Electronic Broker Impacts on the Value of Postponement

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Abstract

Global and electronic markets are increasingly forcing manufacturing enterprises to become more competitive. As a result, many manufacturing enterprises are seeking to manage their supply chains more effectively. Product differentiation timing is one important factor in supply chain management. Under an early product differentiation process, finished products are manufactured and stored in a distribution center until delivery. Under a delayed product differentiation process, partially completed product components are manufactured and stored in a distribution center; later, based on demand information, finished products are completed from the product components. The difference in value between early product differentiation and delayed product differentiation is the value of postponement. Prior research has analytically shown that the value of postponement is affected by information precision in demand forecasts. In this article, we investigate whether adding a market-making electronic broker to a supply chain increases the value of postponement. We hypothesize that it may do so by providing greater accuracy in demand forecasting. We test this relationship by comparing the results of several agent-based simulations that vary between early and late differentiation strategies and the use of an electronic broker.

1. Introduction

The attention given to issues surrounding supply chain management continues to grow. Beginning with early research on channel structure[10][13] and coordination [19][29], the scope of supply chain considerations has broadened to include, for example, communication strategies in supply chains [30], multi-market coordination issues [9], as well as material management concerns [23]. Supply chain management considerations now reach across the personal computer industry, clothing, and the automobile manufacturing industry, to name a few [15][16][18]. And the role of information technology is now recognized as an important and valuable component of supply chain effectiveness [27].

Of particular interest in this paper is the role of information technology in delayed product differentiation in a supply chain. The value of delayed product differentiation was originally posited by Alderson [7], who suggested that demand information might better be used later in the distribution channel where it was presumed to be more accurate to guide the form, identity and distribution of products. This stream of research has continued, so that recently Lee and Tang [24] have modeled the costs/benefits of redesign strategies for delayed differentiation, and Anand and Mendelson[8] have modeled delayed differentiation in a supply chain to analyze the effects of information in postponement strategies.

In this paper, we employ a simulation approach to analyze the impact of an electronic broker [14][35] on the value of postponement in a supply chain (defined as the difference in profits between early and late product differentiation). We focus on the impact of an electronic broker because it increases the precision of demand information, and in doing so may affect postponement strategies in the distribution channel.

This paper is organized as follows: In section 2, we discuss the issues related to delayed product differentiation. In Section 3, we list hypotheses that are later tested. In section 4, we discuss the methods we use to test our hypotheses, the use of simulations as well as the benchmarking of our model. In section 5, we present the results of our study. Finally, in section 6, we discuss the implications of our research findings.

2. The Value of Postponement

Demand uncertainty is increasing in a number of markets. Because of increased product proliferation, diminished lead times, global differences in product specifications and preferences, the requirements for firms to produce more product variations with less forecasting information are increasing. Anand and Mendelson point out that these developments are particularly salient for fast clock-speed industries such as hi-tech, as well as industries with long production and lead times such as the fashion industry. Product proliferation has a large impact on hi-tech industries because quickly diminishing value of inventories makes managing the supply chain through maintaining large

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amounts of safety stock highly expensive. In the case of the fashion industry, long production lead times require that the creation of clothing is done before sufficient demand information is available for making style decisions that are compatible with the upcoming seasons.

One consideration in obviating the demand uncertainty problems associated with the above examples is known as postponement, or delayed product differentiation [39][43][48][49][24]. Under postponement, the differences that make up product variety are added as late in the supply chain as is possible, in order to take advantage of better and more recent demand information. Thus, with postponement, laser printers sent to Europe are not fitted with the appropriate power supply until after their destination is decided. So, too, with the laser printers that are sent to locations in the United States, with the appropriate power supply added later as well.

The difference in profits between early differentiation (e.g. making finished laser printers before their destination is identified) and delayed differentiation (making finished laser printers only after their destination is identified) is known as the value of postponement. The value of postponement for a given production process is contingent on a variety of factors such as demand correlation, demand variation, and information precision and timing[8]. So, for example, in the case of demand correlation, the value of postponement is very small when product demand is highly correlated, (e.g. when roughly equal demand exists for both European and American version of a laser printer, making the demand for one region's products a good predictor of the demand for another region's products.) Concerning demand variation, when overall product demand changes sharply from period to period, the value of postponement is high.

In the remaining sections, we consider the impact of an electronic broker on the value of postponement, and juxtapose our finding to those of Anand and Mendelson's analytical results.

