used to calculate a partitioned expected gain.

2.3 Modeling a Disruption and Contingency Action

Modeling a disruption and the implementation of the proposed contingency plan is straightforward. Before the internet disruption occurs, the period gain is calculated by equation 2 and the new state probabilities for the next period are determined with equation 1 using the probability transition matrix $\mathbf{P^{IS}}$ and the expected immediate reward matrix $\mathbf{q^{IS}}$ from the optimal information sharing policy:

$$\boldsymbol{\pi}\left(0\right) = \boldsymbol{\pi}^{\mathbf{IS}} \cdot \mathbf{P^{IS}}$$
$$g(0) = \boldsymbol{\pi}\left(0\right)\cdot \mathbf{q^{IS}}$$

At the loss of information, the same two equations are used to track the expected gain, but with $\mathbf{P^{N}}$ and $\mathbf{q^{N}}$ from the optimal solution under no information sharing instead:

$$\boldsymbol{\pi}\left(n\right) = \boldsymbol{\pi}\left(n-1\right)\cdot \mathbf{P^{N}}$$
$$g(n) = \boldsymbol{\pi}\left(n\right)\cdot \mathbf{q^{N}}$$

When internet communication with the retailer is reestablished, $\mathbf{P^{IS}}$ and $\mathbf{q^{IS}}$ from the optimal information sharing policy can be applied again to calculate the profit per period:

$$\boldsymbol{\pi}\left(n\right) = \boldsymbol{\pi}\left(n-1\right)\cdot \mathbf{P^{IS}}$$
$$g(n) = \boldsymbol{\pi}\left(n\right)\cdot \mathbf{q^{IS}}$$

The expected gain per period can be calculated for a supply chain following an information sharing policy; this per-period gain can be multiplied by the length of a horizon for a total anticipated expected gain in the absence of an information disruption. Across the same horizon, the expected gain per period in the event of an information disruption and subsequent switch to a no information sharing policy can be calculated according to above equations. These period gains can be summed over the horizon to represent the actual expected gain in the event of an information disruption. To compare different scenarios, the Percent Revenue Loss (PRL) is defined as:

$$PRL = \frac{g^{IS} \cdot N - \sum_{n=1}^{N} g(n)}{g^{IS} \cdot N}$$

where g^{IS} is the expected per-period gain under an information sharing policy, $g(n)$ is the expected gain of the system of period n, and the horizon under consideration is N periods long (N includes the disruption as well as initial recovery).

3 Experimentation

Two experimental designs are performed to investigate the effects of changing the cost parameters on the expected gain of the supply chain (as measured by PRL). The first design is a factorial arrangement, where each factor has a “low” and “high” level. This design reveals both the effects of increasing one parameter at a time and the effects of increasing multiple parameters simultaneously. The second design is more simple in nature; each parameter is increased individually to study the effects of a single parameter increase on the expected supply chain gain. The range of values selected for each parameter is chosen to reflect potential applications; the upper bound of that range is pushed until the expected gain for the supply chain becomes negative.

The initial values for both experimental designs are primarily based on the design used by Wei *et al.* [19], where values were chosen from experience in the retail apparel industry. The demand profiles used are truncated normal distributions with mean 5 and coefficients of variation (CV) ranging from 0.2 to 0.8.

3.1 Experimental Design 1

For the first design of experiments, a factorial arrangement is applied to six parameters (h_s, h_r, w_s, l_r, f_s, and T) for each of four demand profiles with varying standard deviations. This arrangement results in 256 different sets of parameters as inputs to the model.

Table 1: Experimental Design 1 – Factorial design.

Mean	**CV**	c_s	c_r	h_s	h_r	w_s	w_r	l_s	l_r	f_s	f_r	V	T
5	0.2	15	15	1	1	10	0	0	100	50	0	100	1
	0.4			2	2	20			200	100			5
	0.6												
	0.8												

In general, an increase in any parameter or combination of parameters except for the holding cost of the supplier results in an increase in PRL. All cases where the holding cost for the supplier is set to its high level of $2/unit/period result in a lower PRL; that is, the higher value of h_s reduces the effects of an information disruption on the expected gain of the supply chain. The base case (where all parameters are set to their low level) is compared with five cases in Figure 4 through Figure 7. These cases were selected from the larger population tested because they demonstrate high levels of revenue loss. Each scenario is a different combination of h_s, h_r, w_s, l_r, and f_s, as applied to each of the four demand profiles. Figure 3 demonstrates the expected gain of a supply chain during and after an information disruption of one period under one of the scenarios tested in the factorial design. At time 1, the supply chain is operating at steady state under an information sharing policy. Internet communication is lost at time 2 for one period, and decisions made during that period are pursuant with the optimal no information sharing policy. Even though internet communication is restored in period 3, the system does not return to steady state until 53 periods after the disruption.

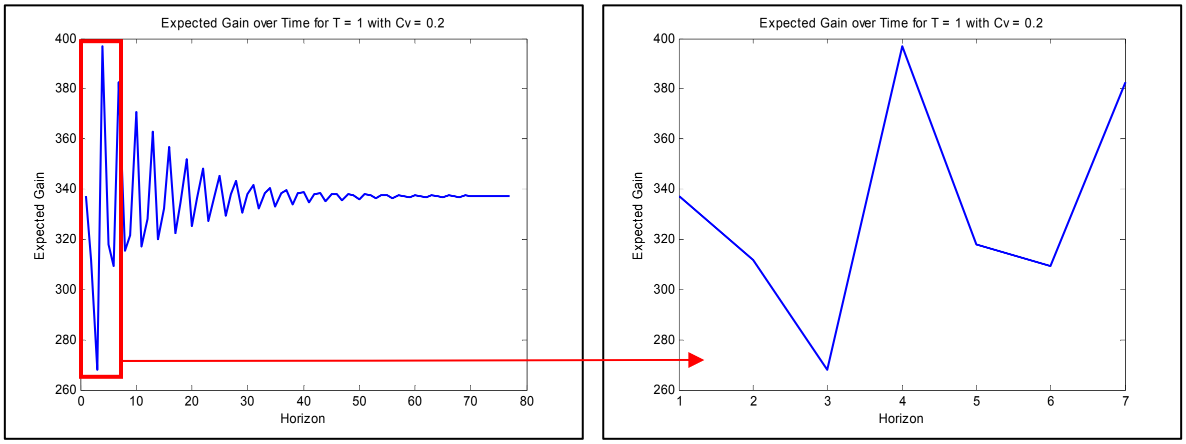

Figure 3: Expected gain during a one-period disruption and initial recovery for case where h_r, f_s, and w_s are set to high and CV = 0.2.

The length of the recovery phase used for PRL calculations has a large effect on the reported loss. For a scenario where the system converges quickly to steady state after a disruption, a lengthy recovery phase could imply that little revenue was lost during the disruption. On the other hand, for a scenario such as that in Figure 3, a short recovery phase in the PRL calculation may imply that the system actually profited from the information disruption (for example, a recovery phase of two periods would include the initial spike after the return of information communication, where a higher-than-normal expected gain was achieved). In both of these extreme cases, a recovery phase that is too short or too long may correspond with misleading revenue loss values; comparisons drawn from such values are not useful. For purposes of calculating the PRL with the intent of comparing several cases, a recovery of five periods was assumed. From the trials performed, five periods appeared to capture the oscillation of the expected gain during the recovery phase without overly emphasizing either the disruption or the subsequent return to steady state. In Figure 3, this translates into using the expected gain for periods 2 through 7 (one period of disruption and five periods of initial recovery) in PRL calculations. Figure 4 and Figure 5 illustrate the revenue loss results (in terms of percentages and absolute dollars) for an information disruption of one period, and Figure 6 and Figure 7 show results for the same scenarios under a disruption of five periods.

