

A Reverse Pricing Model for Multi-Tier Supply Chains

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Abstract

In recent years, reverse pricing has been marketed as a new pricing mechanism in e-commerce. Several e-markets such as priceline.com are being based on reverse pricing, thus on bids by potential customers instead of static prices by vendors. In this paper, we investigate whether it can also be used in business-to-business scenarios. In particular, we look at its potential contribution to reducing the bullwhip effect in multi-tier supply chains with local information and stochastic demand. The bullwhip effect suggests an increasing order variability as one moves down a supply chain. We propose to adopt reverse pricing for operational procurement decisions. We evaluate our proposal by conducting a simulation study using an agent-based simulation system, and can show that the novel approach results in a significant reduction of the bullwhip effect.

1. Introduction

In the past 15 years, e-commerce research has contributed to the development, investigation, and realization of new coordination mechanisms that go beyond traditional matchmaking. In particular, forms of dynamic pricing such as auctions, tenders, stock exchanges, and bilateral negotiations have been studied to a great extent [1, 2, 3]. Bringing these mechanisms to supply chains (SC) requires analyzing decision making in industrial settings, and could help solving problems that occur in SCs only.

An important observation in many SCs is known as the bullwhip effect (BWE), which suggests that order variability increases when one moves away from the final customer demand [4, 5]. The BWE is most relevant in deep multi-tier SCs. This phenomenon can have a dramatic effect on the SC participants and the overall SC efficiency; it can result in an increase of costs of 10 to 30% [4].

Current approaches for reducing the BWE can be

distinguished in (1) information sharing, i.e., providing customer demand information to all SC participants in order to improve local demand forecasts [6], and (2) collaboration, i.e., integration of all activities based on a SC-wide plan [7]. Empirical studies, however, indicate that implementing these approaches has to overcome many economic, social, and technical barriers [8]. For example, a survey on collaborative planning in 136 Swiss companies reported that only 20% of the companies share point-of-sales data [9].

Considering the limitations of information sharing and collaborative planning, this paper solely considers SCs in which each participant decides about procurement and production based on local information only. The interaction with other participants is restricted to receiving orders from customers and issuing orders to suppliers.

In such a SC, the price play a dominating and in many cases an exclusive role for coordinating supply and demand. Therefore, the objective of our work is to design a new coordination mechanism that adopts reverse pricing and specifically addresses the setting of multi-tier SCs. This mechanism is aimed at reducing the BWE. We investigate SCs with local information and stochastic demand from a procurement perspective, which provides models for operational procurement decisions and inventory management; hence it is directly relevant to the BWE. The role of pricing, however, has been widely neglected by the literature on the BWE, since prices are regarded as externally controlled and fixed.

The remainder of our paper is structured as follows: In section 2, we review existing work. Section 3 describes conventional procurement decisions and provides a standard model. In section 4, we introduce reverse pricing. In section 5, we design a coordination mechanism that integrates concepts of reverse pricing and microeconomics. In section 6, we evaluate our proposal by conducting a simulation study using a multiagent-based simulation system. Finally, section 7 draws conclusions, and points out avenues of future research.

2. Related work

The related work to ours can be grouped in approaches aimed at reducing the BWE and dynamic pricing in SCs. Next, we begin with reviewing three groups of BWE-related approaches.

Improving demand forecasts: A major reason that causes the BWE is the uncertainty linked with forecasting the (stochastic) demand and calculating the optimal order. The role of various forecasting methods and parameters has been studied by many researchers [10, 11, 12]. For instance, Chen et al. evaluate the moving average and exponential smoothing forecast techniques; they note that exponential smoothing forecasts result in a higher BWE compared to moving average forecasts [11]. The more demand information is considered, the smaller the increase in order variability becomes [10].

Sharing demand information: Information sharing has also received a lot of attention [10, 13, 6]. The rationale is that historical data about the final customer demand can help aligning demand forecasts in preceding SC tiers. For instance, in [13] it is shown that the BWE can be reduced if the participants share information and adopt soft computing methods for forecasting. A complete elimination of the BWE, however, can not be achieved even if all demand information is being shared across all tiers [10].

Coordinating SC activities: These approaches extend the degree of cooperation by arriving at harmonized local plans, or even a centralized plan for ordering and production respectively. Lack of coordination is, in general, a major cause for the BWE [7]. There exists a wealth of research on respective coordination approaches. With regard to the BWE, negotiation-based approaches for synchronizing local plans between independent SC participants have been explored [14]. This is also subject of multiagent collaborative planning, e.g., [15].

