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The impact of transportation disruptions on supply chain performance

Martha C. Wilson *

College of Business Administration, California State University, Sacramento 6000 J Street, Sacaremento, CA 95819-6088, United States

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Abstract

This paper investigates the effect of a transportation disruption on supply chain performance using system dynamics simulation, comparing a traditional supply chain and a vendor managed inventory system (VMI) when a transportation disruption occurs between 2 echelons in a 5-echelon supply chain. The greatest impact occurs when transportation is disrupted between the tier 1 supplier and warehouse. In the traditional structure the retailer, warehouse, and tier 1 supplier experience the greatest inventory fluctuations and the highest goods in transit to their facilities. These impacts are less severe for the VMI structure, although unfilled orders are approximately the same for each.

Keywords: Supply chain; System dynamics; Transportation disruption; Supply chain risk

1. Introduction

The vulnerability of supply chains has undoubtedly received more attention since the attacks on the World Trade Centers on September 11, 2001, even though supply chains have always been faced with assessing their vulnerabilities and managing risk. Risks faced by supply chains are quite diverse, arising from sources both within and external to the supply chain. These include disruptions, delays, information and networking, forecasting, intellectual property, procurement, customers, inventory, and capacity (Chopra and Sodhi, 2004).

Supply chain disruptions are costly (Hendricks and Singhal, 2005), and we need to understand how a disruption affects a supply chain in order to develop appropriate strategies for ameliorating the impact. A disruption is defined as an event that interrupts the material flows in the supply chain, resulting in an abrupt cessation of the movement of goods. It can be caused by a natural disaster, labor dispute, dependence on a single supplier, supplier bankruptcy, terrorism, war, and political instability. There are many examples of disruptions resulting from these types of events. The Kobe earthquake in 1994 left many companies without parts (Yoshiko, 1995); the northeastern US blackouts in August 2003 adversely affected many businesses (Brooks and Vogel, 2003);

* Tel.: +1 916 278 7198; fax: +1 916 278 5437.
E-mail address: mcwilson@csus.edu

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a fire at one of Ericsson's sub-suppliers created serious problems for Ericsson (Norrmann and Jansson, 2004). The labor strikes that shut down 29 ports on the West coast of the US in October 2002 caused the closure of the New United Motor Manufacturing plant in Fremont, California (Sarkar et al., 2002). This labor strike is an interesting example for the US because many suppliers to US industries are located in China. East Asia accounts for over 90% of the shipping through the Port of Long Beach, trading primarily with China, Hong Kong, Japan, South Korea and Taiwan.[1] The Port of Los Angeles, located next to the Port of Long Beach also trades primarily with East Asia, importing furniture, apparel, electronic products, toys, and computers.[2] Seventy five percent of the total dollar value of imports to the West Coast are handled by these two ports (Raine, 2004). Although businesses were aware of the impending labor strikes and could take some measure to avoid the full impact of a disruption, it was still a costly shutdown that affected many businesses and consumers.

Unlike disruptions in general, a transportation disruption can occur only as a result of a subset of the drivers identified by Chopra and Sodhi (2004), which include natural disasters, labor disputes, terrorist activities, and infrastructure failures, for example. This research makes a distinction between a transportation disruption and other types of disruptions. For comparison, consider supplier-related disruptions that could shut down a plant (supplier bankruptcy) or drastically reduce capacity (the fire at Ericsson). These types of disruptions not only stop the flow of goods, but also the production of goods, whereas a transportation disruption stops only the flow of goods and, in that sense, is probably less severe. The uniqueness of a transportation disruption is its specificity, distinctive in that goods in transit have been stopped, although all other operations of the supply chain are intact. For that reason, a transportation disruption arises when the material flow is interrupted between two echelons in a supply chain, temporarily stopping the transit of these goods, regardless of the source of the disruption.[3]

This paper investigates how a transportation disruption affects the supply chain performance of a traditional supply chain and a vendor managed inventory system. Applying system dynamics simulation, this study determines how each of these structures responds to a transportation disruption between different echelons in the supply chain. Supply chain response is measured by the number of unfilled customer orders, inventory fluctuations, and the behavior of goods in transit. Finally, this paper briefly discusses how individual supply chain risks are connected and suggests strategies for mitigating the risk from a transportation disruption.

1.1. Literature review

Not only have Chopra and Sodhi (2004) categorized nine types of risk in order to develop risk mitigation strategies, but also Kleindorfer and Saad (2005), who have identified two categories of risk: risk from coordinating supply and demand, and risks resulting from disruptions to normal activities. The supply chain management literature has addressed many of these risks, discussed how they are interconnected, and analyzed the supply chain response. This is especially evident for studies that fall in the risk category Kleindorfer and Saad described as coordinating supply and demand. Although these studies may not be labeled as "risk studies", they are certainly concerned with managing risk associated with mismatches between supply and demand throughout the supply chain. Examples include research on inventory and capacity planning, demand uncertainty and forecast accuracy, information distortion, purchasing and procurement strategies, and price variation (Lee and Billington, 1992; Levy, 1995; Lee et al., 1997a,b; Sterman, 1989; Chen et al., 2000; Lee, 2002; Cachon, 2004; Zsidisin and Ellram, 2003). These studies have also suggested several methods for mitigating risks, which include information sharing, electronic data interchange, collaborative planning forecasting and replenishment, lead time reductions, consistent low prices, and vendor managed inventory. Vendor managed inventory, however, is not new, having been conceived by Magee (1958) and revisited by Lee et al. (1997a).

[1] Port of Long Beach web site: http://www.polb.com/html/1_about/overview.html.

[2] Port of Los Angeles web site: http://www.portoflosangeles.org/factsfigures_Portataglance.htm.

[3] Although a disruption in transportation will certainly delay the arrival of goods at their destination, a distinction is being made between a transportation disruption and a transportation delay, which falls into another risk category. Because the risk drivers for a delay are different than those for a disruption, a distinction must also be made in order to develop specific strategies for risk mitigation (Chopra and Sodhi, 2004).

In contrast to the types of risk posed by mismatches between supply and demand, supply chain disruptions, the second category identified by Kleindorfer and Saad (2005), has not been as widely studied. Lee and Wolfe (2003) developed strategies for mitigating security breaches that can disrupt supply chains. Kleindorfer and Saad (2005) provided a conceptual framework for assessing and mitigating the risk of a disruption. They also used data from the US chemical industry to provide guidelines for managing the risk of a supply chain disruption. Norrmann and Jansson (2004) conducted a case study on how a fire at one of Ericsson's sub-suppliers affected the company, and discussed how Ericsson modified their approach for managing supply chain risk after the fire.

Transportation disruptions per se have received less attention than supply chain disruptions. Although Giunipero and Eltantawy (2004) note that a potential transportation disruption is a source of risk, and that it could "quickly cripple the entire supply chain" (p. 703), their discussion is fairly general and does not offer risk measurement or mitigation strategies for a transportation disruption.

Because this research uses simulation modeling to study the risk of a transportation disruption, previous simulation studies were reviewed. Several studies have successfully applied simulation modeling to understand supply chain behavior. Simulation modeling has been used to investigate the effect of uncertainty (Petrovic, 2001), the impact of order release mechanisms (Chan et al., 2001, 2002), the effect of partial shipments on customer service levels (Banerjee et al., 2001), and the impact of transshipments on service levels and costs (Banerjee et al., 2003). These studies, however, did not use system dynamics simulation. The complexity of supply chains, especially those which encompass several echelons, warrants a perspective that considers the supply chain structure and the feedback inherent in these structures, which is provided by system dynamics modeling. System dynamics, pioneered by Forrester (1961), has provided insights into supply chain behavior and has been used to investigate the effect of different policies on supply chain performance. Towill (1996) discussed how system dynamics can be used to enhance business performance by obtaining greater insight into business processes, and he demonstrated how supply chain responses differ for various supply chain improvements. Subsequently, Disney et al. (1997) applied system dynamics and used a genetic algorithm to establish demand, pipeline, and inventory policies that would result in quick supply chain responses that were robust to changes in lead time and randomness in demand. Appropriate settings for pipeline control were also investigated by Mason-Jones et al. (1997). Together, these studies verified the best settings of the design parameters used for smoothing demand, adjusting inventory, and adjusting work in process. Disney and Towill (2002) extended this research on "best design" parameters to establish the stability criteria for a vendor managed inventory supply chain. Other researchers have applied system dynamics modeling to study the effects of transshipments on supply chain behavior (Hong-Minh et al., 2000) and the effect of VMI on transport operations (Disney et al., 2003).

1.2. Methodology

This research applies system dynamics simulation modeling to study the effects of a transportation disruption. Two simulation models were built—one of a traditional supply chain structure and the other, a vendor managed inventory system. The supply chains are modeled in continuous time for a 5-echelon supply chain using the software ithink®. These models apply the criteria developed by Disney et al. (1997), Mason-Jones et al. (1997), and Disney et al. (2003) to establish pipeline and inventory control parameters. The models are each run for 600 days with a disruption of 10 days occurring at the 200th day. The two models are discussed in more detail in the next section.

2. Model description

2.1. Model structure

The supply chain modeled in this research contains five sectors: the retailer, the warehouse, the tier 1 supplier, the tier 2 supplier, and the raw material supplier. Fig. 1 shows how goods and information flow between each partner in the chain for each scenario.

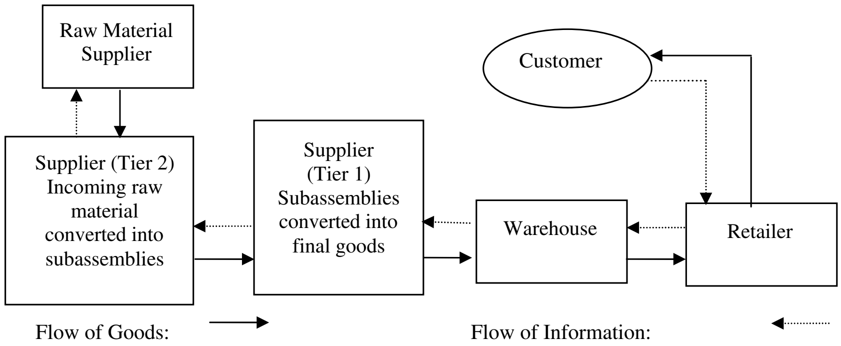

Fig. 1. Flow of goods and information: the traditional structure.