3. Impacts of an Electronic Broker

The model of an electronic broker used in our research is based on the Custom Mass Production (CMP) model discussed in [14]. Fundamentally, the model entails joining together buyers with locally unique preferences, in a global electronic format, to form a market that suppliers can serve in a cost-effective way. The model was characterized as an electronically brokered CMP channel that allowed buyers to acquire customized products at prices that reflected economies of scale. This was achieved through buyer consolidation: using collaborative filtering to identify like-minded buyers, negotiating satisfactory product configurations to allow for self-generated market niches, and negotiating contracts with various suppliers. The model assumed that there were more similarities in buyers' custom preferences than traditional market research methods could detect or suppliers could exploit through traditional distribution channels. The CMP broker, then, represents individual buyers in a multi-stage bargaining action.

Within the bounds of supply chain management, a CMP broker changes the characteristics of Information Precision. We assume that because a CMP broker helps define product configurations that are agreed upon by a group of individuals, individual make-to-order requests may instead become batched, make-to-order requests. In the case of information precision, we assume that information precision in demand forecasting becomes certain insofar as large scale orders are made through buyer consolidation, and forecasting for non-stock items is obviated with the presence of a CMP broker.

With regard to supply chain management, and particularly focusing on the value of postponement, we are interested in evaluating the effects of a CMP broker along several dimensions: 1) inventory costs in early and late differentiation, 2) lead times in early and late differentiation, and 3) the overall value of postponement. We are also interested in evaluating whether early or delayed differentiation is the best strategy to use when a supply chain is enabled by a CMP broker.

Within this realm of inquiry, we ask two questions. First, because work done by Anand and Mendelson [8] showed that the value of postponement increased in demand variability and information precision, and because a CMP-broker facilitates greater information precision in demand forecasting, we believe it is likely that an CMP-broker enabled supply chain will increase the value of postponement over a non CMP-broker supply chain. Thus, in our first hypothesis, we state:

- **H1**: A CMP-broker enabled supply chain will, in the face of increasing demand variability, produce a greater value of postponement than a non-brokered supply chain.

Second, because Anand and Mendelson[8] showed that the value of postponement falls with demand correlation, but that it increases with information precision, we believe it is likely that a CMP-broker enabled supply chain will have a greater value of postponement as demand correlation decreases than a non-brokered supply chain. This is because of the additive effect anticipated by a CMP-broker's greater information precision regarding demand forecasting. Thus, our second hypothesis is as follows:

- **H2**: A CMP-broker enabled supply chain will, in the face of decreasing demand correlation, produce a greater value of postponement than a non-brokered supply chain.

4. Methodology

To evaluate the effects of a CMP-broker on a supply chain, we employ a simulation methodology. The use of simulations in research has broadened over time to include a widening range of applications, ranging as far as to evaluate descriptions of bounded rational but adaptive economic systems[12][11], normative implications characterized by intentional rational economic behavior[32] as well as issues as complex as organizational learning[22][21]. Within the topic of this paper, simulations have also been used to evaluate supply chain characteristics[20].

The limitations of simulations include the fact that they are dependent upon researchers' theoretical assumptions and the initializing values of the independent variables. Some of these concerns may be obviated by changing the assumptions of the model or by altering the initial variables or both, and performing a sensitivity analysis over the manifold versions of the model. The problems of simulations generally include, as with any abstraction, their omission of detail, limiting somewhat the complexity of individuals and decisions and processes. Additional problems include attempting to verify the models under consideration.

To capture the salient characteristics of the supply chain in our study, we began by recognizing that there are five elements of a simulation[44].

- Researcher specified assumptions about the model being tested
- Parameters (fixed values and control variables)
- Inputs, or independent variables
- Algorithms, or process decision rules that convert input values to outputs
- Outputs, or dependent variables

We explain these elements in the sections that follow, and detail the Swarm implementation tool kit, which we used as a simulation platform, in appendix A.

4.1 Modeling Assumptions

Our simulation model of a supply chain is based on a simple, three-node chain described in [8]. They compared Inventory, Sales, and Profits under delayed and early differentiation to quantify the value of postponement (VOP). They assumed the same demand and cost environments for early and delayed differentiation, and found the following relationships (which we used to benchmark and verify our simulation model):

(1) Delayed differentiation (DD) reduces inventory costs
(2) DD increases VOP
(3) VOP increases in Demand variability
(4) Profits fall with Demand variability
(5) VOP falls with Demand Correlation
(6) DD reduces average inventory
(7) Profits increase under DD with increased information precision

All of the above relationships were benchmarked and confirmed with our simulation model.[1]

4.2 Fixed Simulation Parameters

Our simulations actually consist of two models; one for delayed differentiation (DD) and one for early differentiation (ED). The two models are identical in all respects, except for the way in which they use information to guide the manufacturing process. Both models have parameters that were identically fixed during all simulations. They included the following parameters.