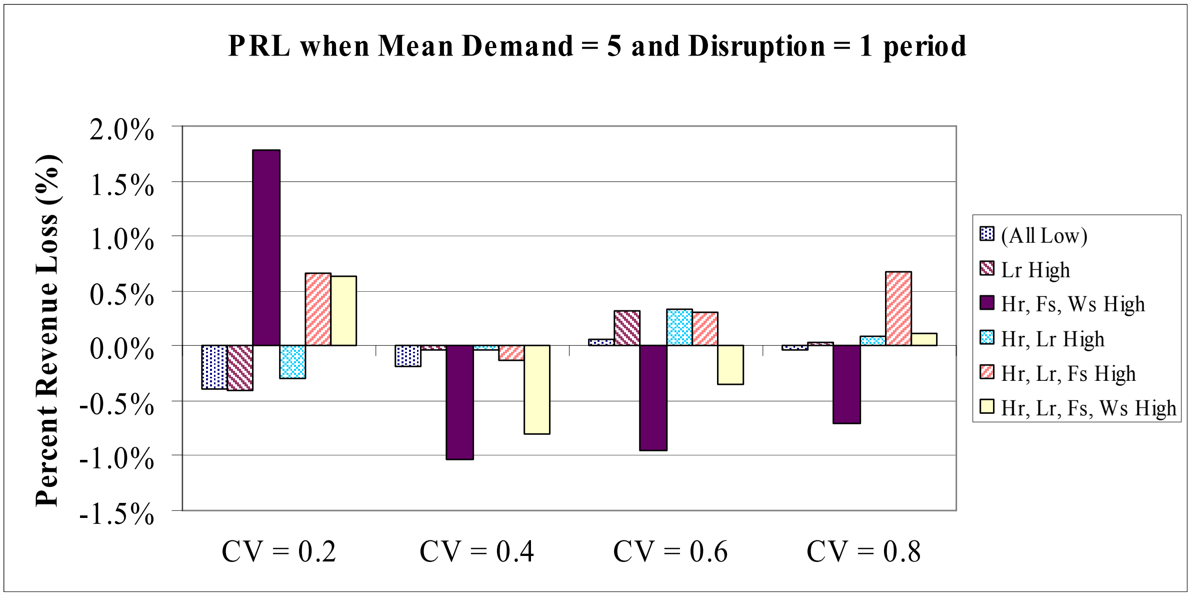

Figure 4: Percent Revenue Loss for six cases of the factorial experimental design; T = 1.

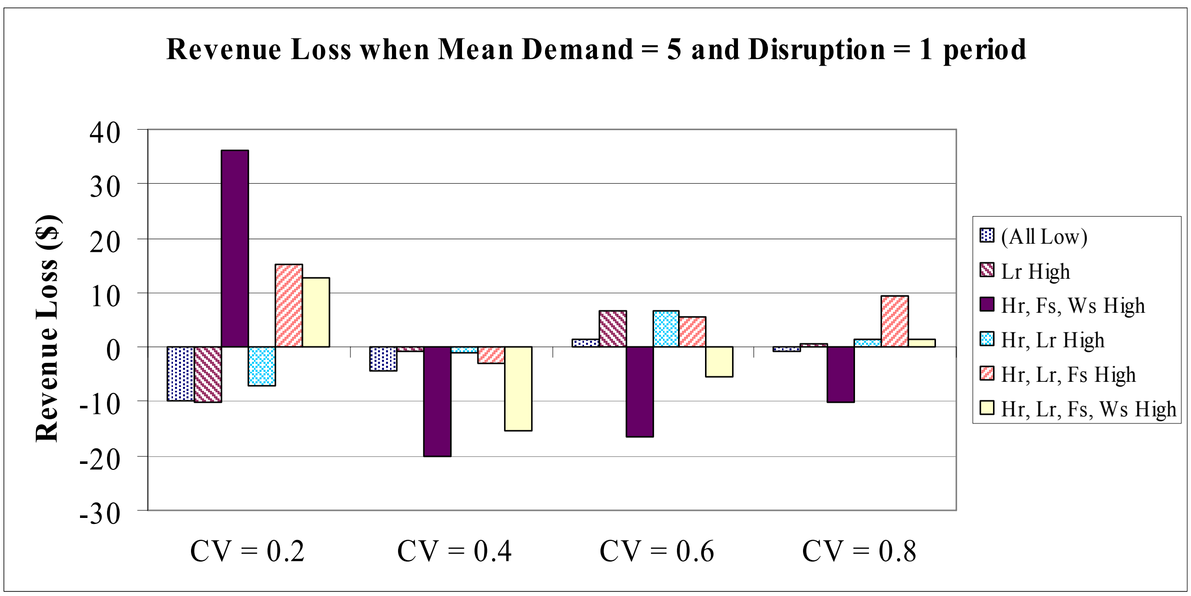

Figure 5: Revenue loss in dollars for six cases of the factorial experimental design; T = 1.

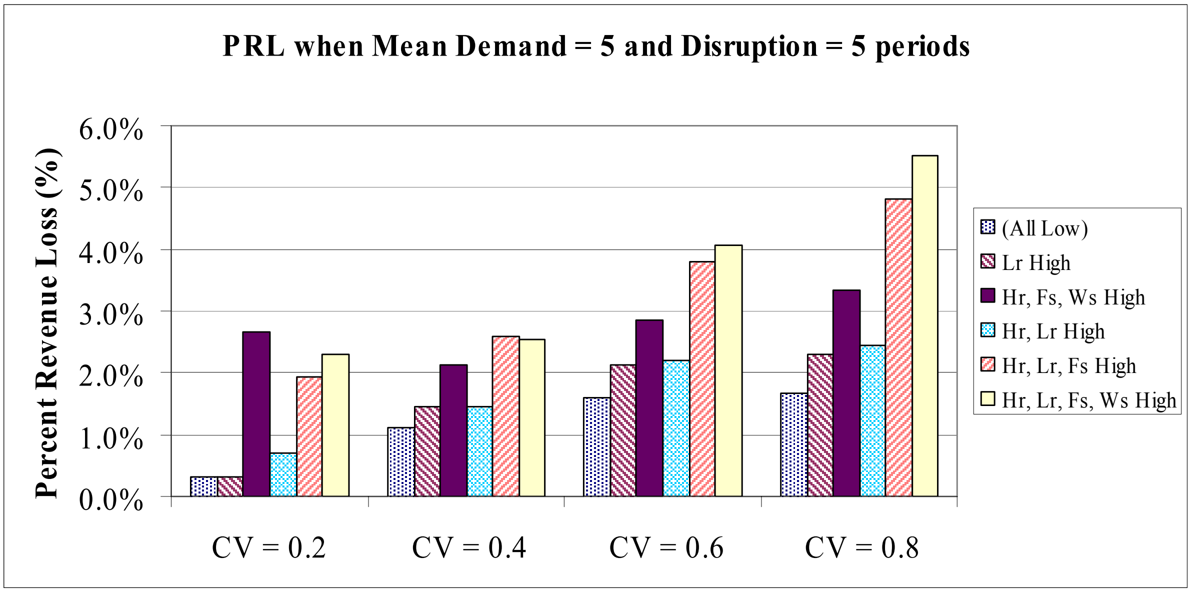

Figure 6: Percent Revenue Loss for six cases of the factorial experimental design; T = 5.

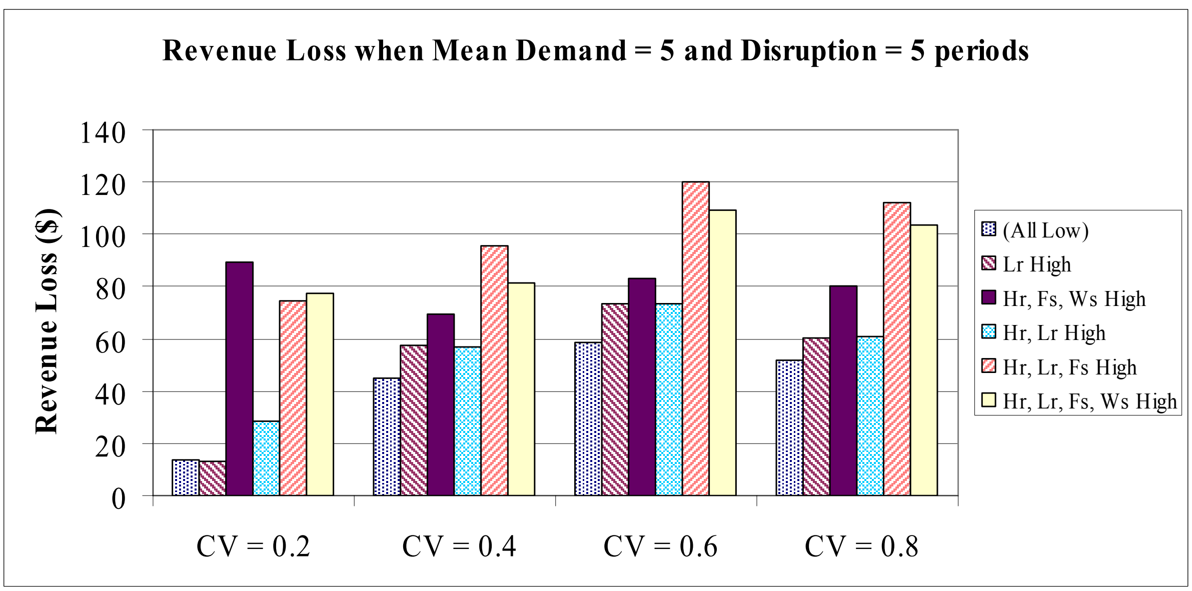

Figure 7: Revenue loss in dollars for six cases of the factorial experimental design; T = 5.