Dynamic pricing has been the subject of extensive research in the past; this interest was greatly influenced by commercial implementations of auctions and reverse auctions on the Internet. With regard to SCs, various types of dynamic pricing have been studied for improving procurement, inventory management, and short-term production planning, e.g., [1, 2]. For instance, [16] describes the relation between dynamic pricing mechanisms and inventory replenishment strategies in the face of demand uncertainty. This simulation study showed that the loss in expected profits under limited replenishment opportunities is significantly smaller when adopting a dynamic pricing strategy as compared to fixed prices. Dynamic pricing

for time-limited goods can increase the profits of the supplier by estimating the demand curve and maximizing the gross returns when the buyer demand curve is unknown [17]. It has to be noted, however, that the integration of dynamic pricing in SCs is still in an early stage. In particular, the effect on true multi-tier SC has been studied rarely; hence most researchers address the direct relation between suppliers and buyers, thus a simple two-staged SC.

The brief review of related work points to the fact that (1) local approaches on demand forecasts can reduce the BWE, but their impact on the BWE is limited, especially in multi-tier SCs, (2) cooperative approaches such as information sharing and coordination have a greater impact on the BWE, though their application is often restricted due to barriers and lack of trust between SC participants, and (3) dynamic pricing provides a rich set of mechanisms for supporting coordination between suppliers and buyers. To our best knowledge, reverse pricing as a very special form of dynamic pricing has not been adopted for coordination of supply and demand in SCs. Considering these observations, we propose using reverse pricing for procurement decisions, since it sustains decision making with local information.

3. Basic model of procurement decisions

In this section, we describe procurement decisions in SCs with local information. Such a decision consists of (1) selecting the supplier, (2) calculating the order quantity and (3) determining the time of order. Considering a full spectrum of inter-related goods, the respective decision models can get very complex in terms of parameters and variables. Therefore, we simplify the relevant part of the SC and look at a linear one-product SC only [4, 10], in which each participant adds value to the good. Figure 1 depicts a SC consisting of four participants denoted by j .



Figure 1. Multi-tier supply chain

The SC is characterized as follows:

- The lead time L is constant for each participant; it is defined as the duration between receipt of the order by participant j and delivery of the ordered goods to participant $j+1$.
- The SC is subject to a stochastic customer demand $D_{t,j}$. The aim of the whole SC is to fulfill this demand in all periods t . Only the last participant

(here: retailer) has access to historic data about the final customer demand $D_{t,c}$ with expected value μ and standard deviation σ .

The procurement decision consists of three steps:

1. *Demand forecast:* At the beginning of period t , the participant j estimates its customer demand $\hat{D}_{t,j}$ as well as the standard deviation of the forecast error $\hat{\sigma}_{t,j}$ based on historical data for τ periods.
2. *Inventory policy:* The inventory is managed by a standard (s, S) inventory policy, which is a periodic review, order-up-to policy with a fixed review time. It determines the order-up-to point $q_{t,j}$ for the next period by [10]:

$$q_{t,j} = L\hat{D}_{t,j} + z\sqrt{L}\hat{\sigma}_{t,j} \quad (1)$$

The constant z relates to the α -service level [11] that has to be met.

3. *Order calculation:* The order calculation $y_{t,j}$ considers the order-up-to point and demand of the previous period [10]:

$$y_{t,j} = q_{t,j} - (q_{t-1,j} - D_{t-1,j}) \quad (2)$$

Note that $y_{t,j}$ may be negative [4, 10], thus excess inventory is returned without costs.

We formalize the decision in algorithm 1.

Algorithm 1: Procurement decision	
1	Input:
2	$D_{t,j}, D_{t-1,j}$: Customer demand in t and $t-1$.
3	L : Lead time.
4	z : α -service level.
5	$\hat{D}_{t,j}$: Estimated demand received by participant j in t .
6	$\hat{\sigma}_{t,j}$: Estimated standard deviation of forecast error.
7	Output:
8	$y_{t,j}$: Order placed by participant j in t .
9	Process:
10	$q_{t,j} \leftarrow (L\hat{D}_{t,j} + z\sqrt{L}\hat{\sigma}_{t,j})$: Order-up-to point in t .
11	$y_{t,j} \leftarrow q_{t,j} - (q_{t-1,j} - D_{t-1,j})$: Order quantity in t .