- *Model parameters*. In addition to the basic structure of the supply chain, both models also define how orders and parts move between and within nodes of the supply chain. Numeric values define the order and part forwarding times, production times, inventory costs, and startup inventory quantity. In the simulations, the startup inventory quantity was zero, initial production time was 0.2 hours for each part, while the customization time was 0.1 hours for each part. Inventory costs were computed as the holding time multiplied by a fixed cost: $(Part_{exitTime} - Part_{arrivalTime}) * cost$. For manufactures, the cost was \$0.40 per part, while the cost was \$0.60 per part for distributors.
- *Order and part parameters*. All orders originate at customers, pass through a broker, arrive at the distribution node and then are passed onto the manufacturing nodes. All parts originate at a supplier and are passed onto the manufacturing nodes.
- *Part parameters*. In the DD model, finished product A is manufactured from parts 2 and 6, where 2 is manufactured from parts 0 and 1. The ED (early differentiation) model has a similar fixed structure. (See figures 1 and 2.)
- *Timing parameters.* All simulations were run for 50 days with a time step of 1.0 hour. A simple exponential forecasting function was used to predict demand quantity for finished products. The formula was as follows:

  Forecasted Demand =
  α ** Actual Demand + (1 -* α*) * Forecasted Demand*
  Actual Demand ≡ *Actual demand from previous period*
  Forecasted Demand ≡ *Forecasted demand from previous period.*

  The forecast horizon was 10 days. The parameter, α, was set at 0.5.

4.3 Independent Simulation Variables

Information precision in conjunction with demand correlation and variability were the independent simulation variables. Information precision is a measure of the accuracy of the incoming demand information as it is passed from the broker to the most “upstream” node of the supply chain. The demand variables of correlation and variability concern the configuration of orders as they are passed from the broker to the supply chain.

The simulations relied on the following definitions for the independent variables.

- *Demand correlation*. Consider the market demand for quantities of two products, A and B, at time *t*. The correlation between these demand quantities, DQ_A and DQ_B, is one if $DQ_A = DQ_B$ and less than one if $DQ_A \neq DQ_B$. Demand correlation = DQ_A/DQ_B, where $DQ_A \leq DQ_B$.
- *Demand variability.* The market demand for a quantity of a product A at time *t* can be represented as normal

[1] There is some ambiguity with assumption 4 for ED. This is illustrated in section 6.

distribution over a range, [low,high]. If low = high, then there is no variability in DQ_A at each time *t*. Obviously, the larger the value (high - low), the more variability in the demand quantity. Demand variability = (high - low), where for each time *t*, DQ = Normal Distribution [low,high].

- *Information precision*. Generally, for each of the above types of demand information (DI), one can assume that the information received by the supply chain is accurate. That is, $DI_{received} = DI_{actual}$. However, demand information can be inaccurate.
  Let ρ be the precision of the demand information (DI). Then, we model $DI_{received}$ as follows:

  $$DI_{received} = DI_{actual} + (DI_{actual} * \rho)$$

  Thus, if ρ is 0, then the demand information is accurate; that is, $DI_{received} = DI_{actual}$. However, if ρ is 1, then the demand received is twice the actual demand. Thus, in this model, imprecise demand information consistently overestimates the actual demand.

The experiments consisted of simulations with different values of information precision for different configuration of demand information.

4.4 Simulation Functions

The simulation begins with the arrival of orders. Each node of the supply chain fulfills orders that arrive from its “upstream” nodes by producing products from parts that arrive from its “downstream” nodes. Two production policies were considered: build-to-stock (BTS) and build-to-forecast (BTF). These basic simulation functions are described below.

- *Order arrival*. Orders arrive for each product after each *arrival interval* elapses. Each order has an associated *quantity* described as a normal distribution. A supply chain node that receives a customer order for a finished product can send orders to its own suppliers for any necessary parts. Thus, a customer order can create a cascade of orders through the supply chain network. In the simulation, a node fulfills its orders by one of two production policies under the constraints of the fixed simulation parameters (see section 4.2).
- *Build to Stock Production*. In a build-to-stock (BTS) production policy, a node produces products as a means to maintain a specific quantity of inventoried products[28]. The inventory quantity held is determined using an economic order quantity model:

  $$EOQ = \sqrt{\frac{(2 \times demanQuantity \times orderCost)}{inventoryCost}}$$

- *Build to Forecast Production*. In a build-to-forecast (BTF) production policy, a node produces products as a means to fulfill an expected quantity of future orders, as determined by a forecast[28]. As orders arrive at a node, the node can continually update its expectation of future orders. (Section 4.2 defined the exponential forecasting function used.)
- *Information sharing*. Supply chain nodes can share information. For example, an “upstream” node can share its demand forecast with a “downstream” node. This allows the downstream node to update its demand forecast to be consistent with the upstream node. Figures 1 and 2 illustrate such information sharing.
- *Part arrival*. Part arrival is similar to order arrival.