In the traditional arrangement, demand information flows upstream, beginning with the customer. The information flowing between the sectors is not identical. The retailer receives customer demand information; however, the warehouse only receives retail order information, not customer demand information. Likewise, the tier 1 supplier receives warehouse order information and the tier 2 supplier receives orders from the tier 1 supplier. The raw material supplier bases their decisions on the order information they receive from the tier 2 supplier. In this arrangement the upstream partners do not directly receive customer demand information, unlike in the VMI structure. Further, the only information that is passed up the chain is demand information.

Fig. 2 illustrates the relationship between orders placed and goods shipped for the retailer and the warehouse using causal loop diagrams. The retail sector is at the top of Fig. 2, and warehouse, at the bottom. A plus sign indicates that two variables move in the same direction, and the minus sign indicates that two variables move in opposite directions. For instance, when customer demand increases, retail inventory decreases, which is indicated by the minus sign at the end of the arrow between customer demand and retail inventory level. Likewise, as retail inventory increases, the total retail inventory gap decreases. However, as the gap decreases, so do the orders placed with the warehouse, a movement in the same direction indicated by the plus sign on the arrow pointing at "Orders placed with warehouse". The larger minus signs inside the parentheses within the loops indicate a negative loop, or a self-correcting feedback system which contains the mechanisms to seek a steady state rather than spin out of control.[4]

Beginning at the top of the diagram with the retail sector, the target for retail inventory and the desired pipeline inventory are set. These values are based on lead time and average demand, discussed in the section on inventory policy. Next, the gap between the desired and actual levels of inventory and pipeline inventory determine the total retail inventory gap. As this gap increases, the retailer places orders for more goods with the warehouse. The retailer also considers any changes in customer demand when placing orders with the warehouse, indicated by the arrow pointing from "Smoothed Customer demand" to "Orders placed with warehouse". Customer demand is smoothed in order to avoid overreactions to changes in customer demand and to ensure the stability of the simulation model. As customer demand rises, orders placed with the warehouse will also rise, and fall when customer demand falls. The "Orders placed with warehouse" by the retailer then go into the warehouse's order backlog, triggering shipments to the retailer. As goods are shipped, the retail pipeline inventory goes up, which reduces the retail pipeline gap. As the pipeline gap decreases, so does the total retail inventory gap. (The plus sign at the end of the arrow going from retail pipeline gap to total retail inventory gap indicates movement in the same direction, so as retail pipeline gap goes down, total retail inventory gap goes down.) Eventually, the goods in the retail pipeline inventory go into retail inventory, increasing the retail inventory level. Increases in retail inventory also cause the total retail inventory gap to go down. This cycle continues, which contains two loops. One loop begins at total retail inventory gap and continues to retail pipeline gap. The other begins at total retail inventory gap, and continues to retail inventory level.

[4] The design of this model, which used the parameters suggested by previous researchers, ensures the stability of this model, which is not always guaranteed by a negative feedback loop.

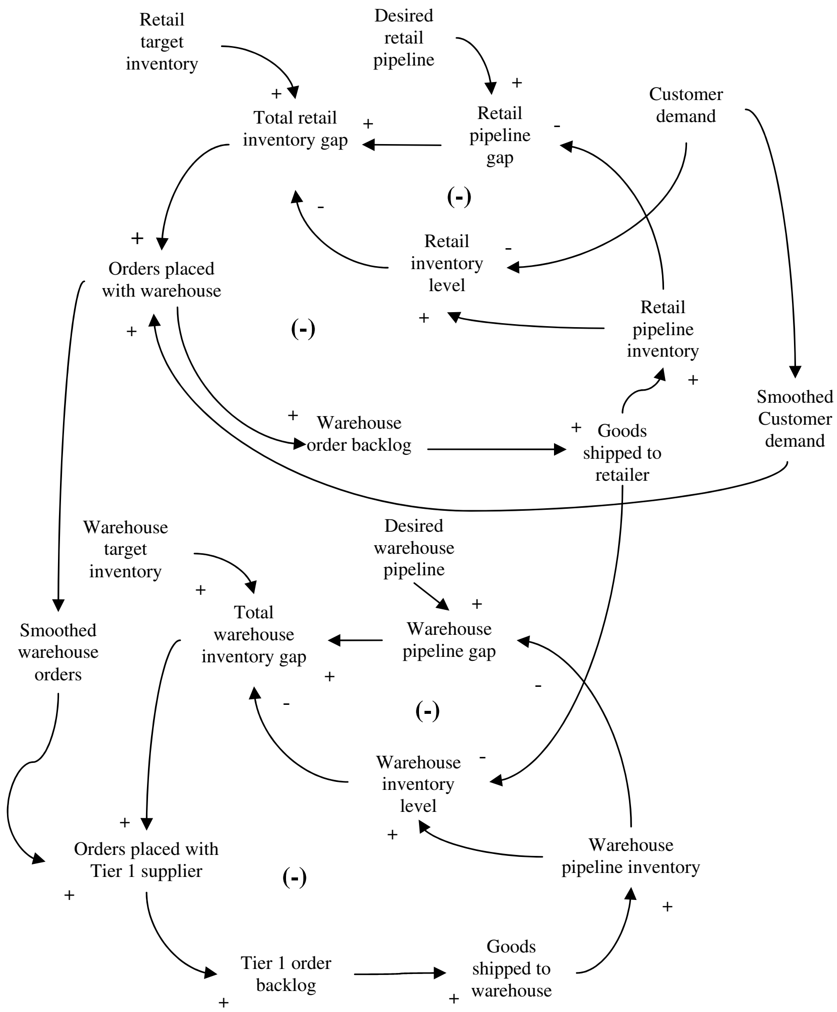

Fig. 2. Causal loop diagram of retail and warehouse sectors, traditional structure.

The causal loops depicting the warehouse behavior work exactly the same as the retail loops except for two minor differences that are really a matter of semantics. Warehouse inventory level declines in response to goods shipped to the retailer (the warehouse "customer"), and the orders the warehouse places with the tier 1 supplier are based on the smoothed orders the warehouse receives from the retailer. The logic works the same way for the other echelons, which are not shown here.[5]

Vendor managed inventory is modeled in a similar fashion, except for how customer demand information is passed along the supply chain. Fig. 3 depicts a VMI system in which the warehouse becomes a distribution center. The distribution center does not receive customer demand information because the tier 1 supplier determines the number of items to be shipped to the warehouse based on customer demand.

In the VMI structure, both the tier 1 supplier and the retailer receive customer demand information. The tier 2 supplier, however, only receives orders from the tier 1 supplier, and does not have access to customer demand information. Likewise, the raw material supplier receives orders from the tier 2 supplier, and is not

[5] The raw material supplier does not order from another upstream supplier. Therefore, there is a minor difference between the causal loop diagram for the raw material supplier and the other echelons.

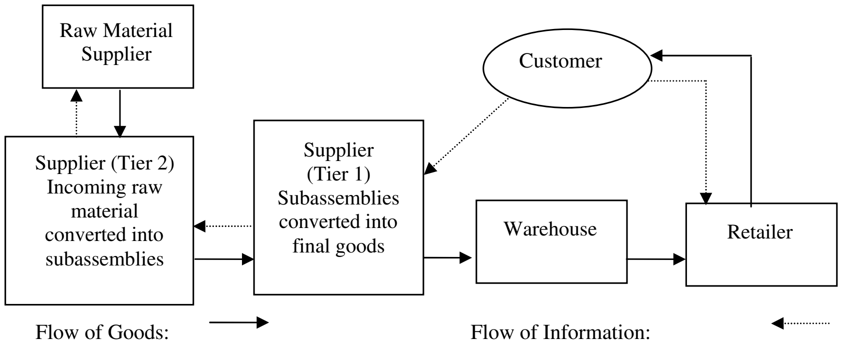

Fig. 3. Flow of goods and information: vendor managed inventory.

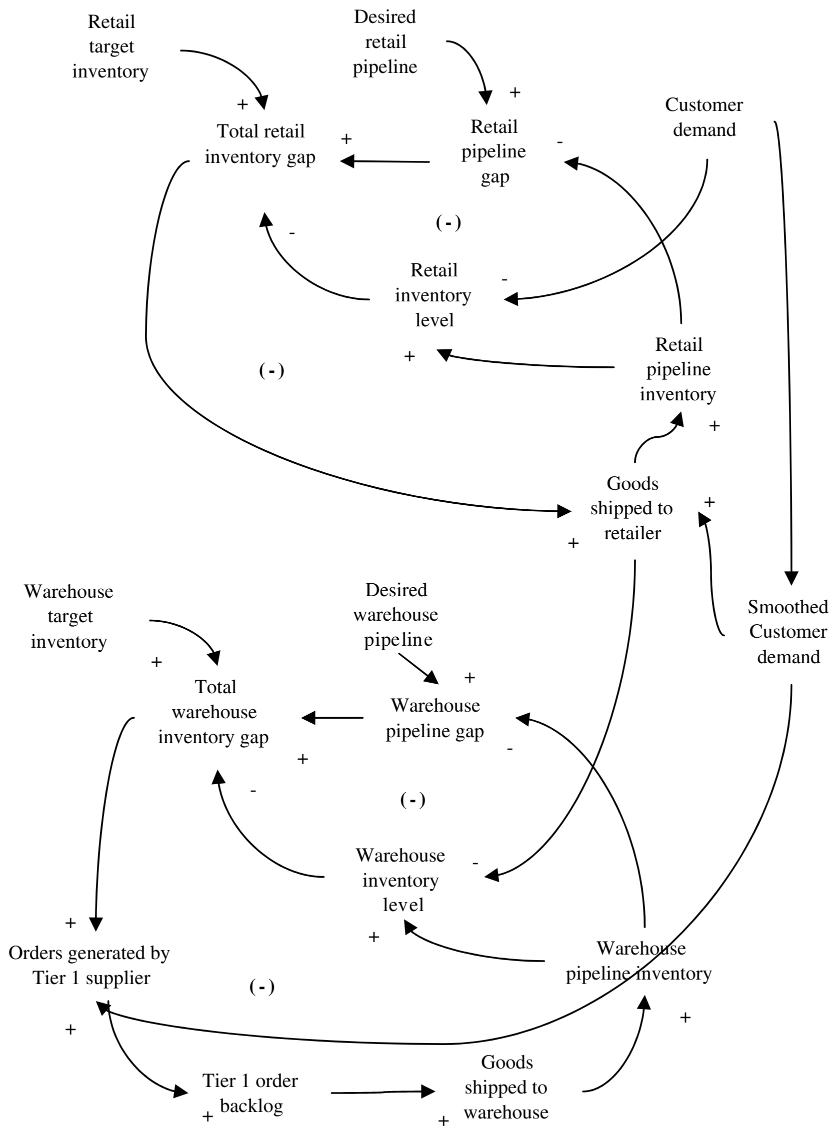

Fig. 4. Causal loop diagram for vendor managed inventory.

aware of final customer demand. Therefore, the upstream portion of this supply chain behaves the same as a traditional supply chain.