As demonstrated in Figure 4, several of the PRL results for T = 1 are negative, implying that the supply chain benefited from an information disruption of one period. Figure 5 shows that all of these negative values are associated with expected gains no greater than \$20. These results are dependent on the arbitrary definition of the recovery period for the PRL calculation; if the expected gain for a given scenario oscillates such that the recovery period ends when the expected gain is at a high point rather than a low point, the PRL may actually be negative. For all scenarios, over the long run of the systems' return to steady state, revenue was lost. The PRL calculations merely capture the short run for purposes of direct comparison of the different scenarios. When each of those six scenarios is subjected to a lengthier information disruption, all PRL values become positive. That is, when the information disruption lasts for a longer amount of time, the supply chain has the potential to lose more money. Some of the absolute losses experienced by the supply chain exceed \$100, corresponding with around 4-5% of the gain expected during the disruption period and the five subsequent periods.

To identify the parameters responsible for any loss in gain, the expected gain was partitioned into costs associated with each of the nonzero parameters. Without exception in the 256 trials of this experimental design, changes in the expected gain were driven by either the order cost to the supplier (f_s) or the unit wholesale cost (w_s) to the supplier. That is, the largest portion of the change between the expected gain under the steady state information sharing policy and the minimum expected gain achieved during the disruption was attributable to one of those two costs. This result is supported by the analysis of variance of the model. Table 2 lists the sums of squares associated with each of the five cost parameters and their interaction effects. The sums of squares in each column represent how much of the variation of the percent revenue loss data is attributable to each of the 31 main and interaction effects. In each column (i.e., combination of information disruption length and demand profile), the largest component of the total sum of squares corresponds to either the fixed order cost to the supplier or the unit wholesale cost to the supplier.

Table 2: Sums of squares for components of factorial design.

These data correspond to the PRL values expressed as percentages.

	T = 1				T = 5			
	CV = 0.2	CV = 0.4	CV = 0.6	CV = 0.8	CV = 0.2	CV = 0.4	CV = 0.6	CV = 0.8
h_s	0.8105	0.0881	0.0236	0.0349	1.9895	0.3861	0.2770	0.1910
h_r	1.7764	0.0035	0.0003	0.0166	1.4837	0.0040	0.0422	0.1041
l_r	0.8638	0.1445	0.3362	1.0031	0.0691	0.9806	3.9977	13.2798
f_s	**2.5789**	0.2235	0.2183	0.2957	**8.8807**	**10.3797**	**19.1856**	**34.2316**
w_s	0.6110	**3.0227**	**3.1138**	**3.2421**	0.0063	0.1266	0.0016	0.3484
h_s*h_r	1.4567	0.0119	0.0001	0.0021	1.2183	0.0021	0.0007	0.0019
h_s*l_r	0.7384	0.0104	0.0352	0.0046	0.0415	0.0004	0.0055	0.0015
h_s*f_s	0.2241	0.0493	0.0095	0.1422	0.1510	0.0002	0.0047	0.0025
h_s*w_s	0.0494	0.0297	0.0007	0.0030	0.0583	0.0026	0.0002	0.0003
h_r*l_r	0.0276	0.0003	0.0028	0.0015	0.0004	0.0000	0.0019	0.0096
h_r*f_s	0.5495	0.0002	0.0002	0.0281	0.2206	0.0003	0.0029	0.0037
h_r*w_s	0.0571	0.0015	0.0004	0.0069	0.0649	0.0013	0.0012	0.0001
l_r*f_s	0.0022	0.0002	0.4857	1.1638	0.0010	0.0326	0.8803	2.6793
l_r*w_s	0.1316	0.0045	0.0057	0.0002	0.0177	0.0008	0.0083	0.1812
f_s*w_s	0.0735	0.0372	0.0136	0.0564	0.0758	0.0525	0.1045	0.2474
h_s*h_r*l_r	0.1636	0.0091	0.0000	0.0171	0.0068	0.0015	0.0001	0.0011
h_s*h_r*f_s	0.7823	0.0123	0.0046	0.0008	0.2740	0.0020	0.0003	0.0008
h_s*h_r*w_s	0.0339	0.0015	0.0000	0.0113	0.0546	0.0000	0.0002	0.0003
h_s*l_r*f_s	0.0358	0.0565	0.0015	0.0124	0.0349	0.0000	0.0146	0.0085
h_s*l_r*w_s	0.1346	0.0163	0.0207	0.0073	0.0116	0.0007	0.0046	0.0001
h_s*f_s*w_s	0.0003	0.0275	0.0032	0.0070	0.0026	0.0026	0.0000	0.0006
h_r*l_r*f_s	0.0079	0.0001	0.0000	0.0006	0.0117	0.0001	0.0024	0.0011
h_r*l_r*w_s	0.0007	0.0060	0.0006	0.0272	0.0013	0.0011	0.0001	0.0003
h_r*f_s*w_s	0.0496	0.0066	0.0001	0.0029	0.0149	0.0000	0.0010	0.0002
l_r*f_s*w_s	0.0045	0.0003	0.0281	0.0614	0.0024	0.0014	0.0300	0.0801
h_s*h_r*l_r*f_s	0.0192	0.0146	0.0030	0.0192	0.0002	0.0018	0.0015	0.0011
h_s*h_r*l_r*w_s	0.0057	0.0008	0.0001	0.0013	0.0000	0.0000	0.0001	0.0016
h_s*h_r*f_s*w_s	0.0765	0.0005	0.0006	0.0220	0.0164	0.0001	0.0000	0.0021
h_s*l_r*f_s*w_s	0.0041	0.0354	0.0664	0.0092	0.0001	0.0028	0.0143	0.0000
h_r*l_r*f_s*w_s	0.0070	0.0042	0.0000	0.0182	0.0006	0.0001	0.0004	0.0001
h_s*h_r*l_r*f_s*w_s	0.0000	0.0011	0.0003	0.0029	0.0000	0.0001	0.0011	0.0022
Total SS	**11.2764**	**3.8203**	**4.3753**	**6.2220**	**14.7109**	**11.9841**	**24.5850**	**51.3826**

The number of periods to recovery was measured in addition to comparing the PRL for each case. During the simulation, if two consecutive state probability vectors were arbitrarily close to each other, the system was considered to have converged to steady state operation. There appeared to be very little variability involved in the length of the recovery period across the test scenarios of the factorial design; each of the eight columns in the following summary table lists statistics from 32 scenarios. For the purposes of this summary, a system was said to have converged if the sum of the absolute values of the differences between two consecutive state probability vectors was less than 0.01.

Table 3: Expected number of periods required for a system to return to steady state after an information disruption

The following statistics are averaged over all cases of the factorial design for each of four demand profiles (CV = 0.2, 0.4, 0.6, and 0.8).

	T = 1				**T = 5**			
CV	**0.2**	**0.4**	**0.6**	**0.8**	**0.2**	**0.4**	**0.6**	**0.8**
Minimum	34	11	7	5	34	11	7	5
Maximum	54	13	8	6	53	13	8	6
Mean	49.75	11.91	7.09	5.91	49.22	11.84	7.03	5.88
Standard Deviation	4.16	0.64	0.30	0.30	4.26	0.57	0.18	0.34

The choice of 0.01 as the convergence requirement is arbitrary; the following graph illustrates the fall of the difference between two consecutive state probability vectors as the system iterates towards steady state for a representative case. The two peaks illustrate the system's tendency towards steady state during a five-period information disruption, and then again during recovery.

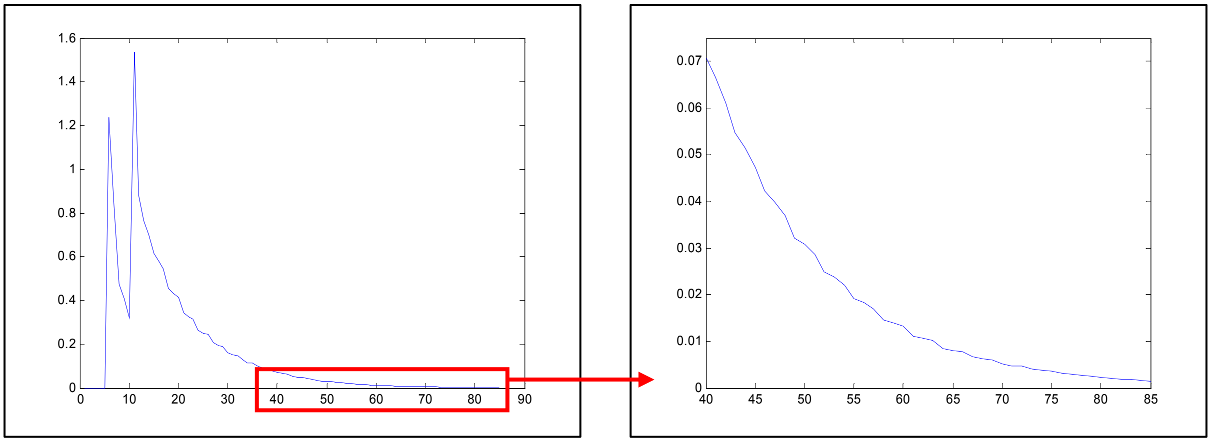

Figure 8: Convergence of state probability vectors for the scenario where h_r, l_r, f_s, and w_s are set to high.