In such a supply chain, the BWE can be measured by the quotient of the variance of the order quantity $y_{t,j}$ in tier j and the variance of the final customer demand $D_{t,c}$ [10].

4. Reverse pricing in procurement

In this section, we introduce the basic concepts of reverse pricing. Afterwards, we reason about its applicability for procurement decisions in SCs with local information and stochastic demand.

4.1 Foundations of reverse pricing

The emergence of electronic markets on the Internet has given attention to dynamic pricing mechanisms. The most prominent forms are auctions in consumer-to-consumer e-commerce (e.g., eBay) and reverse auctions for strategic procurement in business-to-business scenarios. In recent years, reverse pricing (also known as ‘name-your-own-price’) as popularized by marketplaces such as priceline.com, has become a growing interest in e-commerce. Reverse pricing gives customers an active role: The price of a transaction is not given by the seller, but mainly determined by the buyer’s bid [3, 18]. The process of classic reverse pricing is as follows:

1. The seller sets the minimum price for the good; this price remains unknown to the buyer.
2. The buyer determines a price and submits his bid.
3. If the bid price is equal or higher than the minimum price, then the transaction will take place with the bid price. Otherwise, the buyer can not bid for the same good for a predefined time.

In German reverse pricing, which is a modification of classic reverse pricing, higher bids can be submitted [18], thus the process continues with step 2.

Currently, reverse pricing is being used in markets which have the following characteristics: The buyers are individual consumers. Subject of transactions are homogenous, fully specified goods. The lot size per good is often one. Similarly, the number of goods per transaction is one. In those markets, the benefits of reverse pricing compared to other pricing mechanisms are an increase of the seller’s revenue and a fast decision on the transaction [3, 18]. However, the application of reverse pricing in business-to-business scenarios has not been studied so far.

4.2 On using reverse pricing for procurement

How must reverse pricing be viewed from the perspective of procurement decisions in SCs with local information and with regard to the BWE?

First, it has to be noted that conventional models for inventory management treat the price of a good as a constant, thus it is an exogenous parameter. The adaptation of any dynamic pricing mechanism would lead to a different situation; respective models would have to consider the price variation and the resulting changes in revenues (seller’s side) and costs (buyer’s side).

Price variation itself is one major cause of the BWE [4, 5], because it allows buyers to exploit the benefits of discounts by ordering more goods than needed in

the current period and putting them on stock for meeting demands in future periods. Therefore, a further variation of prices by reverse pricing could promote this behavior and thus aggravate the BWE.

Moreover, classic reverse pricing excludes buyers for a limited time from the transaction, if the bid price is lower than the minimum price. This rule would prevent a transaction in the current period and thus harm or even disrupt the SC.

These considerations show that critical boundaries for an adaptation of reverse pricing in SCs must be taken into account. Therefore, we will use the *regulative function* of prices when designing our reverse pricing model. It is being reflected in the relation that the higher prices have a stewing effect on the demand, thus on the buyer's order behavior. If we integrate this effect into the model, then one could expect that it results in a reduction of order variances, thus a reduction of the BWE.

5. Reverse pricing model for supply chains

In this section, we specify a reverse pricing model for SCs with local information and stochastic demand. We look at the inter-relationships between order behavior on the buyer's side and supply behavior on the supplier's side. Both can be represented by demand and supply functions (or curves) respectively. These functions describe how demand and supply depend on the price for each unit of the good. The intersection of both functions determines the equilibrium price and the equilibrium quantity. The equilibrium price is the price at which the quantity demanded equals the quantity supplied. The equilibrium quantity represents the quantity bought and sold at the equilibrium price.

The adaptation of reverse pricing for procurement decision calls for specifications of the three steps of reverse pricing; due to their independent nature, we change the order of steps one and two:

1. *Buyer's bid*: For calculating the bid of the buyer we refer to the demand function. A commonly used, though simple form is the linear demand curve, thus an increasing price P causes a decreasing demand Q [19]:

$$Q_d = a - bP, \text{ where } a > 0 \text{ and } b > 0 \quad (3)$$

Therefore, the demand function describes the bidding behavior of the buyer.