4.5 Dependent Simulation Variables

Each simulation run tracks a number of dependent variables, including: cycle time, fulfillment rate, inventory cost, and capital utilization. Inventory cost is the focus on the following experiments and discussion. However, cycle time and capital utilization are referenced as well. Each of these is defined below.

- *Inventory cost*. Inventory costs are computed for each node. It is the holding time multiplied by a fixed cost: $(Part_{exitTime} - Part_{arrivalTime}) * cost$. The graphs of section 5 illustrate the total inventory costs for all nodes of the supply chain excluding the suppliers or customers.
- *Cycle time*. Cycle times are computed for the most upstream node of each supply chain. It is the order fulfillment period: $(Product_{exitTime} - Order_{arrivalTime})$.
- *Capital utilization*. Capital utilization is computed for each node. It is the percentage of time that a node is busy: (BusyTime / TotalTime).

Each of these dependent variables were used to assess the effects of information precision and different configurations of demand information.

4.6 Benchmarking the Models

We applied two general methods to benchmark our simulation models. First, we compared the analytic results Anand and Mendelson with our simulation results. Our analysis of inventory costs partially overlaps. Thus, we were able to make a general comparison between our simulated inventory costs and their analytically derived costs. (These results are discussed in sections 5.) Second, we were able to duplicate the results of the information sharing strategies and manufacturing policies reported in[41]. In fact, our simulation uses the same simulation framework; however, the components are configured to represent the Anand and Mendelson models.

Our simulation models are based on the three-node supply chain described in (Anand and Mendelson, 1999). Their model consists of a supplier, a manufacturer, and a distribution center. The manufacturer produces products using a Build-to-Stock policy. Next, the distribution center uses market demand information to produce a finished product from the intermediate manufactured product. Our simulation models are essentially the same.

Figures 1 and 2 illustrate the two supply chain models. Both models consist of a supplier (S), two manufacturing nodes (M_1, M_2), and a distributor (D). While not illustrated, a common broker is prepended onto the head of the supply chain before the distributor; it is in contact with the consumer market.

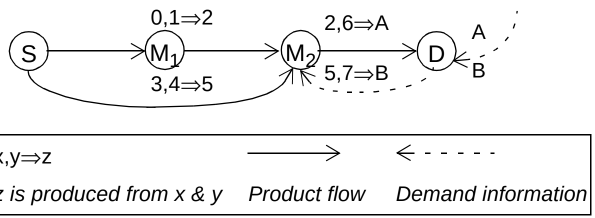

Figure 1. Early differentiation supply chain model.

While the two models manufacture the same products using the same number of parts, they differ in their means of manufacturing. As illustrated in figure 1, early differentiation produces products through independent streams of manufacturing. For example, product A is manufactured first by constructing the intermediate product 2 from parts 0 and 1. Finally, A is constructed by combining intermediate product 2 with part 6.

In contrast to the early differentiation model, the delayed differentiation model uses a common intermediate product to produce both final products. For example, as illustrated in figure 2, product A is manufactured first by constructing the common intermediate product 12 and then combining it with part 13.

In both models, demand information concerning the quantity of each final product is passed on from the distributor to the final manufacturing process (M_2). Such demand information is used to forecast future demand and thereby determine the quantity of products to be manufactured. However, such demand information is not passed onto the initial manufacturing process (M_1). Thus, manufacturing processes M_1 and M_2 use a Build-to-Stock and Build-to-Forecast policies, respectively[28]. These are the same policies as those of Anand and Mendelson. They are used to model existing policies as well as the actual information disconnect that occurs from the earlier time of the intermediate manufacturing to the later time of product customization. That is, the intermediate manufacturing node M_1 must begin manufacturing before an accurate forecast of the product mix is known. At a later time, customization can done by manufacturing node M_2, when a better demand forecast is available. Thus, M_1 does Build-to-Stock while M_2 does Build-to-Forecast.

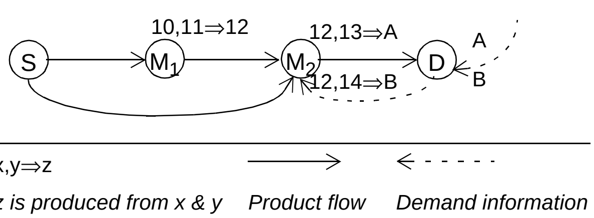

Figure 2. Delayed differentiation supply chain model.