The causal loop diagram in Fig. 4 shows how the tier 1 supplier, the vendor, manages downstream inventory. The main difference between the VMI and the traditional supply chain structures are shown in the "retail loop". The retailer no longer places orders with the warehouse and there is no longer a warehouse order backlog. Instead, goods are automatically sent to the retailer based on the inventory gap and the smoothed customer demand. Additionally, the tier 1 supplier determines how much to send to the warehouse based on the warehouse inventory gap and smoothed customer demand. Unlike in the traditional supply chain structure, the tier 1 supplier bases their decision on how much to send to the warehouse, "Orders generated by the Tier 1 supplier", from actual customer demand and not on orders they have received from the warehouse. This is shown by the arrow starting from "Smoothed customer demand" and extending to "Orders generated by Tier 1 supplier".

To help clarify this logic, Table 1 shows selected equations for ordering and shipping for the traditional supply chain and the VMI structure. A blank cell in the column for VMI indicates that there is no corresponding equation.

Other aspects of the models are identical. In both the traditional and vendor managed inventory models, the transit times and processing times are the same, shown in Fig. 5. It is assumed that the warehouse processing time is insignificant.

2.2. Model assumptions

Several assumptions were made regarding customer demand, inventory policy, processing and transport capacity, and operational details.

Final customer demand is normally distributed with a mean of 10 units per day and a standard deviation of 2.

The model assumes a continuous review inventory system for each partner in the supply chain where the inventory held by each tier is set at a constant target level based on this formula[6] (see Figs. E1 and E2):

$$S = \mathrm{LT} \cdot \overline{D} + \text{safety stock} \tag{1}$$

where S is the target level, LT is the lead time, $\overline{D}$ is the average demand, with a smoothing time of T_a, safety stock is the (number of days of desired coverage)(average demand).[7]

In addition to setting a target inventory level for goods held by each tier, desired pipeline inventory and desired work in process are also computed. The desired pipeline inventory refers to goods in transit and the desired WIP refers to the work in the production process for the tier 1 and tier 2 supplier. The specific equations for the retailer and warehouse are shown in Table 1. The general form of these equations are

$$\text{Desired pipeline inventory} = (\text{average demand})(\text{transit time}) \tag{2}$$

$$\text{Desired WIP} = (\text{average demand})(\text{production lead time}) + \text{safety stock} \tag{3}$$

The order quantity placed with the upstream supplier is based on the gap between the actual and the target inventory level as well as the pipeline gap. The inventory gap is

[6] The model was first conceived and run with target inventory levels that varied with demand. However, since customer demand really is kept constant throughout the model, and perturbations are introduced only as a result of a transportation disruption, it seemed reasonable to take a conservative approach in analyzing transportation disruptions by using constant rather than variable inventory targets. With variable inventory targets, the impact of a transportation disruption is more severe. Also, constant inventory targets results in reaching a steady state much more quickly for the tier 2 supplier sub-assembly inventory, another benefit of selecting constant inventory targets. The two graphs (Fig. E1 and E2) show the difference between constant inventory targets and variable inventory targets for a Type 1 transportation disruption which occurs between the warehouse and the retailer beginning on day 200 and ending on day 210. These results are for the traditional supply chain model.

[7] The number of days of coverage concept is based on the technique used by Sterman in Business Dynamics, 2000.

Table 1
Selected equations for inventory policy for the traditional supply chain and VMI structures

Traditional structure	Difference	VMI
Retail inventory control		*Retail inventory control*
avg sales = exponentially smoothed demand over period T_a	No difference	avg sales = exponentially smoothed demand over period T_a
desired retail pipeline = avg sales * wh to retail transit time	No difference	desired retail pipeline = avg sales * wh to retail transit time
target: retail inventory = 15	No difference	target: retail inventory = 15
retail inventory gap = target: retail inventory − retail inventory + retail pipeline gap	No difference	retail inventory gap = target: retail inventory − retail inventory + retail pipeline gap
Retail: placing/receiving orders from warehouse		*Retail: receiving shipments from warehouse*
WH Backlog(t) = WH Backlog($t-dt$) + (wh ordering – wh filling) * dt INIT WH Backlog = 0	No order backlog for VMI	
wh ordering = (retail inventory gap/retail inv adj time) + avg sales	Part of order backlog structure, orders placed by retailer with the warehouse	
retail inv adj time = wh to retail goods transit time	No difference	retail inv adj time = wh to retail goods transit time
wh filling = retail shipping	Part of order backlog structure	
retail shipping = MIN(WH Backlog, Warehouse Inventory)	For VMI, retail orders shipped from warehouse are based on average sales. There is no backlog	retail shipping = (retail inventory gap/retail inv adj time) + avg sales
Warehouse inventory control		*Warehouse Inventory Control*
Warehouse Inventory(t) = Warehouse Inventory($t-dt$) + (warehouse receiving – retail shipping) * dt	No difference	Warehouse Inventory(t) = Warehouse Inventory($t-dt$) + (warehouse receiving – retail shipping) * dt
INIT Warehouse Inventory = 20		INIT Warehouse Inventory = 20
avg_wh_ordering = SMTH1(wh_ordering,4)	Because the retailer doesn't place orders with warehouse, there are no orders to "smooth".	
desired wh pipeline = avg wh ordering * tier1 to wh transit time	VMI bases pipeline target on avg customer demand	desired wh pipeline = avg sales * tier1 to wh transit time
target: wh inv = 30	Target is lower for VMI	target: wh inv = 20
wh gap = target: wh inv-Warehouse Inventory + wh pipeline gap	No difference	wh gap = target: wh inv-Warehouse Inventory + wh pipeline gap
Warehouse: placing/receiving orders from tier 1 supplier		*Warehouse: receiving orders from tier 1 supplier (manufacturer, Mfg)*
Mfg Backlog(t) = Mfg Backlog($t-dt$) + (mfg ordering – mfg filling) * dt	Same mechanism, but "mfg ordering" is called "shipments to warehouse" in VMI	Mfg Backlog(t) = Mfg Backlog ($t-dt$) + (shipments to warehouse – mfg filling) * dt
INIT Mfg Backlog = 0		INIT Mfg Backlog = 0
mfg ordering = (wh gap/wh inv adj time) + avg wh ordering	In VMI, Shipments to warehouse are based on average customer sales, not on average orders received from the warehouse	Shipments to warehouse = wh gap/wh inv adj time + avg sales
mfg filling = warehouse shipping	No difference	mfg filling = warehouse shipping
warehouse shipping = MIN(Mfg Backlog, Mfg Final Goods Inventory)	No difference	warehouse shipping = MIN(Mfg Backlog, Mfg Final Goods Inventory)
wh inv adj time = tier1 to wh transit time	No difference	wh inv adj time = tier 1 to wh transit time

Note: "wh" stands for warehouse, and "mfg" for manufacturer, or tier 1 supplier.
Equations for managing and controlling inventory are the same for the remaining upstream echelons.

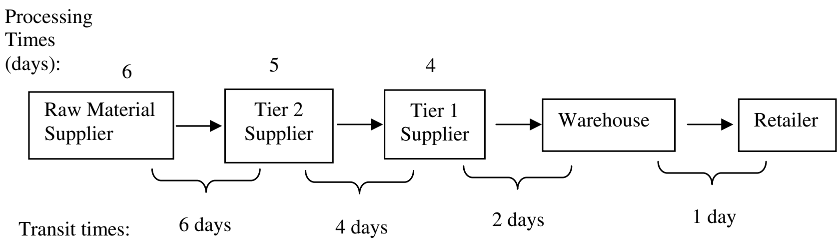

Fig. 5. Transit and processing times.