The demand profile with CV = 0.2 yielded the most variation. In all cases tested, models using this distribution took longer to return to steady state than the other distributions. Similarly, models using the distribution with CV = 0.4 took longer to converge than those using CV = 0.6, and models using the distribution CV = 0.8 took the least amount of time to converge. The lesser amount of demand variability associated with the distributions with smaller coefficients of variation causes processes that are nearly cyclic in nature; these processes take longer to converge. Because the transition probability matrices are stochastic, the absolute value of the largest eigenvalue is one. The second-largest eigenvalue determines the rate of convergence of the matrix; the closer the absolute value of this eigenvalue is to 1, the longer it takes for the matrix to converge [3]. Information on these eigenvalues for the transition matrices of the optimal information sharing policy for 32 sets of cost parameters is summarized in Table 4. This data supports the behavior of the system gain in the trials:

Table 4: Absolute values of second-largest eigenvalues of the transition probability matrix for the optimal information sharing policy.

CV	0.2	0.4	0.6	0.8
Minimum	0.8660	0.6531	0.5089	0.4274
Maximum	0.9190	0.7084	0.5805	0.4836
Mean	0.9103	0.6883	0.5392	0.4615
Standard Deviation	0.0107	0.0197	0.0178	0.0151

3.2 Experimental Design 2

The second design of experiments investigates the effects of changing one parameter at a time on the expected gain of the system. Each of the five nonzero cost parameters (h_s, h_r, w_s, l_r, and f_s) was increased individually for each of four demand profiles and two lengths of information disruption. Each parameter increase was halted when the increase drove the expected gain of the supply chain below zero. This arrangement resulted in 224 different sets of parameters as inputs to the model; these combinations are outlined in Table 5 through Table 9.

As in the first experimental design, the losses experienced when the information disruption endured for one period were less significant than those experienced by the supply chain when the disruption lengthened to five periods. Half of the PRL values for a disruption of one period were negative, but the majority of those represented losses of less than $20. In contrast, only ten of the 112 trials conducted for a disruption of five periods resulted in negative revenue losses; all ten values occurred when the unit wholesale cost to the supplier was increased beyond 30. Because many of the results for the second experimental design are similar to those of the first experimental design, only the results from trials with an information disruption of length five periods are outlined here in Figure 9 through Figure 13 and in Tables 5 through 9. For results corresponding to an information disruption of a single period, please refer to the appendix.

In addition to affecting the expected gain of the supply chain, changes in the parameters affected the optimal policies for the supplier and the retailer. Increasing the inventory holding costs (h_s or h_r) corresponded with intuitive decreases in the order quantities for the supplier and the retailer, respectively. Increasing the fixed order cost to the supplier (f_s) caused the supplier to only order when their on-hand inventory level was two units or less. Changes in the lost sales cost to the retailer (l_r) and the unit wholesale cost to the supplier (w_s) had less effect on the policies.

3.2.1 Results from Experimental Design 2a

The holding cost for the supplier (h_s) was increased from its base level of \$1 per unit per period to an eventual maximum of \$40 per unit per period, as outlined in Table 5. The first increase from \$1 to \$10 elicits only a small response in the revenue loss; only when the holding cost increases beyond \$20 does the PRL begin to respond wildly (Figure 9). Such a large increase in the holding cost has a strong effect on the supplier's ordering policy. Higher per-unit inventory costs drive the supplier to hold less inventory and to order less to maintain that smaller inventory.

Table 5: Experimental Design 2a – Increasing the holding cost for the supplier, h_s.

Mean	CV	c_s	c_r	h_s	h_r	w_s	w_r	l_s	l_r	f_s	f_r	V	T
5	0.2	15	15	1	1	10	0	0	100	50	0	100	1
	0.4			10									5
	0.6			20									
	0.8			30									
				40									

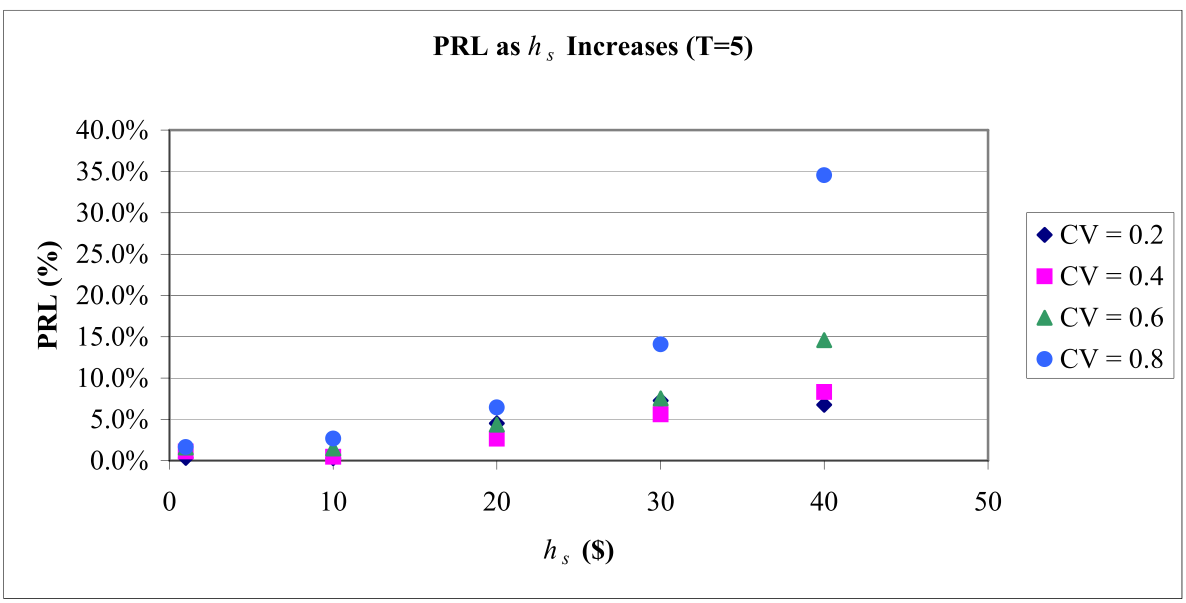

Figure 9: Increasing the holding cost for the supplier, h_s.

The four series correspond with demand profiles of differing coefficients of variation (CV = 0.2, 0.4, 0.6, and 0.8). The graph illustrates results for an information disruption of length five periods (T = 5); for results pertaining to an information disruption of length one period, see the appendix.

3.2.2 Results from Experimental Design 2b

The holding cost for the retailer (h_r) was increased from its base level of \$1 per unit per period to \$30 per unit per period (Table 6). Increases in h_r have less effect than the increases in h_s. Even when the holding cost is \$30, only one demand profile corresponds with a PRL greater than 15% (Figure 10). Beyond h_r of \$30, the retailer's costs are sufficient to push the expected net revenue of the supply chain below zero. As with the holding cost of the supplier, a higher per-unit inventory cost to the retailer causes the retailer to hold less inventory and to order less to maintain that smaller inventory.

Table 6: Experimental Design 2b – Increasing the holding cost for the retailer, h_r.

Mean	CV	c_s	c_r	h_s	h_r	w_s	w_r	l_s	l_r	f_s	f_r	V	T
5	0.2	15	15	1	1	10	0	0	100	50	0	100	1
	0.4				10								5
	0.6				20								
	0.8				30								

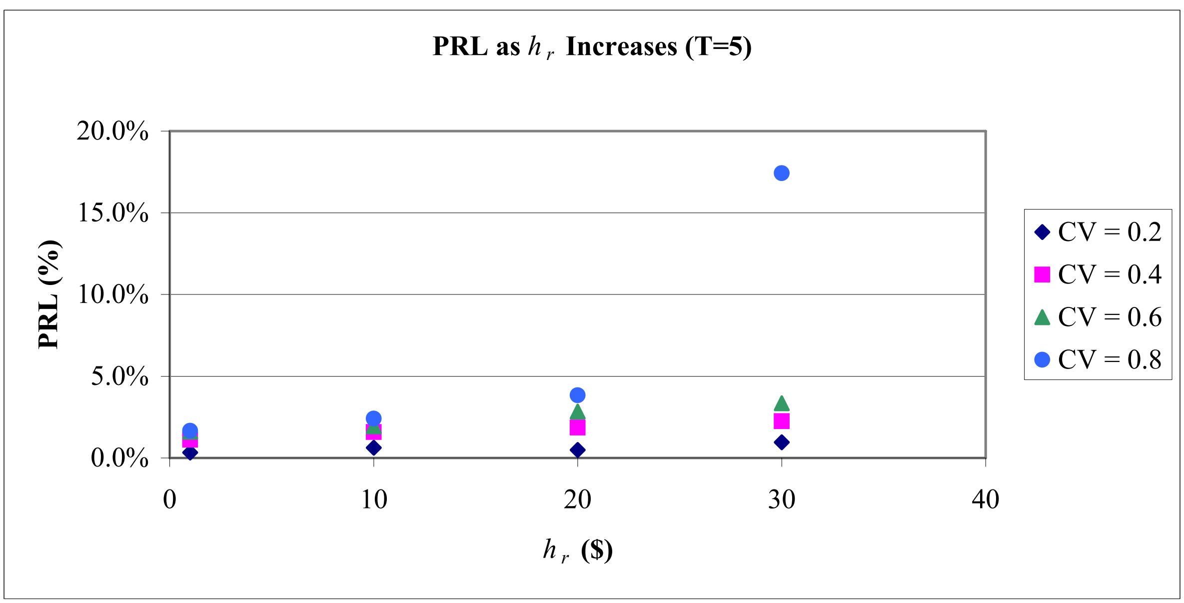

Figure 10: Increasing the holding cost for the retailer, h_r.