5. Experiments

Here, we report the results of 48 simulations. To provide an understanding of how these simulations were generated, table 1 is provided. It can be used to compare the results between early and delayed differentiation for demand correlation with perfect (CMP broker supplied) demand information.

Table 1 illustrates an empty experiment report table for comparing early and delayed differentiation for demand quantity correlation with perfect information precision ($\rho = 0$). (The dependent variable values for each of the four simulations are not shown.) This table illustrates just one of a number of experiments run. For each of the demand variables (correlation and variability), six different values were considered. For each of those experiments, two different values of information precision were considered. Such experiments were conducted for both ED and DD. Thus, a total of 48 simulations were run (2 * 2 * 6 * 2).

(ρ = *0)*	**Early Differentiation**	**Delayed Differentiation**
Low Demand (correlation)		
High Demand (correlation)		

Table 1: An empty result form for four simulations (ρ = 0).

5.1 Information Precision

The broker generates demand information that is passed to the distributor and then to the second manufacturer (M_2). For each final product, the demand information indicates the quantity requested by a customer. Demand information can be accurate; that is, $DI_{received} = DI_{actual}$. However, demand information can be inaccurate. (See section 4.2.) Moreover, note that the introduction of misinformation occurs as each node. Thus, the effect is cumulative from node D to node M_2 (where information sharing is provided).

In each of the following experiments, information precision, ρ, was considered at 0 (CMP broker) and 2 (no broker). Additionally, each experiment also shows the results of modifying another variable—specifically, demand quantity correlation and demand quantity variability.

5.2 Demand Correlation

For different values of demand quantity correlation, figure 3 illustrates the inventory costs for early differentiation (ED), while figure 4 illustrates the inventory costs for delayed differentiation (DD). The X-axis represents different degrees of demand quantity correlation, from 6 to 1, where 1 is high correlation. These map to the following order quantities for products A and B.

(1) A[5,5] B[5,5]
(2) A[4,4] B[6,6]
(3) A[3,3] B[7,7]
(4) A[2,2] B[8,8]

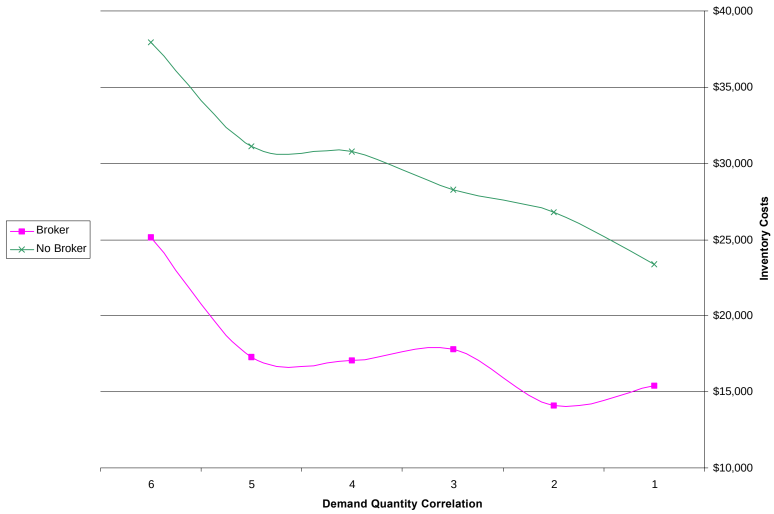

Figure 3. Inventory costs vs. demand correlation for early differentiation.

(5)A[1,1] B[9,9]
(6)A[0,0] B[10,10]
The range [low,high] indicates the normal distribution from which an order quantity will be drawn.

Figure 3 illustrates how inventory costs decrease with increasing order quantity correlation for early differentiation (ED). The effect is most understandable with perfect information precision (CMP broker) and for delayed differentiation, as illustrated in figure 4.

Figure 5 illustrates the savings in inventory costs obtained by delayed differentiation over early differentiation for Broker and No Broker. This can be considered the value of postponement as obtained through inventory cost savings. Notice that the value of postponement decreases in demand quantity correlation. Intuitively, it confirms that, as variability of the product mix decreases, the need to postpone the decsion concering product mix decreases; moroever, a more accurate product mix can be established.