2. *Seller's minimum price*: For calculating the minimum price of the supplier we refer to the supply function. The linear form is [19]:

$$Q_s = c + dP, \text{ where } c < 0 \text{ and } d > 0 \quad (4)$$

3. *Matching*: By comparing bid price and minimum price for the requested quantity we decide on the validity of the bid, thus on the transaction. Due to the considerations in section 4.2, it is necessary to arrive at a transaction in all cases. Thus the matching will only modify the quantity, if required.

Step 1 and 2 require that equilibrium price P^* and equilibrium quantity Q^* as well as estimates for the price elasticity of demand¹ E_d and supply² E_s are available. Then we can determine the parameters a and b of the demand function as well as c and d of the supply function. Figure 2 shows the relationship between demand and supply as described.

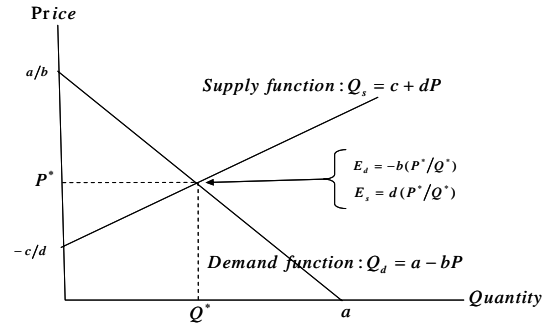


Figure 2. Demand and supply function

Next, we specify each step in more detail and provide the respective algorithms.

5.1 Step 1: Buyer's bid

The parameters a and b of the demand function must be calculated for each time period t and for each SC participant j by using the equilibrium quantity, the equilibrium price, and the price elasticity of demand:

- Let $Q_{t,j}^*$ be the equilibrium quantity and $P_{t,j}^*$ the equilibrium price.
 - Let E_d be the price elasticity of demand, which is generally given by $E_d = -b_{t,j}(P_{t,j}^*/Q_{t,j}^*)$ [19]. Solving this equation for b yields [19]:
- $$b_{t,j} = -E_d(Q_{t,j}^*/P_{t,j}^*) \quad (5)$$
- To determine the parameter a , we note that Q^* and P^* must be on the demand curve. Thus, it

¹ The price elasticity of demand measures how much the quantity demanded of good changes when its price changes.

² The price elasticity of supply tells us the percentage change in quantity supplied for each percent change in price.

must be that $a_{t,j} = Q_{t,j}^* + b_{t,j}P_{t,j}^*$. Substituting the expression in equation (5) for b and then by canceling P^* and factoring out Q^* , we get [19]:

$$a_{t,j} = (1 - E_d)Q_{t,j}^* \quad (6)$$

Any demand curve has a corresponding *inverse demand curve* that expresses the price as a function of quantity. We can find the inverse demand curve by taking the equation for the demand curve, thus equation (3), and solving it for P in terms of Q_d . The inverse demand curve is:

$$P_{t,j} = (a_{t,j}/b_{t,j}) - (1/b_{t,j})Q_{t,j} \quad (7)$$

Using demand $D_{t,j}$ instead of quantity $Q_{t,j}$ in (7):

$$P_{t,j} = (a_{t,j}/b_{t,j}) - (1/b_{t,j})D_{t,j} \quad (8)$$

we arrive at the price that the buyer is willing to pay for $D_{t,j}$. This price $P_{t,j}$ is regarded as the bid price denoted by $B_{t,j}$. In algorithm 2, we summarize the determination of the buyer's bid.

Algorithm 2: Demand curve and buyer's bid	
1	Input:
2	$D_{t,j}$: Customer demand in t .
3	E_d : Price elasticity of demand.
4	$P_{t,j}^*$: Equilibrium price.
5	$Q_{t,j}^*$: Equilibrium quantity.
6	Output:
7	$B_{t,j}$: Bid price in t .
8	Process:
9	$b_{t,j} \leftarrow (-E_d(Q_{t,j}^*/P_{t,j}^*))$: Coefficient b of the demand curve.
10	$a_{t,j} \leftarrow ((1 - E_d)Q_{t,j}^*)$: Coefficient a of the demand curve.
11	$B_{t,j} \leftarrow ((a_{t,j}/b_{t,j}) - (1/b_{t,j})D_{t,j})$: Bid price.