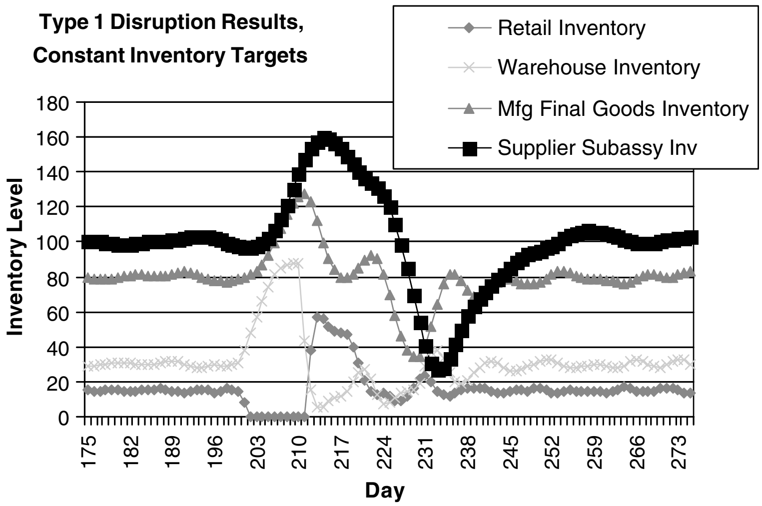

Fig. E1. Model behavior with constant inventory targets, traditional structure.

$$\text{Inventory gap} = \text{target inventory} - \text{actual inventory} + \text{pipeline gap} \tag{4}$$

where

$$\text{Pipeline gap} = \text{desired pipeline inventory} - \text{goods in transit} \tag{5}$$

The tier 1 and tier 2 supplier must also determine how much to produce, based on the gap between actual and target inventory as well as the WIP gap. The total inventory gap is

$$\text{Inventory gap} = \text{target inventory} - \text{actual inventory} + \text{WIP gap} \tag{6}$$

where

$$\text{WIP gap} = \text{desired WIP} - \text{goods in process} \tag{7}$$

Finally, orders are placed with the upstream supplier based on the gap:

$$\text{Quantity ordered} = \text{inventory gap}/\text{inventory adjustment time} + \text{average demand} \tag{8}$$

where inventory adjustment time,

$$T_i = T_w = \text{transit time} \tag{9}$$

In the case in which products are made, production is begun when a similar signal is received:

$$\text{Production starts} = \text{inventory gap}/\text{production adjustment time} \tag{10}$$

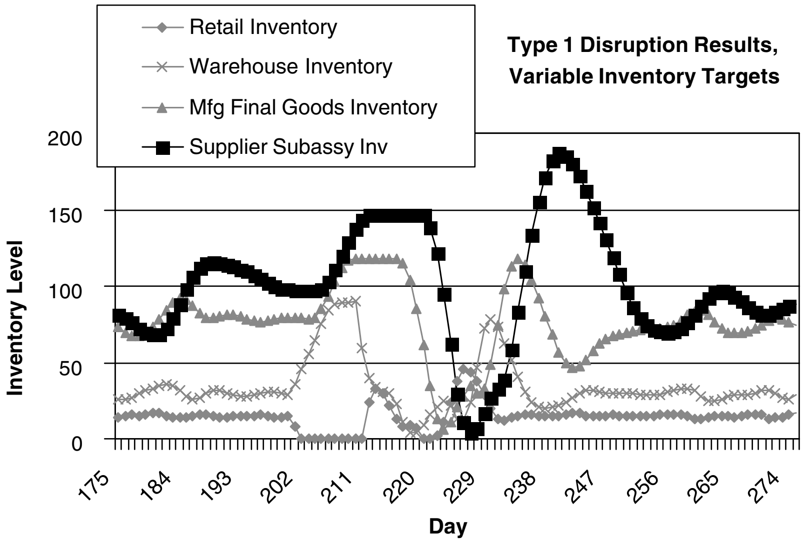

Fig. E2. Model behavior with variable inventory targets, traditional structure.

where production adjustment time,

$$T_i = T_p = \text{production lead time} \tag{11}$$

As demand is smoothed by each upstream echelon, the smoothing constant, T_a equals twice the lead time, T_p.

$$T_a = 2T_p \tag{12}$$

These equations show the general structure of the inventory ordering and production policy. The adjustment factors are based on the best design parameters for a 4-echelon supply chain discussed by Mason-Jones et al. (1997), as well as the best design parameters for a VMI system discussed by Disney and Towill (2002). Mason-Jones et al. (1997) developed parameter settings for pipeline feedback that ensure good control of material flow when used for simulating "to make" models. Their research drew upon the previous ideas developed by Towill (1982) and Popplewell and Bonney (1987). They demonstrated that the parameter settings for T_i, inventory adjustment time, T_w, transit time, and T_a, inventory adjustment time, are directly related to process or order lead time, T_p. Furthermore, setting these parameters to the recommended settings shown in Eqs. (9), (11) and (12) result in a supply chain design that is responsive but still demonstrates low variations within each echelon. Similarly, Disney and Towill (2002) used dynamic simulation to illustrated that in a VMI supply chain if $T_i = T_w$, a stable system is guaranteed which is robust to stochastic delays and the distribution of those delays. This research also used these parameters which had already been extensively studied and established as good estimates for simulating supply chain operations.

Table 2 shows the specific parameter settings used in this model, including the initial inventory settings. The parameter settings are slightly different for the VMI: initial warehouse inventory and target warehouse inventory are both set to 20 units. Also, the demand average time, T_a, for the warehouse is not applicable in the VMI model because the Tier 1 supplier is using the average sales information from the retailer to determine the number of units to ship to the warehouse.

It is assumed that transportation capacity is infinite. The reason for assuming infinite capacity is to simplify the model, making it easier to interpret the results which are not confounded by constrained transport capacity. Although the question regarding the impact of constrained transport capacity should receive further attention, it is more appropriate to address this specific question in future research.

Manufacturing capacity is unconstrained for the same reason that transport capacity is unconstrained. It could certainly be addressed in future research.

Table 2
Parameter settings for the traditional and VMI models

	Raw material supplier		Tier 2 Supplier (sub-assemblies)				Tier 1 supplier (final goods)				Warehouse		Retailer	
	Raw material in-process	Raw material Inventory	Goods in-transit	Raw material inventory	Subassyin process	Subassy inventory	Goods in-transit	Subassy inventory	Final goods in process	Final goods inventory	Goods in-transit	Inventory	Goods in-transit	Inventory
Initial inventory levels	60	120	60	90	50	100	40	60	40	80	20	30, 20 for VMI	10	15
Target inventory levels		120		90		100		60		80		30, 20 for VMI		15
Transit times, T_w			6				4				2		1	
Production lead times, T_p	6				5				4					
Inventory adjustment times, T_i		6		6		5		4		4		2		1
Number of days of expected average demand used to compute safety stock		6		3		5		2		4		1		0.5
Demand averaging time, T_a		12				10				8		4, NA for VMI		2

2.3. Model parameters

Three performance measures are used in the simulation models: unfilled customer orders, maximum and average inventory levels, and maximum goods in transit.

The transportation disruptions can occur at 4 different points in the supply chain: between the retailer and warehouse, the warehouse and the tier 1 supplier, the tier 1 supplier and the tier 2 supplier, and the tier 2 sup-

Table 3
Types of transit disruptions

Type of disruption	Description
Type 1	Interruption in transportation between the warehouse and the retailer
Type 2	Interruption in transportation between the tier 1 supplier (manufacturer) and the warehouse
Type 3	Interruption in transportation between the tier 2 supplier and the tier 1 supplier
Type 4	Interruption in transportation between the raw material supplier and the tier 2 supplier

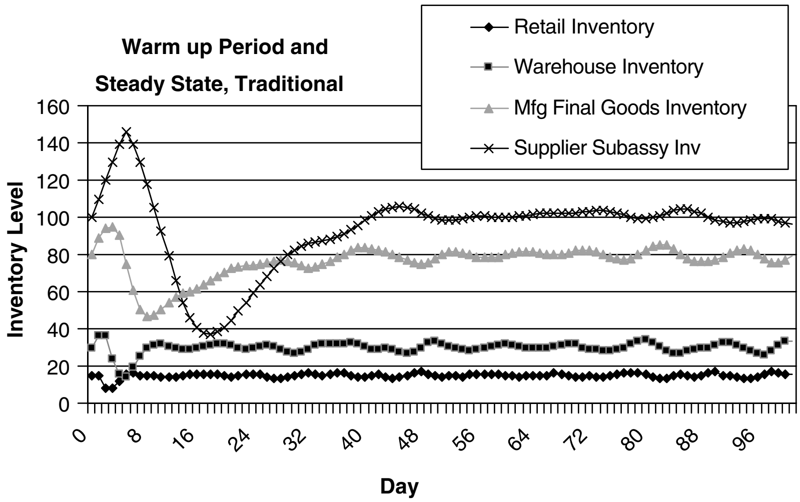

Fig. E3. Traditional structure, inventory levels.

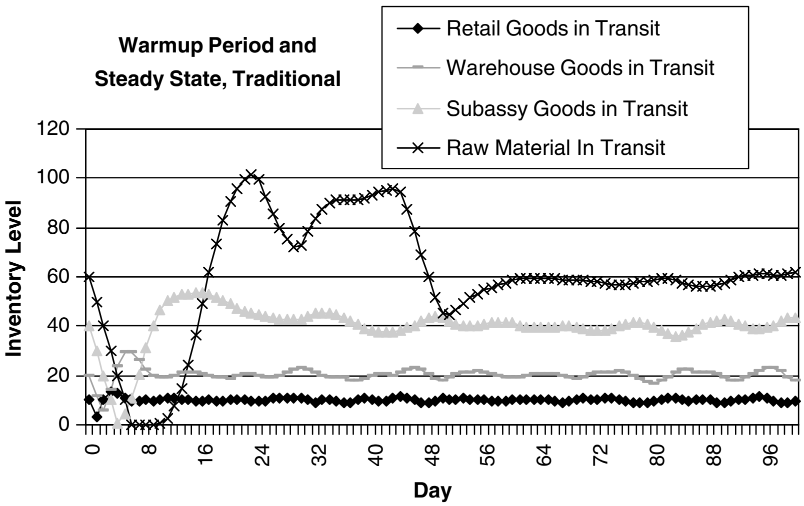

Fig. E4. Traditional structure, goods in transit.

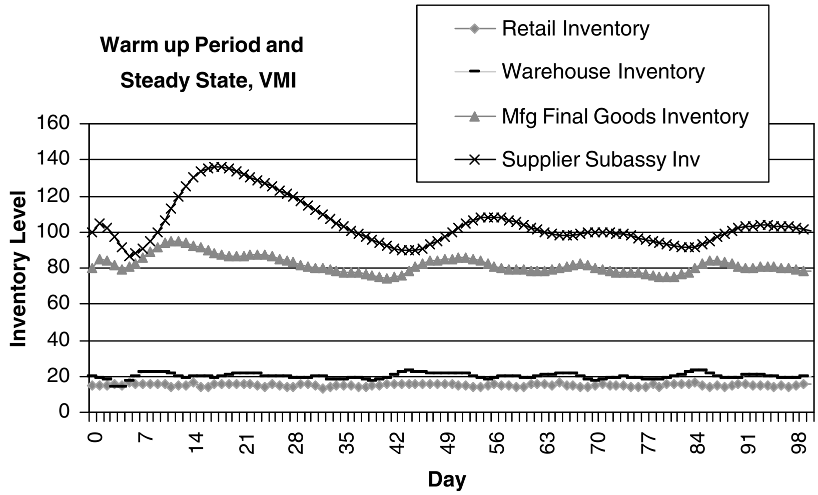

Fig. E5. VMI, inventory levels.

plier and the raw material supplier. These are referred to as a Type 1, Type 2, Type 3, and Type 4 disruption, respectively, and are summarized in Table 3.