5.3 Demand Variability

For different values of demand quantity variability, figures 6 and 7 illustrate the inventory costs for early and delayed differentiation. The X-axis represents different

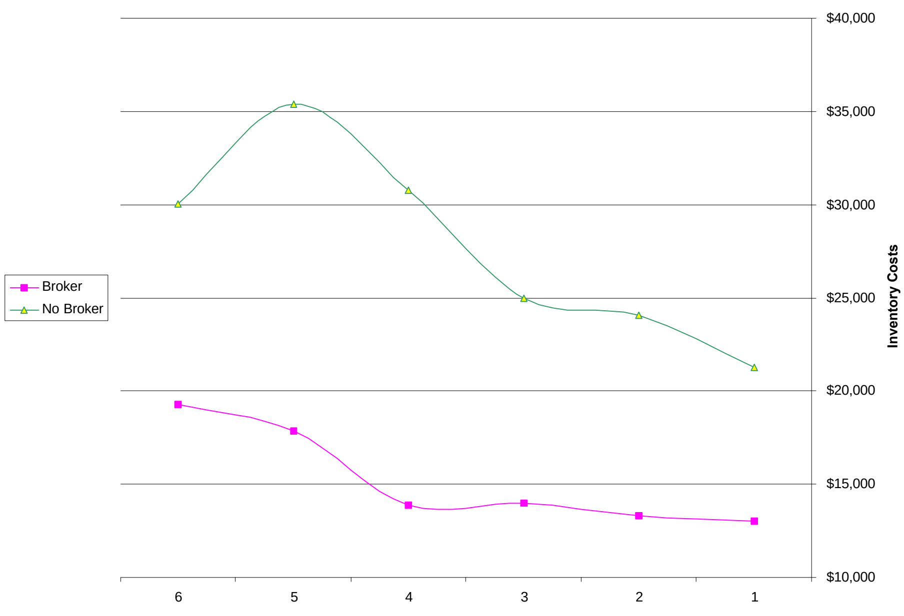

Figure 4. Inventory costs vs. demand correlation for delayed differentiation.

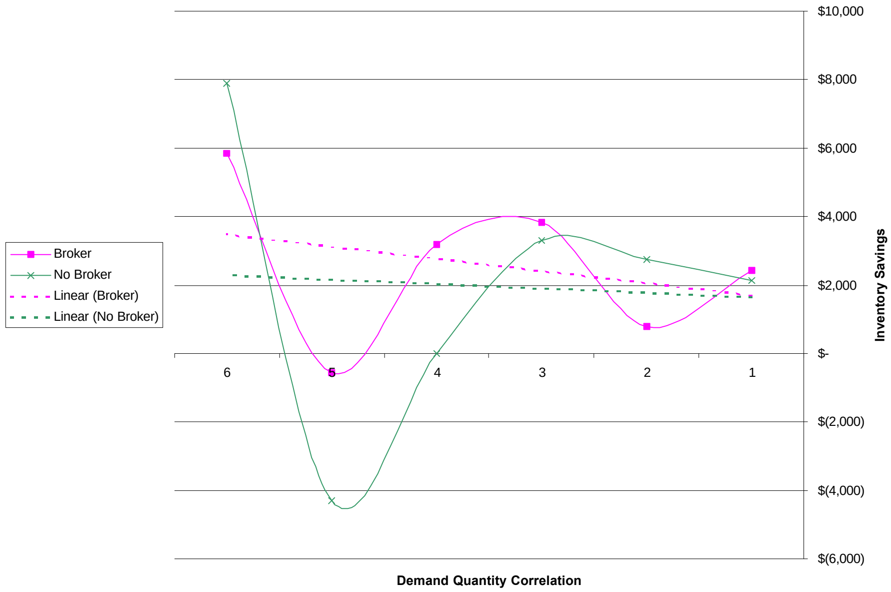

Figure 5. Value of postponement for demand quantity correlation.

degrees of demand quantity variability, from 1 to 6. These map to the following order quantities for products A and B.

(1)A[5,5] B[5,5]
(2)A[4,6] B[4,6]
(3)A[3,7] B[3,7]
(4)A[2,8] B[2,8]
(5)A[1,9] B[1,9]
(6)A[0,10] B[0,10]

Again, the range [low,high] indicates the normal distribution from which an order quantity will be drawn.

Figure 6 illustrates how inventory costs increase with increasing order quantity variability for early differentiation, while figure 7 illustrates the reverse for late differentiation.

Figure 8 illustrates the savings in inventory costs obtained by delayed differentiation over early differentiation for Broker and No Broker. Notice that the value of postponement increases in demand quantity variability.

6. Discussion

In section 3, we posed two hypotheses to test. Here, we discuss how the simulation results illuminate the hypotheses. Note that all graphs show the “bullwhip effect”[25]. Forrester illustrated this classic demand amplification, in which a slight disturbance in demand at the retail level is amplified as it moves through the channel[17].