5.2 Step 2: Seller's minimum price

Similar to the preceding section, we calculate the parameters c and d of the supply function:

- Let E_s be the price elasticity of supply, which is given by $E_s = d_{t,j}(P_{t,j}^*/Q_{t,j}^*)$. Solving this equation for d yields [19]:

$$d_{t,j} = E_s(Q_{t,j}^*/P_{t,j}^*) \quad (9)$$

- The respective transformations yield [19]:

$$c_{t,j} = (1 - E_s)Q_{t,j}^* \quad (10)$$

$$P_{t,j} = -(c_{t,j}/d_{t,j}) + (1/d_{t,j})D_{t,j} \quad (11)$$

The latter equation defines the seller's minimum price, which we denote by $\underline{p}_{t,j}$. Algorithm 3 contains the formal specification.

Algorithm 3: Supply curve and seller's minimum price	
1	Input:
2	$D_{t,j}$: Customer demand in t .
3	E_s : Price elasticity of supply.
4	$P_{t,j}^*$: Equilibrium price.
5	$Q_{t,j}^*$: Equilibrium quantity.
6	Output:
7	$\underline{p}_{t,j}$: Seller's minimum price in t .
8	Process:
9	$d_{t,j} \leftarrow E_s(Q_{t,j}^*/P_{t,j}^*)$: Coefficient d of the supply curve.
10	$c_{t,j} \leftarrow ((1 - E_s)Q_{t,j}^*)$: Coefficient c of the supply curve.
11	$\underline{p}_{t,j} \leftarrow -(c_{t,j}/d_{t,j}) + (1/d_{t,j})D_{t,j}$: Seller's minimum price.

5.3 Step 3: Matching

In our model, the supplier receives an incoming bid including bid price and quantity. The decision whether the demand is valid and will be fulfilled is solely up to the supplier. This procedure can be found in many actual supplier relationships, thus is not restricted to reverse pricing: The supplier will not accept *any* order quantity, but limit it in terms of its own capabilities. In particular, these capabilities are determined by the inventory level, the delivery time of its own suppliers, and the service level that needs to be met. Such a limitation is also known as rationing [4, 5].

Therefore, we define a *heuristic* that may result in a reduction of the demanded order quantity. It considers the following two cases:

- If the bid price is equal or higher than the seller's minimum price ($B_{t,j} \geq \underline{p}_{t,j}$), then the transaction takes place for the order quantity which was calculated by the supplier using algorithm 1.
- If the bid price is lower than the seller's minimum price ($B_{t,j} < \underline{p}_{t,j}$), then the order quantity calculated by the supplier using algorithm 1 needs to be modified to $y_{t,j}^{new}$. We interpret the product of bid price and order quantity as the *total willingness to pay* in the current period. Dividing it by the seller's minimum price leads to the allowed order quantity; hence the proportion of bid price to minimum price expresses the reduction:

$$y_{t,j}^{new} = (B_{t,j}/\underline{p}_{t,j})y_{t,j} \quad (12)$$

In both cases, the transaction takes place with the bid price, thus the modification does not change the price. Algorithm 4 summarizes the entire reverse pricing process that begins with calculating the order quantity (algorithm 1), followed by determining both the bid price (algorithm 2) and the minimum price (algorithm 3), and finally deciding on the transaction.

Algorithm 4: Procurement decision with reverse pricing
1 Input:
2 $y_{t,j}$: Order quantity from algorithm 1.
3 $B_{t,j}$: Bid price from algorithm 2.
4 $\underline{p}_{t,j}$: Seller's minimum price from algorithm 3.
5 Output:
6 $y_{t,j}^{new}$: Allowed order quantity in t .
7 Process:
8 if $(B_{t,j} \geq \underline{p}_{t,j})$ then return $y_{t,j}^{new} \leftarrow y_{t,j}$: No modification.
9 if $(B_{t,j} < \underline{p}_{t,j})$ then return $y_{t,j}^{new} \leftarrow (B_{t,j} / \underline{p}_{t,j}) y_{t,j}$: Modification.

6. Simulation

In this section, we describe the simulation study and present the results of our experiments.

6.1 Simulation system

We used HoPIX (Hohenheimer Process Integrator eXtension) which is a simulation system for multi-tier SCs.³ In this agent-based system, each SC participant is being represented by an autonomous software agent. There are two types of agents: Agents without reverse pricing receive incoming orders (demand) and calculate their order quantity according to algorithm 1. Agents with reverse pricing also calculate the order quantity (algorithm 1) and additionally determine the bid price according to algorithm 2. The results are input for the reverse pricing (algorithm 4), thus these agents interact with the supplier agents that behave according to algorithm 3. The two agent types allow comparing the reverse pricing model with the conventional procurement model for the same data set.