The four series correspond with demand profiles of differing coefficients of variation (CV = 0.2, 0.4, 0.6, and 0.8). The graph illustrates results for an information disruption of length five periods (T = 5); for results pertaining to an information disruption of length one period, see the appendix.

3.2.3 Results from Experimental Design 2c

The unit wholesale cost for the supplier (w_s) was increased from $10 per unit per period to $70 per unit per period before the expected net revenue of the supply chain became negative (Figure 11). Changes in this cost parameter have less effect on the PRL than other parameter changes; even a 700% increase failed to budge the PRL beyond ± 2% in all but one case. In addition, changes to w_s failed to cause noticeable changes in the ordering policy for the supplier.

Table 7: Experimental Design 2c – Increasing the unit purchase cost for the retailer, w_s.

Mean	CV	c_s	c_r	h_s	h_r	w_s	w_r	l_s	l_r	f_s	f_r	V	T
5	0.2	15	15	1	1	10	0	0	100	50	0	100	1
	0.4					20							5
	0.6					30							
	0.8					40							
						50							
						60							
						70							

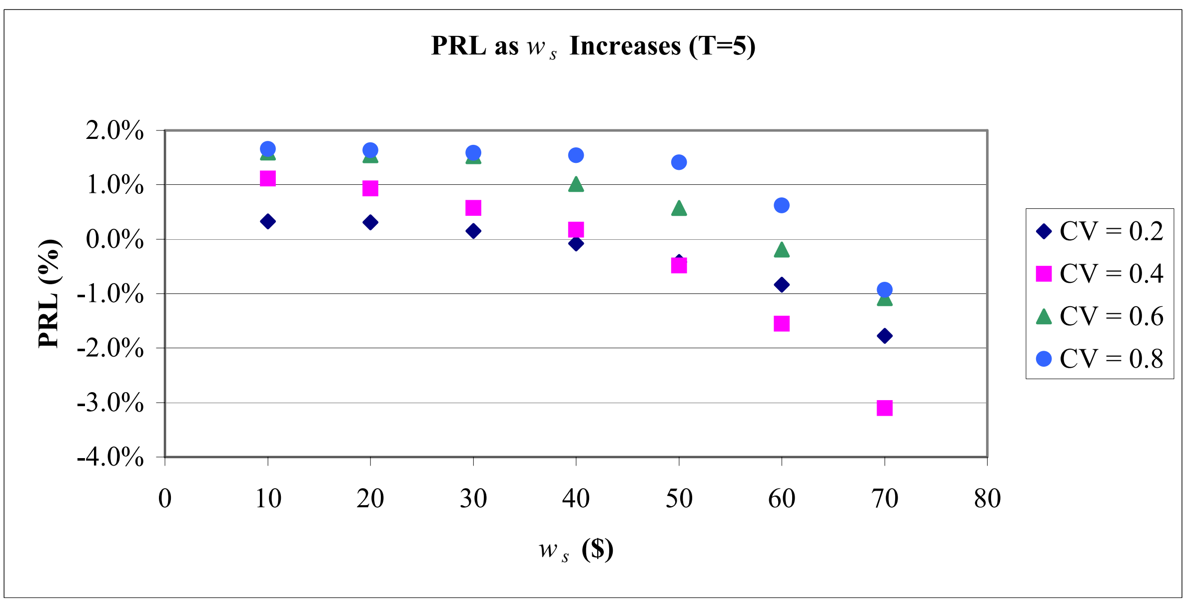

Figure 11: Increasing the unit purchase cost for the supplier, w_s.

The four series correspond with demand profiles of differing coefficients of variation (CV = 0.2, 0.4, 0.6, and 0.8). The graph illustrates results for an information disruption of length five periods (T = 5); for results pertaining to an information disruption of length one period, see the appendix.

3.2.4 Results from Experimental Design 2d

As with the unit wholesale cost to the supplier, the lost sales cost to the retailer has little effect on the policies of the supplier and retailer. Three of the demand profiles are not very sensitive to changes in l_r (Figure 12). The demand profile with the highest coefficient of variation (CV = 0.8) reacts most strongly to changes in the penalty cost; beyond an l_r of \$600, the expected gain of the supply chain becomes negative.

Table 8: Experimental Design 2d – Increasing the lost sales cost for the retailer, l_r.

Mean	CV	c_s	c_r	h_s	h_r	w_s	w_r	l_s	l_r	f_s	f_r	V	T
5	0.2	15	15	1	1	10	0	0	100	50	0	100	1
	0.4								200				5
	0.6								300				
	0.8								400				
									500				
									600				

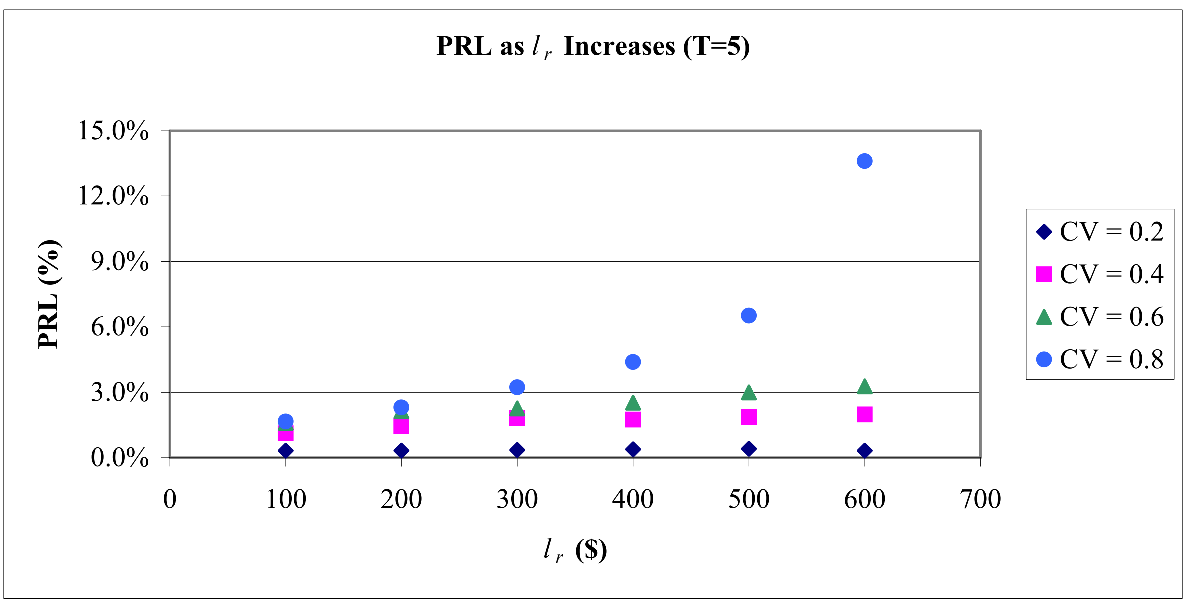

Figure 12: Increasing the lost sales cost for the retailer, l_r.

The four series correspond with demand profiles of differing coefficients of variation (CV = 0.2, 0.4, 0.6, and 0.8). The graph illustrates results for an information disruption of length five periods (T = 5); for results pertaining to an information disruption of length one period, see the appendix.

3.2.5 Results from Experimental Design 2e

Changes in the fixed ordering cost to the supplier are very influential on the revenue loss for all demand profiles (Figure 13). As the fixed ordering cost increases, the supplier's policy shifts to where she only orders when her on-hand inventory is very low (when f_s = 900, the supplier only orders when on-hand inventory is two units or less). When the ordering cost exceeds \$900 per order, the expected net revenue for the supply chain becomes negative.

Table 9: Experimental Design 2e – Increasing the fixed order cost for the supplier, f_s.