The two different supply chains arrangements were simulated with 10 day disruptions at four different points corresponding to each type of transportation disruption. For the traditional supply chain structure and VMI, the simulation is run for 600 days, with the disruption starting on day 200 after the model has had ample time to reach a steady state.[8] (see Figs. E3–E6)

Four replications of the simulation model were run for the base case to determine the minimum number of replications needed for 95% confidence in estimating the value of the performance metrics. These runs indicated that four replications provided results that met this level of confidence except for warehouse goods in transit and sub-assembly goods in transit, which had a 91.8% and 91.6% confidence level for the traditional supply chain structure in the presence of a Type 1 disruption.[9] (See Tables E1–E4.) The results of the simulations are presented in the next section.

3. Discussion of results

3.1. Overview

The metrics used to evaluate the performance of the supply chain are unfilled retail customer orders, maximum number of goods in transit, and maximum and average inventory levels. There is very little difference

[8] The steady state for both the traditional supply chain modeled and the vendor managed inventory model was reached very quickly, after approximately 60 days in the base case. Therefore, the selection of day 200 to simulate a disruption appeared to provide a very safe margin for introducing this change into the model after a steady state had been reached. The graphs (Figs. E3–E6) show the behavior of inventory and goods in transit for the base case and for VMI. Results were the same for the four types of transportation disruptions. By inspection of Fig. E3, a steady state is reached by about day 60. By inspection of Fig. E4, a steady state is reached by about day 65. Inspecting Fig. E5 shows that a steady state is reached by around day 60. Fig. E6 shows that a steady state is reached by around day 60.

[9] The number of replications was based on the results (Tables E1–E4), which show the average and standard deviation for selected values. The average and standard deviation were computed using the data from day 175 through day 275 of the simulation model. Because the inventory is more variable in the presence of disruptions, these values were also computed for a Type 1, Type 2, Type 3, and Type 4 disruption, with similar results. For average unfilled customer orders, greatest variability was for the Type 2 disruption. The level of confidence for this case was 97.5%. Table E2 shows the average maximum goods in transit for a Type 1 disruption for the traditional scenario, the scenario which exhibited the lowest levels of confidence. Table E3 shows the baseline results for VMI, which are similar for all scenarios. For average unfilled customer orders, greatest variability was for the Type 2 disruption, and the level of confidence for this variable was 98.7%. Table E4 shows the results for maximum goods in transit for the Type 2 disruption, which exhibited the lowest levels of confidence. Results for the other scenarios confirmed that 4 replications was sufficient for 99.99% confidence.

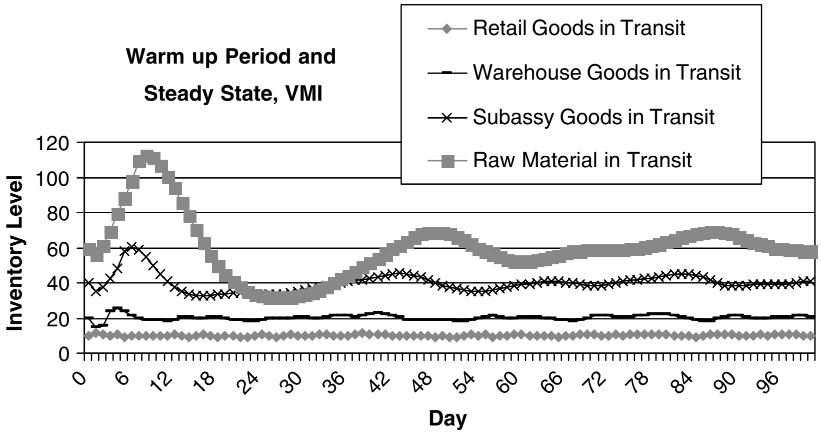

Fig. E6. VMI, goods in transit.

Table E1
Baseline results for four replications, traditional structure

	Retail inventory	Warehouse inventory	Mfg final goods inventory	Supplier subassy inv	Retail goods in transit	Warehouse goods in transit	Subassy goods in transit	Raw material in transit
Mean	15	30	80	100	10	20	40	60
Standard deviation	0.03	0.06	0.10	0.19	0.04	0.09	0.26	0.52
10% error	1.5	3	8	10	1	2	4	6
Confidence level for 4 replications with 10% error	99.99%	99.99%	99.99%	99.99%	99.99%	99.99%	99.99%	99.99%

Table E2
Type 1 disruption results for four replications, traditional structure

	Maximum retail goods in transit	Maximum warehouse goods in transit	Maximum subassy goods in transit	Maximum raw material in transit
Mean	48	32	72	107
Standard deviation	0.6	2.4	5.6	3.9
10% error	4.82	3.15	7.17	10.71
Confidence level for 4 replications with 10% error	99.9%	91.8%	91.6%	99.9%

Table E3
Baseline results for four replications, VMI

	Retail inventory	Warehouse inventory	Mfg final goods inventory	Supplier subassy inv	Retail goods in transit	Warehouse goods in transit	Subassy goods in transit	Raw material in transit
Mean	15	20	80	100	10	20	40	60
Standard deviation	0.03	0.07	0.10	0.17	0.04	0.09	0.10	0.18
10% error	1.5	2	8	10	1	2	4	6
Confidence level for 4 replications with 10% error	99.99%	99.99%	99.99%	99.99%	99.99%	99.99%	99.99%	99.99%

Table E4
Results for Type 2 disruption for four replications, VMI

	Maximum retail goods in transit	Maximum warehouse goods in transit	Maximum subassy goods in transit	Maximum raw material in transit
Mean	14	106	52	93
Standard deviation	0.5	4.0	1.7	2.2
10% error	1.36	10.59	5.24	9.33
Confidence level for 4 replications with 10% error	98.6%	98.7%	99.1%	99.7%

Table 4
Lower and upper bounds for unfilled retail orders, 95% confidence

Maximum and average total unfilled customer orders				
Case	Traditional supply chain		Vendor managed inventory	
	Lower bound	Upper bound	Lower bound	Upper bound
Base	0	0	0	0
Type 1 disruption	83.5	87.4	85.5	90.0
Type 2 disruption	59.3	65.7	62.9	68.7
Type 3 disruption	0	0	0	0
Type 4 disruption	0	0	0	0

between the traditional supply chain structure and a vendor managed inventory structure in terms of unfilled customer orders. Table 4 presents 95% confidence intervals for the total number of unfilled customer orders for each scenario.

By inspection, one can see that there are no statistically significant differences between unfilled retail orders for the traditional supply chain and VMI. The behavior of the two structures, however is markedly different. Consider Figs. 6a and 6b, which show the average inventory held by each supply chain partner for the two different supply chain structures for each scenario.[10] (See Figs. E7 and E8.)

Although the average inventory levels for the traditional supply chain and the vendor managed inventory systems are almost identical in the base case, this similarity quickly disappears when a transportation disruption occurs.[11] The most havoc is created in the traditional supply chain structure when a Type 2 disruption occurs, halting the transportation of goods from the tier 1 supplier to the warehouse. This impact on average inventory levels is shown in Fig. 6a, and is especially apparent in the traditional supply chain for the retailer and the warehouse. Although not as pronounced, both the tier 1 and tier 2 suppliers are slightly better off when a Type 2 disruption occurs in the VMI system, which is shown in Fig. 6b. It is interesting to note that the Type 2 disruption has ripple effects both downstream and upstream in the traditional supply chain, extending downstream to the retailer and upstream to the tier 2 supplier. This occurrence has some intuitive appeal because this type of disruption occurs close to the middle of the chain.

[10] The average inventory level was computed using a 2-step process. First, the average inventory level was computed for each run by averaging the inventory held by each echelon for day 175 through day 275. The average of these 4 values for each run was then computed to determine the overall average inventory for each echelon. The average value can be manipulated by selecting the time frame from each simulation run over which to compute the average. The choice of day 175 through day 275 was chosen because it included values before the disruption at day 200, and lasted long enough for the bullwhip effect in the system to subside for both inventory levels and inventory in transit for all scenarios. The two graphs E7 and E8 illustrate this behavior for a Type 2 disruption for a traditional supply chain, which exhibits more variability than the VMI structure.

[11] Average inventory levels are not identical for the warehouse in the traditional and VMI structures for the base case because target warehouse inventory for the VMI model is 20, whereas it is 30 for the traditional supply chain model.

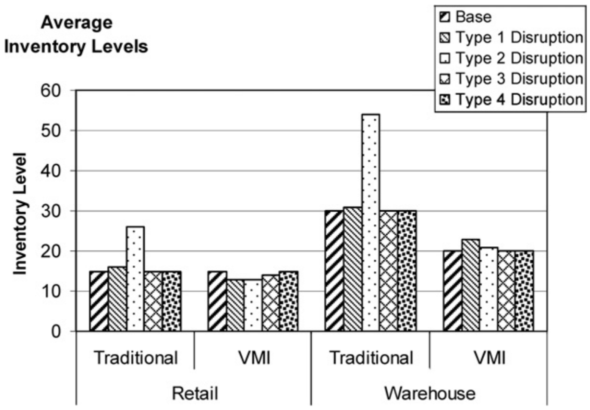

Fig. 6a. Average inventory levels, retail and warehouse.