6.1 H1: Value of Postponement Increases as Demand Variability Increases

Hypothesis H1 states that:

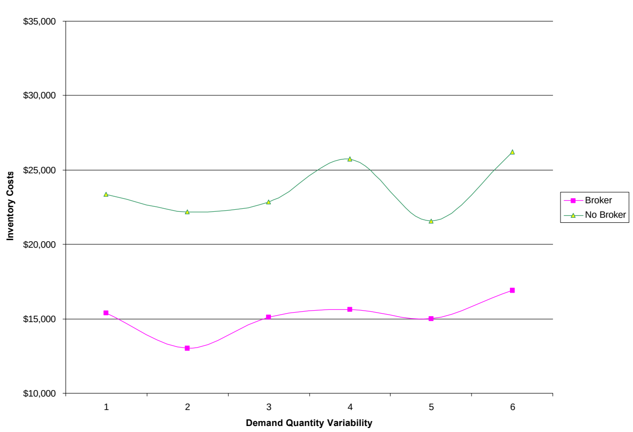

Figure 6. Inventory costs vs. demand variability for early differentiation.

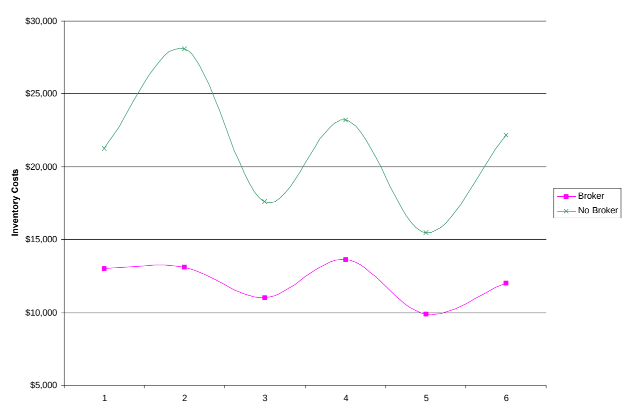

Figure 7. Inventory costs vs. demand variability for delayed differentiation.

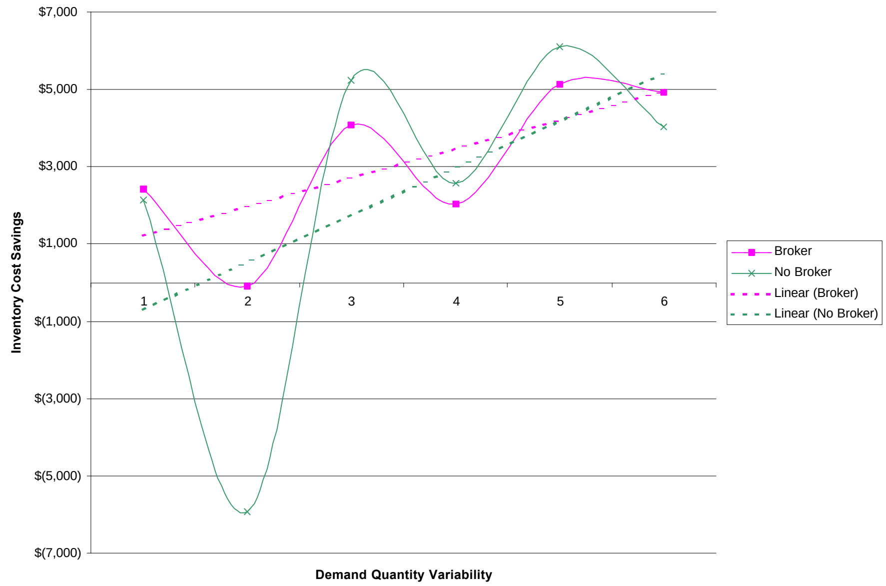

Figure 8. Value of postponement for demand variability.

- **H1**: A CMP-broker enabled supply chain will, in the face of increasing demand variability, produce a greater value of postponement than a non-brokered supply chain.

Figure 8 illustrates that the value of postponement increases with increasing demand variability. For lower and intermediate demand variability, VOP is greater for a brokered supply chain than a non-broker supply chain. For high demand variability, the effect is more ambiguous. This may be due to the decreasing effect of delayed differentiation. That is, as one of the product quantities reaches zero (data point 6), delayed differentiation has no effect as there is only one product stream (cf., [8]).

Introducing a broker can improve the inventory costs in either a ED or DD supply chain. Table 2 shows the average inventory costs and their decrease with the introduction of a broker for demand variability. Note that both ED and DD benefit in the neighborhood of 36 to 43 percent with the introduction of a broker.

		Average Inventory Costs	
		Variability	**% Δ**
ED	**Broker**	$15,206	35.7%
	No Broker	$23,660	
DD	**Broker**	$12,121	43.1%
	No Broker	$21,304	

Table 2: Average Costs and the Percentage Improvement.