Mean	CV	c_s	c_r	h_s	h_r	w_s	w_r	l_s	l_r	f_s	f_r	V	T
5	0.2	15	15	1	1	10	0	0	100	50	0	100	1
	0.4									100			5
	0.6									200			
	0.8									300			
										400			
										500			
										600			
										700			
										800			
										900			

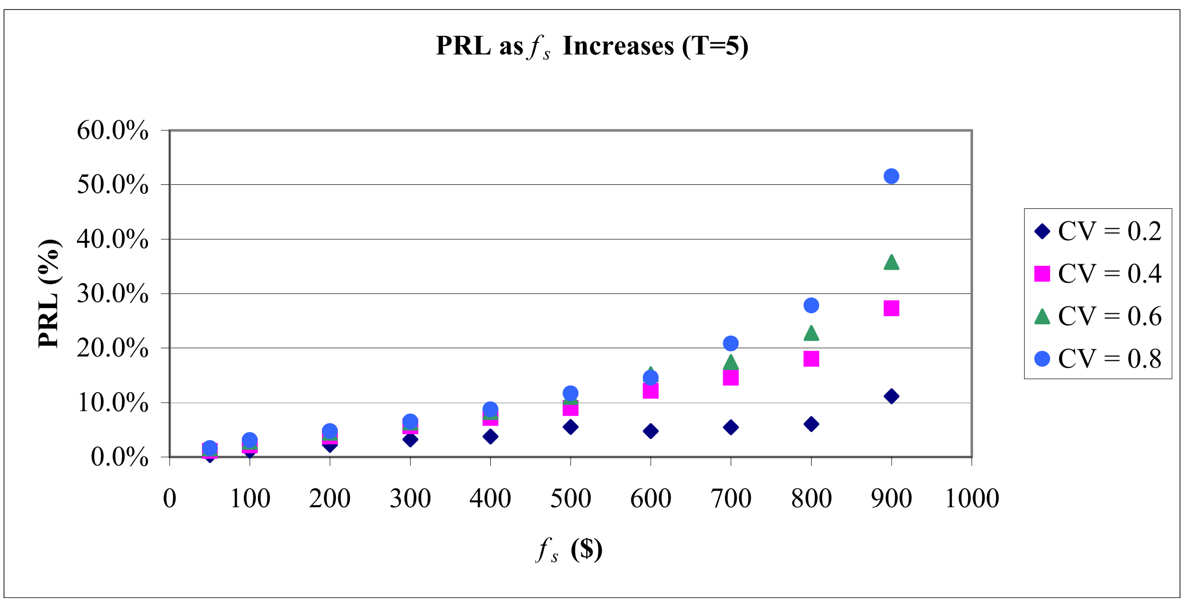

Figure 13: Increasing the fixed order cost for the supplier, f_s.

The four series correspond with demand profiles of differing coefficients of variation (CV = 0.2, 0.4, 0.6, and 0.8). The graph illustrates results for an information disruption of length five periods (T = 5); for results pertaining to an information disruption of length one period, see the appendix.

4 Conclusions and Future Research

Of the factors investigated here, the probability distribution of the end customer demand and the length of the information disruption have the most effect on the revenue loss due to an information disruption. Longer information disruptions and demand distributions with higher coefficients of variation each lead to greater loss for the supply chain. The models appear to be relatively insensitive to reasonable changes in the five cost parameters tested (h_s, h_r, l_r, f_s, and w_s). The following table lists the limit of each parameter (scaled to the unit price V) at which the Percent Revenue Loss exceeds ± 2% [*]. For example, when the holding cost to the supplier h_s exceeds 20% of the unit price V, the PRL is greater than 2%. The cases where parameters were increased to the point of forcing the expected gain of the supply chain below zero without pushing the PRL beyond ± 2%, entries are omitted. In all cases tested, the fixed order cost to the supplier was at least 100% of the unit price before the PRL exceeded ± 2%.

Table 10: Parameter value relative to unit price where PRL exceeds ± 2%.
These data correspond to the PRL data expressed as percentages.

	T = 1				**T = 5**			
Parameter / CV	**0.2**	**0.4**	**0.6**	**0.8**	**0.2**	**0.4**	**0.6**	**0.8**
h_s	0.2	0.3	0.3	0.2	0.2	0.2	0.2	0.2
h_r	-	-	0.3	0.3	-	0.3	0.2	0.1
l_r	-	-	-	-	-	-	2	2
f_s	9	6	5	6	2	1	1	1
w_s	0.6	0.4	0.4	0.4	-	7	-	-

More extreme changes in the cost parameters elicited greater percent revenue loss for the supply chain, and without exception changes in the expected gain of a supply chain due to an information disruption were driven by the fixed and variable ordering costs of the supplier (f_s

[*] The threshold of 2% was determined as a point at which revenue loss as a result of information disruption became more significant. Many scenarios, even with unreasonably large cost parameters, did not reach a higher considered threshold of 5%. On the other hand, almost all scenarios reflected some loss. The choice of 2% distinguishes the cost scenarios where an information disruption would begin to take a toll on a supply chain's net revenue.

and w_s). Changes in the cost parameters and in the length of the information disruption had little effect on the number of periods required for a disrupted system to return to steady state. Instead, the length of the recovery phase was dependent on the demand distribution.

The models that Wei *et al*. [19] developed to quantify the value of information sharing lend themselves to the investigation of the impact on a supply chain by an information disruption. This paper presents the results of an information disruption on a single-product, two-stage supply chain under one contingency plan. Similar methodology could be applied to different supply chain structures. In addition to their two-stage models, Wei *et al*. [19] develop eight models for a three-stage serial supply chain consisting of a manufacturer, a supplier, and a retailer. These eight models illustrate various combinations of inventory information sharing between the three supply chain members; the effects of an information disruption to each of the different models could be explored. Future work could also investigate the impact of a local information disruption (e.g., the retailer can no longer communicate with either the manufacturer or the supplier) versus a global information disruption where no supply chain member is able to communicate with any other member.

This paper analyzes the impact of an information disruption under the implementation of a single contingency plan. Other contingency plans may be reasonable; in working on this problem, another plan has been partially developed. Suppose that the two-stage supply chain is operating at steady state under an optimal information sharing policy and internet communication is eliminated. At that point in time, both the supplier and the retailer have the other's inventory information from the last period before the information disruption. A viable contingency plan for each supply chain member might be to continue applying the information sharing policy where decisions are based on the member's own inventory and the last-known inventory of the other member. This assumption creates system belief states composed of what the supplier and retailer assume the state to be; these belief states may or may not be the same as the actual system state. With each member making decisions based on inaccurate information, the expected gain of the supply chain will degrade.

A subset of this case includes a supplier who has lost communication with a retailer that follows a fixed policy (the supplier knows the parameters of the policy; e.g., “order up to five”). In this scenario, each time the retailer places an order with the supplier, the supplier knows not only her own inventory but has a better estimate of what the retailer’s inventory level is given the order quantity. The impact of an information disruption on such a system depends not only on the cost structure of the supply chain but also on the order frequency from the retailer to the supplier.

At this point, the work considers only single-product supply chains. Additional issues to be explored may include multiple products.

5 References

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Appendix

Additional Results from Experimental Design 2a

When the holding cost of the supplier (h_s) is increased beyond its base value of 1, the revenue loss initially drops. Increasing h_s beyond \$10 (i.e., a 1000% increase) causes an increase of the PRL as illustrated in Figure 14. Such a dramatic increase in the holding cost would influence the supplier to hold less inventory, thereby contributing to leaner operation and higher vulnerability to stockouts. These results are similar to those for a longer information disruption of five periods. The number of periods to recovery is considerably more varied than in the other subsets of the second experimental design; the descriptive statistics are listed in Table 11.

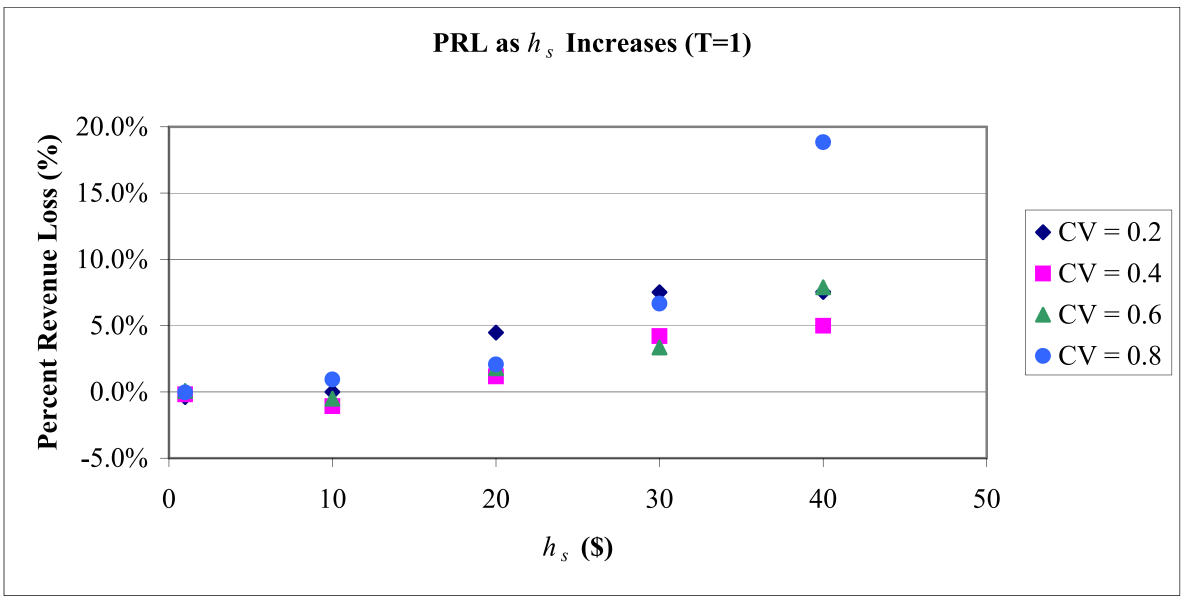

Figure 14: Increasing the inventory holding cost for the supplier, h_s.