6.2 Simulation setting

We defined a four-tier SC (see also figure 1). Only the last tier ($j=4$) knows the final customer demand D_c ; hence all three other tiers make procurement decisions.

We set the following parameters:

³ <http://wi2.uni-hohenheim.de/hopix>

- Final customer demand $D_{t,c}$: normally distributed with expected value $\mu=100$ and standard deviation $\sigma=10$.
- Forecast technique: moving average, i.e., each SC participant j uses a simple moving average to estimate $\hat{D}_{t,j}$ and $\hat{\sigma}_{t,j}$ based on demand data from the preceding τ periods [10]:

$$\hat{D}_{t,j} = (1/T) \sum_{n=1}^T D_{t-n,j} \quad (13)$$

For estimating standard deviation of the forecast error $\hat{\sigma}_{t,j}$ see [10].

- α -service level: 99%, thus z equals 2.33 [11].
- Given equilibrium price for each tier: $P_{t,4}^* = 10$, $P_{t,2}^* = 11$, and $P_{t,3}^* = 12$.
- Equilibrium quantity: we calculate $Q_{t,j}^*$ for each SC participant based on demand data $D_{t,j}$ from the preceding $n=52$ periods:

$$Q_{t,j}^* = (1/n) \sum_{t=1}^n D_{t,j} \quad (14)$$

- Price elasticity⁴ for all tiers: $E_d = -0.8$, $E_s = 1.6$ [19].

We conducted the simulation for various configurations of the forecast method and different lead times, thus the following parameters have been varied:

- T between 5 and 15 (time periods of the moving average forecast)
- L between 1 and 4 (lead time of each tier)

Each simulation run started with a warm-up of 200 periods followed by 40 periods during which we collected data. Due to the stochastic demand, each simulation setting was run twenty times.

The evaluation of the reverse pricing model is based on a standard metric which quantifies the order BWE. It is defined as the quotient of the variance of the order quantity in tier j and the variance of the final customer demand D_c [10]. Values greater than 1 indicate the BWE. We calculated both mean and standard deviation for:

$$O_j^{BWE} = \text{Var}(y_j) / \text{Var}(D_c), \text{ where } j=1..3 \quad (15)$$

⁴ Price elasticities of demand and supply have been estimated for many products using statistical techniques. Estimations for a variety of goods such as food, transportation services, cars etc. can be found in [19].

6.3 Results

6.3.1 Variation of T. In the first set of experiments, we determine the BWE under variation of T. Table 1 and 2 present the data for $L = 2$. In general, the BWE decreases with an increasing T (see also figure 3).

Table 1. BWE for $j=3$ (Wholesaler)

T	Without RP		With RP		Change	
	M	SD	M	SD	M	SD
5	7.68	0.69	4.51	0.55	-41.3%	-20.5%
6	6.27	0.60	4.08	0.44	-35.0%	-26.0%
7	6.24	0.53	3.78	0.35	-39.5%	-33.6%
8	6.22	0.50	3.64	0.31	-41.6%	-37.7%
9	5.78	0.49	3.63	0.30	-37.2%	-37.8%
10	5.69	0.48	3.21	0.29	-43.5%	-40.6%
11	5.65	0.41	3.13	0.28	-44.6%	-32.6%
12	5.65	0.40	2.93	0.27	-48.2%	-34.8%
13	5.52	0.35	2.87	0.23	-48.0%	-32.4%
14	5.28	0.31	2.69	0.22	-49.1%	-30.7%
15	5.23	0.30	2.62	0.19	-49.8%	-38.8%
Mean of Change:					-43.4%	-33.2%

(M: mean; SD: standard deviation; RP: reverse pricing)

Table 2. BWE for $j=1$ (Supplier)