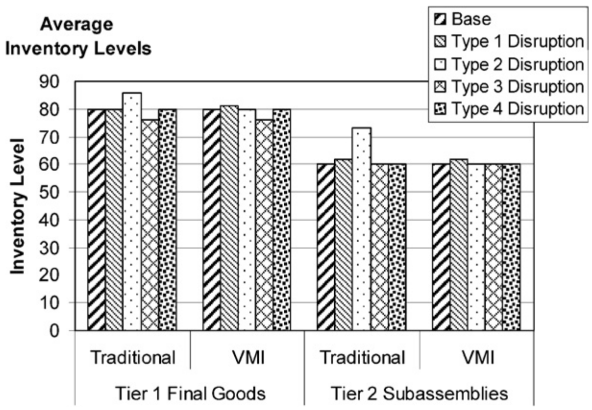

Fig. 6b. Average inventory levels, tier 1 and tier 2 suppliers.

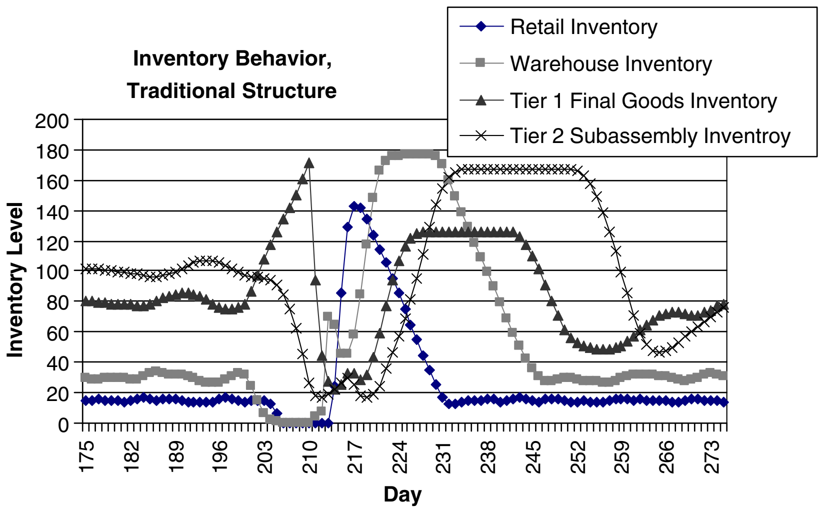

Fig. E7. Inventory levels for day 175 through day 275, Type 2 disruption.

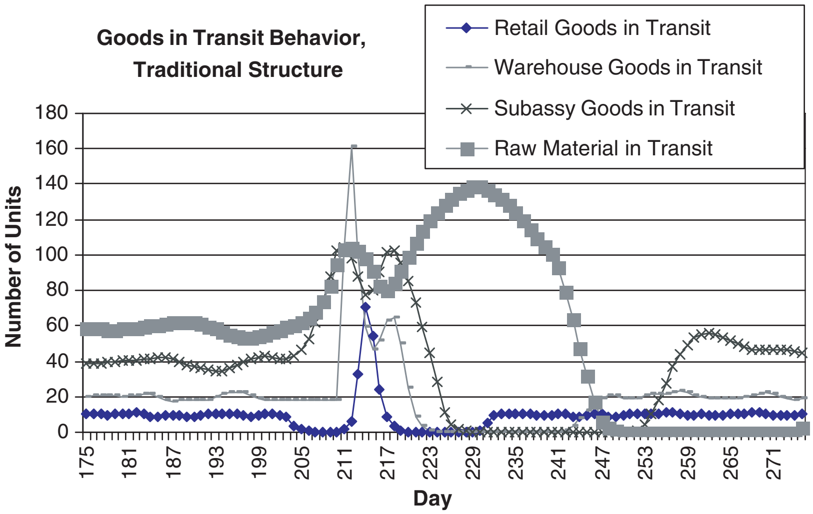

Fig. E8. Goods in transit for day 175 through day 275, Type 2 disruption.

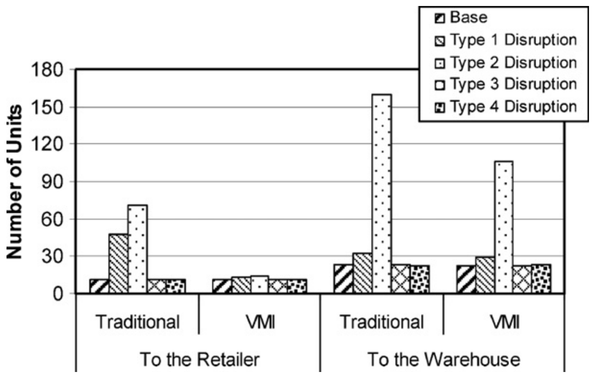

Fig. 7a. Average maximum goods in transit, retailer and warehouse.

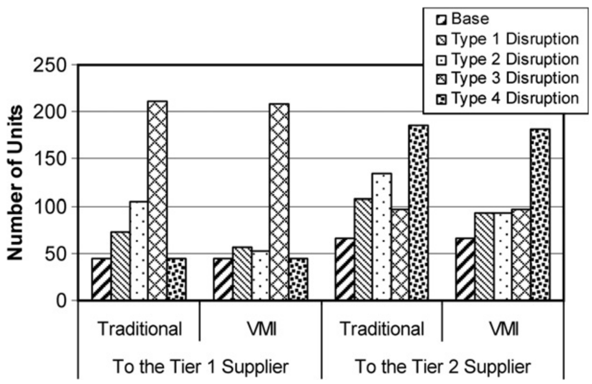

Fig. 7b. Average maximum goods in transit, tier 1 and tier 2 supplier.

Table 5
Average maximum goods in transit

Case	Traditional structure, goods in transit to:				Scenario	VMI Structure, goods in transit to:			
	Retail	Warehouse	Tier 1	Tier 2		Retail	Warehouse	Tier 1	Tier 2
Base	11	23	44	66	Base	11	22	44	66
Type 1 disruption	48	32	72	108	Type 1 disruption	13	29	56	93
% change from base	<u>336</u>	39	64	64	% change from base	<u>18</u>	32	27	41
Type 2 disruption	71	160	105	134	Type 2 disruption	14	106	52	93
% change from base	545	<u>596</u>	139	103	% change from base	27	<u>382</u>	18	41
Type 3 disruption	11	23	211	97	Type 3 disruption	11	22	209	97
% change from base	0	0	<u>380</u>	47	% change from base	0	0	<u>375</u>	47
Type 4 disruption	11	22	44	186	Type 4 disruption	11	23	44	182
% change from base	0	−4	0	<u>182</u>	% change from base	0	5	0	<u>176</u>

Not only are average inventory levels affected, but so is the maximum number of goods in transit. Recall that this model places no capacity constraints on transportation. Figs. 7a and 7b show the average maximum goods in transit to each supply chain partner for the two different supply chain structures for each scenario.

Once again, a Type 2 disruption creates the most havoc in the system downstream for both the traditional structure and the VMI structure, being a bit more problematic for the traditional structure. A Type 2 disruption results in an increase in maximum goods in transit to the warehouse by more than 500% in the traditional supply chain structure, compared to slightly less than 400% for VMI. In the VMI system, however, the retailer is more protected, as the maximum goods in transit to the retailer increases by less than 20%, compared to an increase of more than 300% in the traditional supply chain structure.

Table 5 shows the average maximum goods in transit for each scenario, as well as the percentage increase in this maximum compared to the base case for each type of disruption. Notice the pattern along the diagonals where the percentage changes are underlined which indicates, for the most part, where the greatest impacts will be. For the Type 1 and Type 2 disruptions, the percentage increase in the maximum number of goods transported is less for the VMI model compared to the traditional supply chain. The percentage increases in the maximum goods transported for the Type 3 and Type 4 disruption are similar for both supply chain structures.

The next two sections discuss the inventory behavior for each supply chain structure and provide explanations for the difference in the behavior of the two structures.

3.2. Traditional supply chain

Table 6 shows the average and standard deviation for average inventory levels and unfilled retail orders. These results show statistically significant differences between the base case and a Type 2 disruption for the retailer, the warehouse, and the tier 1 supplier's final goods inventory.[12] A Type 3 disruption also results in a significant difference from the base case for the tier 1 supplier's final goods inventory. The largest increases in average inventory levels are experienced by the retailer and the warehouse for a Type 2 disruption. Also, total unfilled retail are highest for a Type 1 disruption, the disruption closest to the final customer. Averages, however, do not convey a complete picture. It is instructive to look at the behavior of the system during and shortly after a disruption occurs.

Fig. 8 shows the behavior of both the retail and warehouse inventory for a Type 2 disruption. Retail inventory goes down to zero shortly after the disruption, and rises to approximately 140 after the disruption is over

[12] A *t*-test for comparing population means with unequal variances was conducted and the following *t*-statistics were computed when comparing selected scenarios to the base case: retail inventory, Type 2 disruption: 55.4; warehouse inventory, Type 2 disruption: 29.4; tier 1 final goods, Type 2 disruption: 20.8; tier 1 final goods, Type 3 disruption: 13.3.

Table 6
Simulation results for the traditional structure

Case		Average retail inventory	Average warehouse inventory	Average tier 1 final goods inventory	Average tier 2 subassembly inventory	Total unfilled retail orders
Base	Average	15	30	80	100	0.0
	Standard deviation	0.03	0.06	0.10	0.19	0.0
Type 1 disruption	Average	16	31	80	101	85
	Standard deviation	0.20	0.12	0.06	0.10	1.11
Type 2 disruption	Average	**26**	**54**	**86**	102	63
	Standard deviation	**0.38**	**1.62**	**0.53**	1.73	3.0
Type 3 disruption	Average	15	30	**76**	100	0.0
	Standard deviation	0.02	0.13	**0.58**	0.32	0.0
Type 4 disruption	Average	15	30	80	99	0.0
	Standard deviation	0.04	0.09	0.19	1.01	0.0

because the retailer is compensating for the lack of inventory by ordering too much. Similarly, the warehouse also overreacts to the lack of inventory, with maximum inventory climbing to over 160 units.