The four series correspond with demand profiles of differing coefficients of variation (CV = 0.2, 0.4, 0.6, and 0.8); these results are for an information disruption of one period.

Table 11: Recovery for Experimental Design 2a (h_s)

Expected number of periods required for a system to return to steady state after an information disruption; averaged over five cases of Experimental Design 2a for each of the four demand profiles (CV = 0.2, 0.4, 0.6, and 0.8) and two lengths of information disruption (T = 1 and 5).

	T = 1				**T = 5**			
CV	**0.2**	**0.4**	**0.6**	**0.8**	**0.2**	**0.4**	**0.6**	**0.8**
Minimum	6	4	5	5	5	4	4	5
Maximum	53	12	7	7	47	12	7	7
Mean	24.40	6.60	5.60	6.00	14.00	6.40	5.20	5.80
Standard Deviation	23.90	3.21	0.89	1.00	18.47	3.21	1.10	0.84

Additional Results from Experimental Design 2b

In contrast to the results for an information disruption of five periods, the revenue loss due to increases in the holding cost of the retailer is primarily negative for an information disruption of one period (see Figure 15). This is partially due to the arbitrary definition of PRL; in the short run a disruption may appear to improve revenue because of which periods are taken into account. As an example, reference Figure 3. The information disruption dislodges the system from steady state operation, and the reestablishment of internet communication again upsets the state probabilities. The expected gain cycles above and below the gain expected under the information sharing policy until converging again to steady state. Depending on the behavior of the expected gain for a given scenario, the periods where the expected gain exceeds the expected gain under steady state operation could be more numerous than the periods where the expected gain is below that of steady state operation. Such a snapshot could imply that the supply chain revenue increased as a result of the disruption when in actuality revenue was lost over the course of a more extensive horizon. This is the case here, where the holding cost of the retailer is increased. Figure 10 reveals that an information disruption of length five periods does in fact correspond to revenue losses which are all positive.

As in all other trials, the periods necessary for recovery from an information disruption depend heavily on the distribution of the end customer demand; refer to Table 12 for descriptive statistics.

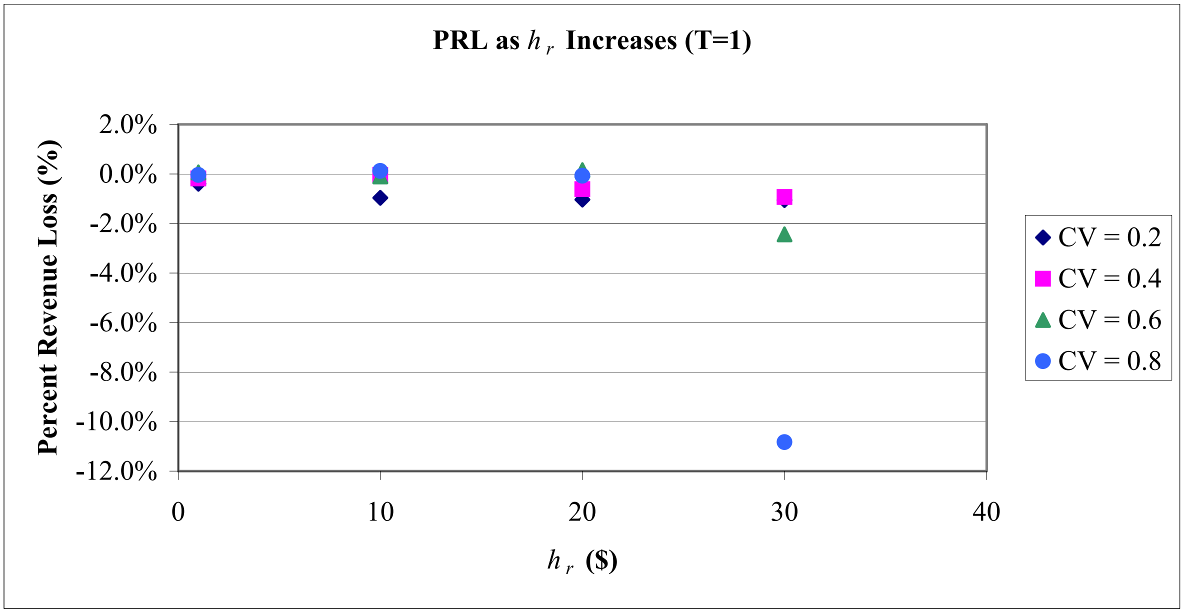

Figure 15: Increasing the inventory holding cost for the retailer, h_r.

The four series correspond with demand profiles of differing coefficients of variation (CV = 0.2, 0.4, 0.6, and 0.8); these results are for an information disruption of one period.

Table 12: Recovery for Experimental Design 2b (h_r)

Expected number of periods required for a system to return to steady state after an information disruption; averaged over four cases of Experimental Design 2b for each of the four demand profiles (CV = 0.2, 0.4, 0.6, and 0.8) and two lengths of information disruption (T = 1 and 5).

	T = 1				T = 5			
CV	**0.2**	**0.4**	**0.6**	**0.8**	**0.2**	**0.4**	**0.6**	**0.8**
Minimum	29	12	7	6	28	12	7	6
Maximum	48	12	10	8	47	14	11	8
Mean	36.50	12.00	8.00	6.50	36.25	12.50	8.25	6.50
Standard Deviation	8.10	0.00	1.41	1.00	7.89	1.00	1.89	1.00

Additional Results from Experimental Design 2c

As illustrated in Figure 11 and again in Figure 16, increases in the unit wholesale purchase cost of the supplier (w_s) lead to decreases in the revenue loss. For an information disruption of a single period, all of the results are either negative or nearly so. The periods to recovery (Table 13) are more uniform than those corresponding with increases in h_s and h_r.

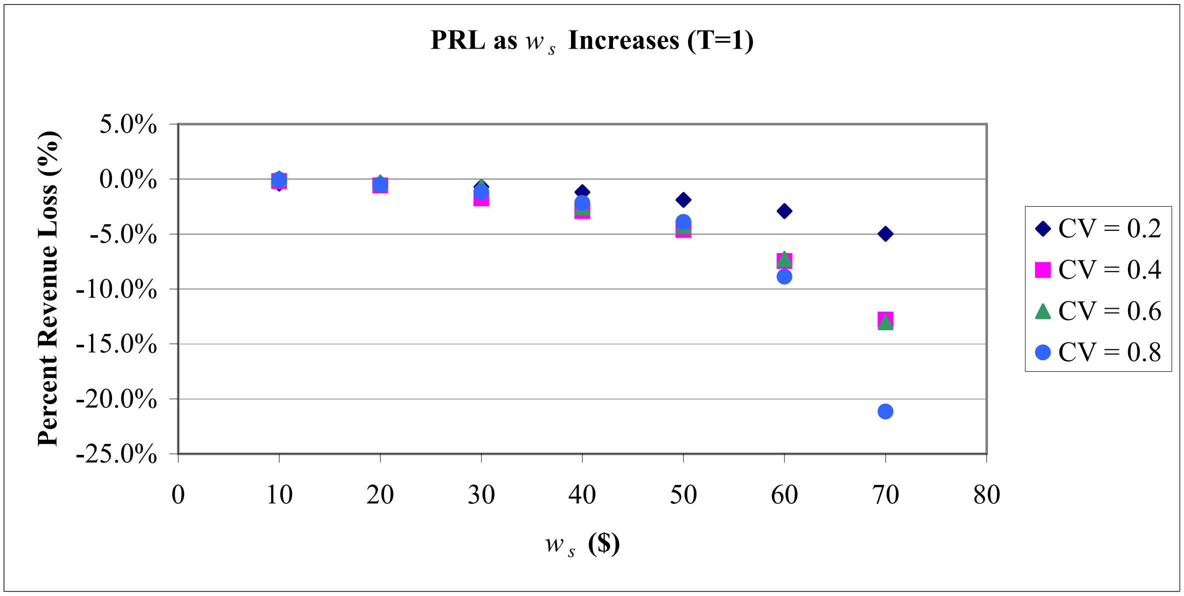

Figure 16: Increasing the unit wholesale cost for the supplier, w_s.