6.2 H2: Value of Postponement Increases as Demand Correlation Increases

Hypothesis H2 states that:

- **H2**: A CMP-broker enabled supply chain will, in the face of decreasing demand correlation, produce a greater value of postponement than a non-brokered supply chain.

Prior research indicates that:

> *While greater correlation increases ED profits, its effect on DD profits is ambiguous. However, the net effect on VOP is unambiguous: it falls with demand correlation. [8].*

Figures 3 and 4 show that inventory costs fall for both ED and DD. Thus, profits increase with demand correlation. Moreover, figure 5 confirms that VOP decreases with demand correlation.

For increasing demand correlation, the value of postponement is greater for a CMP-broker than for non-broker. However, in both cases VOP falls in increasing demand correlation. Said another way, VOP increases as demand becomes less correlated. Moreover, it increases at a greater rate under the CMP-broker.

Table 3 shows the average inventory costs and their decrease with the introduction of a broker for demand correlation. Again, the VOP is higher for a broker than a non-broker, both ED and DD benefit in the neighborhood of 40 to 45 percent with the introduction of a broker.

		Average Inventory Costs	
		Correlation	**% Δ**
ED	**Broker**	$17,797	40.1%
	No Broker	$29,716	
DD	**Broker**	$15,218	45.2%
	No Broker	$27,758	

Table 3: Average Costs and the Percentage Improvement.

7. Conclusion

Based on the assumption that a CMP electronic broker increases information precision, we have tested several of its hypothesized effects on the value of postponement in a simple supply chain. Generally, is has been illustrated that a CMP broker in a supply chain increases the value of postponement in both early and delayed product differentiation. Moreover, a CMP broker improves a delayed product differentiation supply chain more than it improves a early product differentiation supply chain. Yet, because there is typically a significant cost associated with redesigning supply chains to take advantage of delayed differentiation, our results may provide an alternative option for redesign that may prove nearly as profitable as delayed differentiation. That alternative is to simply introduce a CMP broker. While the specificity of our simulation does not provide the necessary level of detail to make this calculation a straightforward one, it does suggest that additional research into the sensitivity of parameters and related trade-offs is potentially useful.

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9. Appendix

We implemented the two supply chain models using a supply chain simulator developed within the Swarm simulation tool kit.

> *Swarm is a multi-agent software platform for the simulation of complex adaptive systems. In the Swarm system the basic unit of simulation is the swarm, a collection of agents executing a schedule of actions. Swarm supports hierarchical modeling approaches whereby agents can be composed of swarms of other agents in nested structures.[31]*

While a number of researchers have used Swarm to simulate supply chains (e.g., [20]), we choose the supply chain simulation framework developed by Strader, Lin and Shaw[26][40][41]. In their framework, an entity (or node) in supply chain network (SCN) ...

> *is composed of several agents, such as an order management agent, an inventory management agent, and a SCN management agent. An entity with manufacturing capability includes a production planning agent, a capacity planning agent, a materials planning agent, a shop floor control agent, and manufacturing systems agent. A SCN Entity Swarm holds entity level information such as suppliers, customers, order transfer delay time, and product delivery time, which are accessible by internal agents and other entities. The encapsulated agents perform certain functions in enabling the movement of information and material within the entity and between entities. [41]*

In [41], Strader, Lin and Shaw describe the interactions among these node subprocesses.

> *... an entity ScnESwarm A receives an order from its customer ScnESwarm C. The order flows to the order management agent (OrdM). According to the customer lead times, the inventory availability information (from InvM), the production plan (from PrdP), and the manufacturing capacity (CapP), the order management agent assigns a due date to the order. If the products are in stock, the order is filled by shipping the products from inventory. If the products are in receiving, the due date is set according to the delivery date of the products.*
>
> *For an entity with manufacturing capability, the order is forwarded to the production-planning agent (PrdP) where the schedule for making the products is planned. The capacity-planning agent (CapP) and the material-planning agent (MatP) are partner agents in generating achievable build plans. The material planning obtains build plans from the production-planning agent to allocate materials for manufacturing. It also contributes information about material availability to production planning for scheduling. The capacity planning agent (CapP) plans capacity by taking the build plan from PrdP and sends capacity usage information to PrdP for scheduling the build plan. The SCN management agent (ScnM) takes the order information to choose suppliers in allocating material sources...*

As can be inferred from the above descriptions, the Strader, Lin and Shaw simulation framework provides a rich, detailed, accurate representation of a supply chain network. Using their framework, we implemented the two supply chain models illustrated in figures 1 and 2. Next, we conducted experiments to uncover the differences between the two models with respect to information precision, demand correlation, and demand variability as affected by an order broker.