These higher inventory levels occur because the warehouse runs out of stock when the Type 2 disruption stops the flow of final goods coming into the warehouse. Although this situation results in slightly fewer unfilled customer orders than a Type 1 disruption (because there's more inventory in the system between the customer and the point of disruption), a Type 2 disruption creates more fluctuation in inventory held by each echelon as well as inventory in transit. When the warehouse runs out of stock, this causes the retailer to run out of stock as well, which exacerbates the bullwhip effect. This behavior is less pronounced when a Type 1 disruption occurs, shown in Fig. 9.

With a Type 1 disruption, the warehouse does not run out of stock, and is able to ship all the orders placed by the retailer after the disruption is over, resulting in lower inventory peaks.

Table 7 shows the average maximum inventory levels for each scenario for comparison. It shows once again that a Type 2 disruption results in the highest inventory levels for the retailer, warehouse, and tier 1 supplier. The tier 2 supplier experiences the greatest inventory levels in the presence of a Type 3 disruption.

This behavior is not as pronounced in the vendor managed inventory system, discussed in the next section.

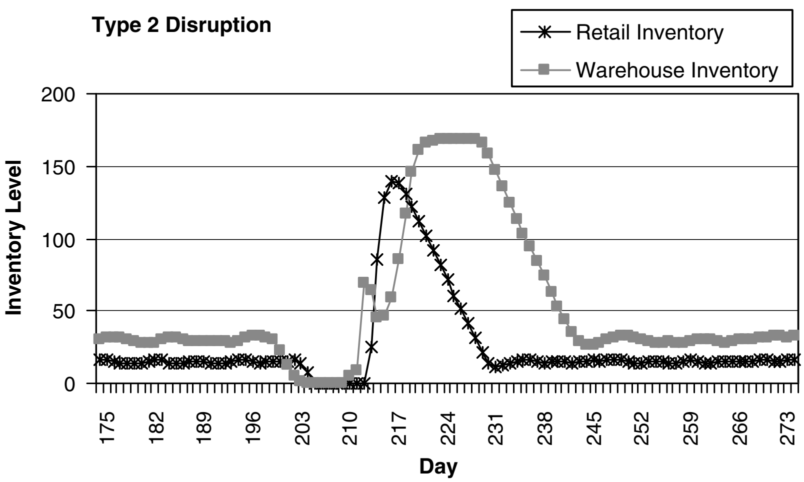

Fig. 8. Retail inventory and warehouse inventory for a Type 2 disruption, traditional structure.

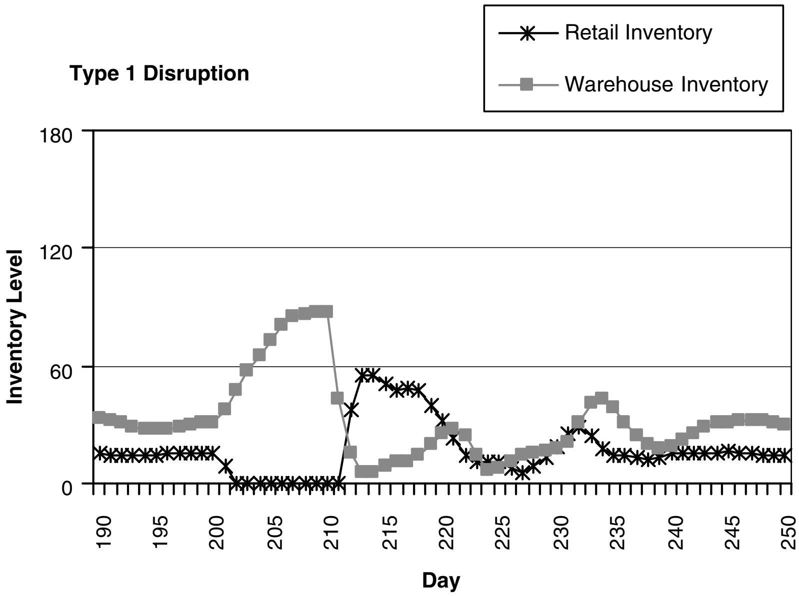

Fig. 9. Retail inventory and warehouse inventory for a Type 1 disruption, traditional structure.

Table 7
Average maximum inventory levels, traditional structure

Case		Retail inventory	Warehouse inventory	Tier 1 final goods inventory	Tier 2 sub-assembly inventory
Base	Average maximum	17	34	85	105
	Standard deviation	0.45	0.21	0.77	1.11
Type 1 disruption	Average maximum	57	88	127	159
	Standard deviation	1.55	0.99	0.65	0.81
Type 2 disruption	Average maximum	142	171	172	173
	Standard deviation	1.7	4.6	1.5	4.0
Type 3 disruption	Average maximum	17	34	85	187
	Standard deviation	0.50	1.26	1.52	0.95
Type 4 disruption	Average maximum	18	34	87	104
	Standard deviation	0.61	0.55	0.73	1.84

3.3. Vendor managed inventory

Table 8 shows the average and standard deviation of inventory levels and unfilled customer orders for vendor managed inventory. Although the average unfilled retail customer orders are slightly higher than in the traditional scenario (see Table 6), they are not statistically different. However, the average inventory levels are much lower.

In comparison to the traditional supply chain, maximum inventory levels for the retailer and warehouse have dropped, shown by comparing Tables 7–9.

For a Type 1 disruption, the retailer benefits the most by the VMI structure, followed by the warehouse. Under VMI, the maximum inventory level for the retailer remains stable at approximately 16 units, and the maximum inventory level for the warehouse rises to approximately 60 units, up from 23 in the base case. For the traditional structure, a Type 1 disruption results in retail inventory rising from an average of 17–57 and for the warehouse, an average of 34–88. The maximum inventory levels are about the same for the tier 1 and tier 2 supplier for both structures for the base case and all types of disruptions.

Table 8
Simulation results, VMI

Case		Average retail inventory	Average warehouse inventory	Average tier 1 final goods inventory	Average tier 2 sub-assembly inventory	Total unfilled retail orders
Base case	Average	15	20	80	100	0
	Standard deviation	0.03	0.07	0.10	0.17	0
Type 1 disruption	Average	13	23	81	102	87.7
	Standard deviation	0.03	0.03	0.03	0.07	1.5
Type 2 disruption	Average	13	21	80	101	65.8
	Standard deviation	0.03	0.40	0.12	0.27	2.5
Type 3 disruption	Average	15	20	76	100	0
	Standard deviation	0.01	0.04	0.25	0.38	0
Type 4 disruption	Average	15	20	80	99	0
	Standard deviation	0.02	0.05	0.10	0.57	0

Table 9
Average maximum inventory levels, VMI

Case		Retail inventory	Warehouse inventory	Tier 1 final goods inventory	Tier 2 sub-assembly inventory
Base	Average maximum	16.4	22.8	84.6	106.0
	Standard deviation	0.4	0.7	1.6	1.4
Type 1 disruption	Average maximum	16.5	59.9	127.6	160.7
	Standard deviation	0.3	0.4	0.9	1.6
Type 2 disruption	Average maximum	16.5	82.4	165.0	163.2
	Standard deviation	0.0	4.2	1.5	1.8
Type 3 disruption	Average maximum	16.8	22.8	84.8	185.7
	Standard deviation	0.3	0.3	0.7	1.0
Type 4 disruption	Average maximum	16.6	23.1	84.3	105.6
	Standard deviation	0.1	0.5	0.4	1.5

The Type 2 disruption in the VMI structure creates the highest levels of inventory for the warehouse and the tier 1 supplier, a result similar for the traditional supply chain. The retailer, however, is spared from the peak in inventory. Fig. 10 shows the behavior of retail and warehouse inventory in the presence of a Type 2 disruption. Compared to the traditional supply chain, shown in Fig. 8, there is less fluctuation in inventory.

Although the warehouse inventory rises sharply, it rises to 80 units, compared to 160 in the traditional supply chain model. The retail inventory does not peak above approximately 15 units as it did in the traditional structure.

3.4. Comparative results

It is certainly clear that although a transportation disruption affects both the traditional and vendor managed supply chain, the impact when the VMI structure is used is much less pronounced. For both structures, a Type 1 disruption results in the greatest number of unfilled customer orders, which is only slightly higher than the unfilled customer orders created in the presence of a Type 2 disruption.

In general, a Type 2 disruption has the greatest "ripple effect" through the supply chain, resulting not only in unfilled orders, but also the highest inventory levels for the retailer in the traditional supply chain structure, and the warehouse, and tier 1 supplier in both structures. Additionally, a Type 2 disruption creates the highest

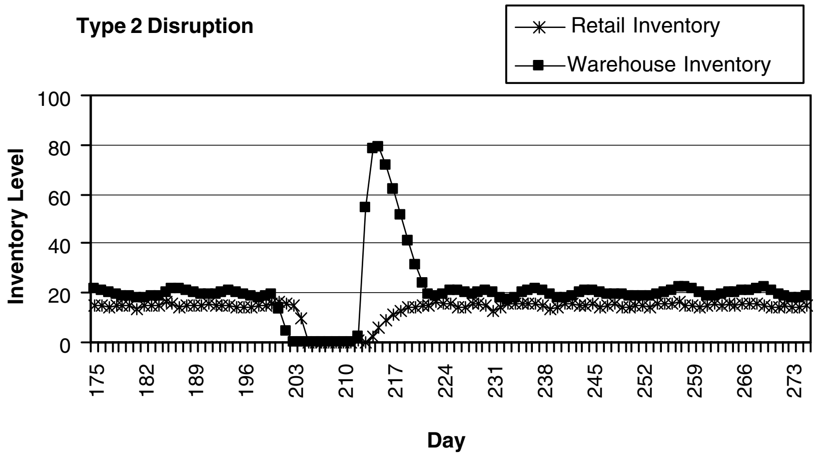

Fig. 10. Retail inventory and warehouse inventory for a type 2 disruption, VMI.

goods in transit to the retailer and warehouse in the traditional structure, and to the warehouse in the vendor managed system.