The four series correspond with demand profiles of differing coefficients of variation (CV = 0.2, 0.4, 0.6, and 0.8); these results are for an information disruption of one period.

Table 13: Recovery for Experimental Design 2c (w_s)

Expected number of periods required for a system to return to steady state after an information disruption; averaged over eight cases of Experimental Design 2c for each of the four demand profiles (CV = 0.2, 0.4, 0.6, and 0.8) and two lengths of information disruption (T = 1 and 5).

	T = 1				T = 5			
CV	**0.2**	**0.4**	**0.6**	**0.8**	**0.2**	**0.4**	**0.6**	**0.8**
Minimum	48	12	7	6	47	12	7	6
Maximum	53	13	7	6	52	13	7	6
Mean	52.29	12.14	7.00	6.00	51.29	12.14	7.00	6.00
Standard Deviation	1.89	0.38	0.00	0.00	1.89	0.38	0.00	0.00

Additional Results from Experimental Design 2d

Unlike the strong increasing trend in revenue loss corresponding to increases in the lost sales cost to the retailer for an information disruption of five periods (Figure 12), the revenue loss for an information disruption of one period is more erratic (Figure 17). However, even a 600% increase in the penalty cost over the base case results in a loss (or gain) of more than a single percent. In absolute terms, all but one of the revenue differences between the disrupted system and the undisrupted system are less than \$10. That is, the difference in expected gain over the horizon under consideration is \$10 different from the expected gain over the same horizon with no information disruption.

The periods to recovery for Experimental Design 2d vary little and depend more on the demand distribution than the changes in the lost sales cost to the retailer; see Table 14.

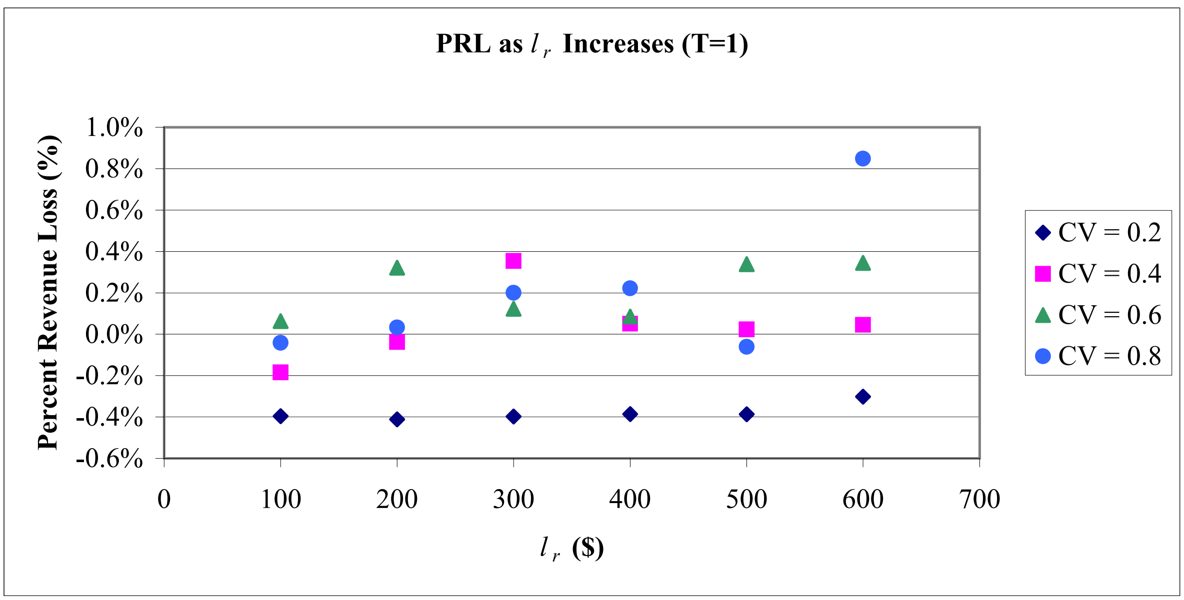

Figure 17: Increasing the lost sales cost for the retailer, l_r.

The four series correspond with demand profiles of differing coefficients of variation (CV = 0.2, 0.4, 0.6, and 0.8); these results are for an information disruption of one period.

Table 14: Recovery for Experimental Design 2d (l_r)

Expected number of periods required for a system to return to steady state after an information disruption; averaged over six cases of Experimental Design 2d for each of the four demand profiles (CV = 0.2, 0.4, 0.6, and 0.8) and two lengths of information disruption (T = 1 and 5).

	T = 1				**T = 5**			
CV	**0.2**	**0.4**	**0.6**	**0.8**	**0.2**	**0.4**	**0.6**	**0.8**
Minimum	48	8	6	5	47	9	6	5
Maximum	51	12	7	8	49	12	7	8
Mean	49.17	10.00	6.50	6.33	48.67	10.33	6.50	6.33
Standard Deviation	0.98	1.67	0.55	1.37	0.82	1.21	0.55	1.37

Additional Results from Experimental Design 2e

Experimental Design 2e involves more trials than the other components of the second experimental design because increases in the fixed order cost to the supplier did not push the expected gain of the supply chain below zero as quickly as increases in the other cost parameters. The trend for both an information disruption of one period (Figure 18) and an information disruption of five periods (Figure 13) is positive; as f_s increases, so does the revenue loss experienced by the supply chain.

Table 15 describes the periods necessary for the system to return to steady state; as in all other cases, the recovery periods depend more on the demand distribution than on changes to the cost parameter.

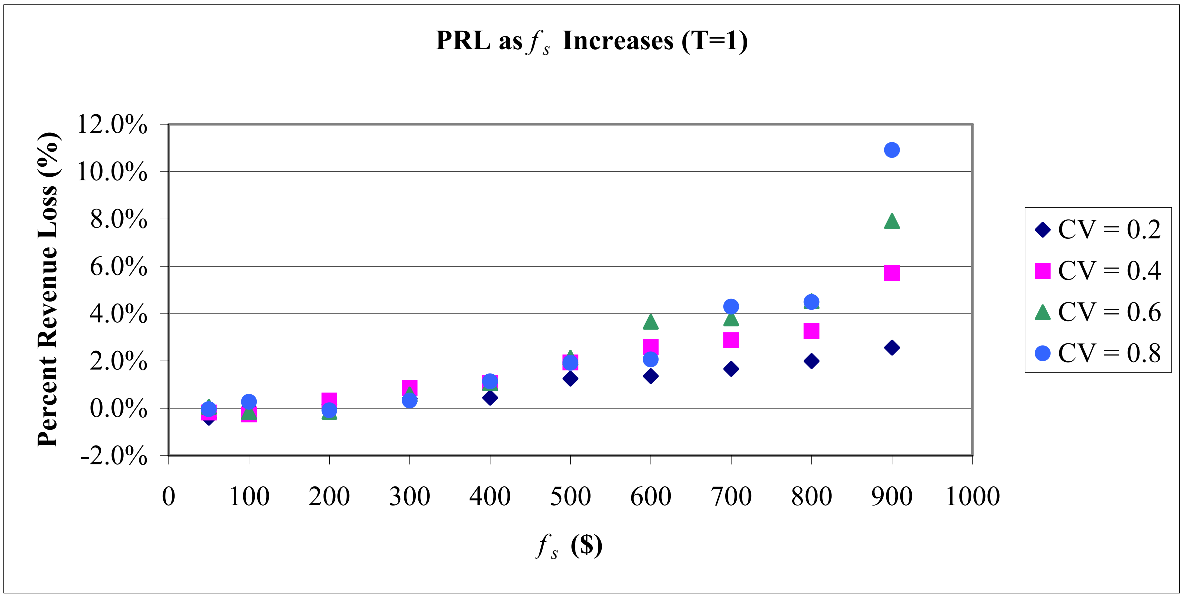

Figure 18: Increasing the fixed ordering cost for the supplier, f_s.

The four series correspond with demand profiles of differing coefficients of variation (CV = 0.2, 0.4, 0.6, and 0.8); these results are for an information disruption of one period.

Table 15: Recovery for Experimental Design 2e (f_s)

Expected number of periods required for a system to return to steady state after an information disruption; averaged over ten cases of Experimental Design 2e for each of the four demand profiles (CV = 0.2, 0.4, 0.6, and 0.8) and two lengths of information disruption (T = 1 and 5).

	T = 1				T = 5			
CV	**0.2**	**0.4**	**0.6**	**0.8**	**0.2**	**0.4**	**0.6**	**0.8**
Minimum	38	12	7	6	30	11	6	6
Maximum	53	15	9	7	52	13	8	6
Mean	44.90	12.90	8.20	6.20	39.20	11.70	7.00	6.00
Standard Deviation	4.28	0.99	0.79	0.42	6.99	0.67	0.47	0.00