Both structures exhibit similar inventory and in-transit behavior for all 4 types of disruptions for the tier 1 and tier 2 supplier, except for the maximum number of goods in transit for a Type 1 and Type 2 disruption. For these scenarios, the maximum goods in transit to the tier 1 and tier 2 supplier are lower for VMI than the traditional structure. For a Type 1 disruption, the goods in transit to the tier 1 supplier are 72 for the traditional structure compared to 56 for VMI. For the Type 2 disruption, goods in transit to the tier 1 supplier are 105 compared to 52 for VMI. Goods in transit to the tier 2 supplier show similar results. For a Type 1 disruption, goods in transit are 108 for the traditional structure compared to 93 for VMI; and for a Type 2 disruption, goods in transit are 134 in the traditional structure compared to 93 for VMI.

The difference in the behavior of the two structures can be attributed to the information sharing. Consider a Type 1 disruption for the VMI structure. Although the retailer experiences lost sales and retail inventory reaches 0, the retailer does not overreact by placing orders with the warehouse, which go unfilled because all goods movement is stopped. The vendor, who is tracking customer demand, does not overreact by sending too much inventory to the retailer. This difference is due to the logic for shipping items to the retailer.[13]

When a Type 1 disruption occurs, retail shipping stops. It resumes when the disruption is over. In the traditional model, orders have piled up at the warehouse, accumulating in the warehouse backlog so that when the disruption is over and shipping resumes, the backlog has increased. Retail shipping rises then sharply in response to the backlog. Figs. 11 and 12 illustrate this behavior.

Comparison of the traditional supply chain and the VMI structure demonstrates that the vendor managed inventory structure is superior to the traditional supply chain structure in providing some protection against the effects of a Type 1 and a Type 2 disruption. Additional implications of these findings are discussed in the next section.

[13] Traditional structure logic:
retail_shipping = Min(Warehouse Backlog, Warehouse Inventory),
warehouse_ordering = (retail_inv_gap/retail_inv_adj_time) + avg_sales.

VMI structure logic:
retail_shipping = retail_inv_gap/retail_inv_adj_time + avg_sales,
where
retail shipping = amount shipped to retailer,
Warehouse backlog = backlog of orders placed by retailer with the warehouse (accumulated orders),
Warehouse ordering = order quantity placed by retailer with the warehouse (individual orders).

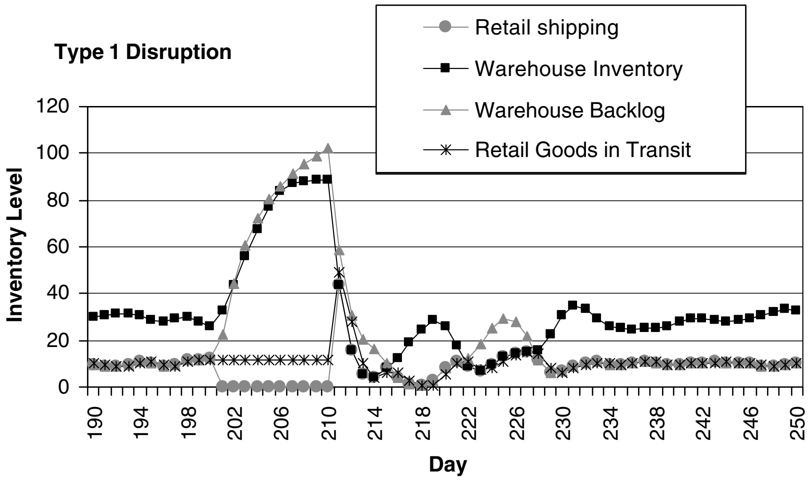

Fig. 11. Shipping/ordering logic and behavior, traditional structure.

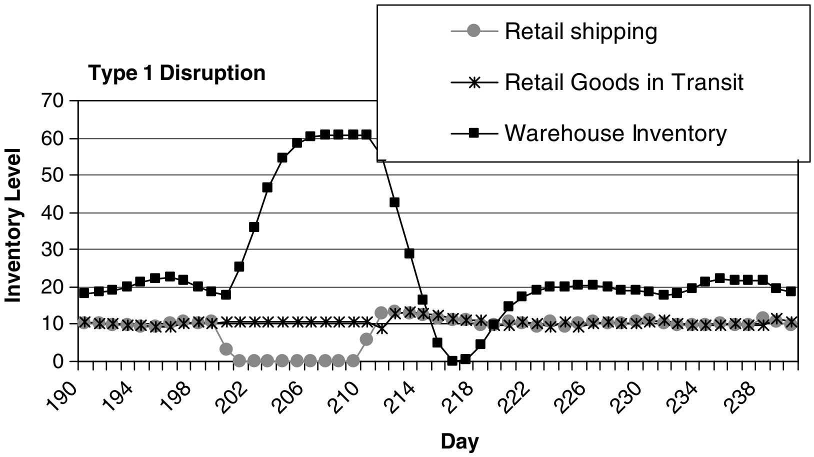

Fig. 12. Shipping logic and behavior, VMI.

4. Conclusion

The Type 2 transportation disruption, which occurs between the tier 1 supplier and the warehouse or distributor, creates the most problems, particularly for the traditional supply chain structure. This finding has implications for the relative locations of the tier 1 suppliers and the warehouses they serve. For example, if a transportation route between a tier 1 supplier and a warehouse is likely to experience a disruption, efforts should be made to identify alternative routes, alternative modes of transportation, alternative suppliers who do not share the same route, or transshipment strategies between warehouses. If a disruption can be anticipated, then measures can be used to protect the supply chain against it. This is an especially important finding in light of the globalization of supply chains. Manufacturing and assembly plants may be located overseas and across international borders, limiting the options available for alternative modes or trade routes if a disruption occurs or is anticipated. The likelihood of a Type 2 disruption when shipping across international borders increases in the presence of security threats.

Another strategy for protecting against a Type 2 disruption is adopting a vendor managed inventory strategy. This strategy requires sharing customer demand information, and retail and warehouse inventory positions with the tier 1 supplier. As this research revealed, the impact of a Type 2 disruption is ameliorated in the presence of vendor managed inventory. Albeit small, this strategy may introduce another type of risk—dissemination of intellectual property such as technical information or business models. These risks are interconnected, but the extent of the risk associated with intellectual property loss in the presence of VMI must be weighed against the risk of a transportation disruption.

A third strategy for reducing the impact of a Type 2 disruption includes carrying additional inventory or having a redundant supplier. The supply chain could add inventory on a permanent basis, increase safety stocks, or build up a buffer of inventory if advance warning of an impending transportation disruption is received. These strategies, however, can be very costly unless a disruption is somewhat predictable. Even then, the amount of time available to build up buffer stock may not be sufficient to meet the anticipated needs, and determining how much to build up could also be troublesome. This strategy is more appropriate for items that have a low holding cost and will not be obsolete, atypical characteristics for goods that flow between a tier 1 supplier and a warehouse. Carrying additional inventory may be a more appropriate strategy for a Type 3 or Type 4 disruption, before additional value has been added through the production process. The downside of this strategy is that it undermines the principles of lean operations, and unless the additional cost of carrying inventory are borne across the entire supply chain, there is no incentive to increase inventory held by upstream suppliers.

Having a redundant supplier is appropriate for high value items that do not share the same disruption risk. However, if a company had two redundant suppliers located in China when the California ports closed down in 2002, they would not have had any protection from the port closure.

Although these other mitigation strategies, carrying additional inventory and having redundant suppliers, were not explored in this research, their viability could be tested through the use of simulation modeling and other types of risk assessment and risk mitigation methods. These mitigation strategies could be addressed within the context of strategic supply chain planning, which includes decisions regarding inventory aggregation, centralization, and standardization of components, to name a few. If a supply chain adopts postponement or mass customization as part of their inventory strategy, risk mitigation solutions for transportation disruptions need to take these inventory methods into account.

The results of this research are very conservative, perhaps understating the benefits of a VMI system because of the assumptions of unconstrained manufacturing and transit capacity, as well as stable customer demand. Nevertheless, this research could be used to establish minimum requirements for additional capacity in the case of a particular type of disruption. For example, in a Type 2 disruption for the VMI structure, goods in transit for the warehouse rose from an average of 22 units to a maximum of 106 units, a 382% increase. Although the maximum goods in transit was not sustained over a very long period of time, it can be used to determine the expected additional capacity required in the event of a Type 2 disruption. Similarly, this type of simulation study can be used to identify additional transportation capacity requirements for a Type 3 or a Type 4 disruption. In each of these cases, maximum goods in transit to the tier 1 and tier 2 suppliers rise substantially in both the traditional supply chain structure and VMI. The cost of securing additional transport capacity can then be balanced against the overall supply chain costs.

Although less severe than the Type 2 disruption, the Type 1 disruption, which occurs between the warehouse and retailer, has an impact similar to the Type 2 disruption, particularly in the VMI structure. The impact could be reduced by identifying the "second best" warehouse–retailer combination in the event of a transportation disruption. The benefit of this exercise could also be helpful in reducing other risks, such as the risk of a stockout at a warehouse, by having a backup plan.

In conclusion, a transportation disruption between the tier 1 supplier and the warehouse, the Type 2 disruption, has the greatest impact on the supply chain, creating a "ripple effect" both downstream and upstream, creating relatively high increases in inventory levels and goods in transit, and resulting in unfilled customer orders. The impact is less severe, particularly for the retailer, when vendor managed inventory is used. A disruption between the warehouse and retailer, the Type 1 disruption, is less severe than the Type 2 disruption, but results in slightly more unfilled orders. Finally, the Type 3 disruption, which interrupts the flow of goods between the tier 1 and tier 2 supplier, causes the inventory levels for the tier 2 supplier to temporarily rise by approximately 80% for both the traditional supply chain and VMI structure. The Type 4 disruption, which interrupts the flow of goods between the raw material supplier and the tier 1 supplier, temporarily increases the goods in transit by approximately 180% for each structure.

Risk mitigation strategies for transportation disruptions need to consider the supply chain structure as well as where this disruption could occur within the supply chain. The relationships between individual risks and the strategies for mitigating these risks should also be considered in any overall risk management plan so that appropriate risks and benefits are shared. This research has demonstrated the potential severity of a transportation disruption between the tier 1 supplier and the warehouse, representing the most important point in the supply chain to begin to develop appropriate risk management strategies for transportation disruptions.

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