T	Without RP		With RP		Change	
	M	SD	M	SD	M	SD
5	13.60	1.25	12.17	1.02	-10.5%	-18.3%
6	11.18	1.17	10.48	0.93	-6.3%	-20.7%
7	10.97	1.08	9.95	0.87	-9.3%	-19.6%
8	10.41	1.03	9.55	0.79	-8.3%	-22.7%
9	8.55	0.99	7.81	0.74	-8.7%	-24.8%
10	8.40	0.98	7.12	0.70	-15.3%	-28.4%
11	8.26	0.89	6.89	0.69	-16.5%	-20.3%
12	7.44	0.78	6.69	0.65	-10.1%	-16.6%
13	7.36	0.68	6.49	0.59	-11.8%	-13.0%
14	6.71	0.60	6.08	0.51	-9.3%	-15.6%
15	6.67	0.51	6.08	0.40	-8.8%	-20.9%
Mean of Change:					-10.4%	-20.1%

(M: mean; SD: standard deviation; RP: reverse pricing)

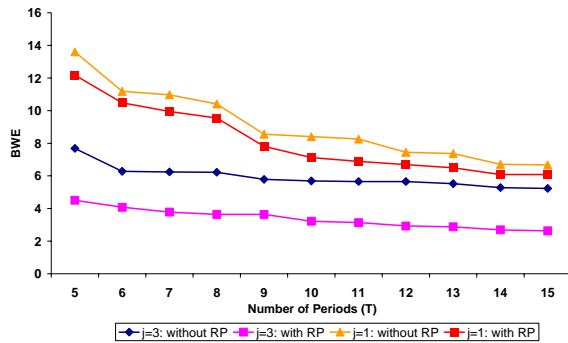


Figure 3. BWE and variation of T
(RP: reverse pricing)

We calculated the BWE for the wholesaler as well as the supplier. The comparison of the conventional procurement decision and the reverse pricing model yields a reduction in the BWE of 35.7 % to 49.8 % (wholesaler; mean: 43.4%) and 6.3 % to 16.5 % (supplier; mean: 10.4%). This observation was confirmed by a reduction in the standard deviation of 33.2% and 20.1% respectively.

6.3.2 Variation of L. In the second set of experiments, we studied the influence of L on the BWE for $T = 10$ (table 3 and 4, figure 4). We observed a high reduction by reverse pricing for the wholesaler between 37.0% and 48.4% (mean: 44%). The reduction, however, for the supplier was smaller (mean: 14.9%).

Table 3. BWE for $j=3$ (Wholesaler)

L	Without RP		With RP		Change	
	M	SD	M	SD	M	SD
1	3.93	0.40	2.10	0.20	-46.5%	-50.0%
2	6.72	0.87	3.47	0.55	-48.4%	-36.7%
3	8.75	2.20	4.90	1.99	-44.0%	-9.7%
4	10.79	4.14	6.80	3.17	-37.0%	-23.4%
Mean of Change:					-44.0%	-30.0%

(M: mean; SD: standard deviation; RP: reverse pricing)

Table 4. BWE for $j=1$ (Supplier)

L	Without RP		With RP		Change	
	M	SD	M	SD	M	SD
1	6.81	0.87	5.11	0.71	-24.9%	-18.6%
2	10.37	1.94	8.81	2.44	-15.0%	-17.1%
3	22.18	5.55	19.33	5.27	-12.9%	-5.1%
4	25.10	7.12	23.41	6.58	-6.7%	-7.5%
Mean of Change:					-14.9%	-12.1%

(M: mean; SD: standard deviation; RP: reverse pricing)

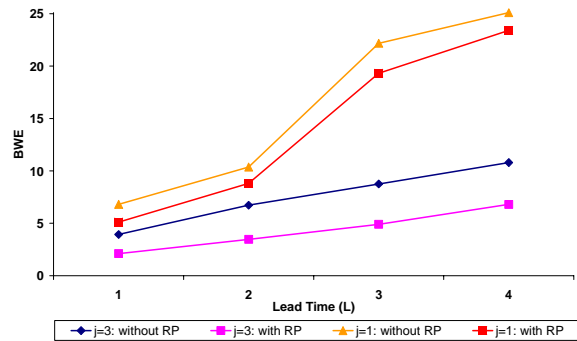


Figure 4. BWE and variation of L
(RP: reverse pricing)

7. Conclusions and future work

In this research, we have investigated whether reverse pricing can be used for supporting procurement decisions in multi-tier SCs with local information and stochastic demand. In particular, we have (1) designed a coordination mechanism based on reverse pricing concepts and considerations of microeconomics, (2) evaluated our proposal by conducting a simulation study for different SC settings, and (3) showed that the novel approach reduces the BWE with regard to order variances, thus it increases the SC efficiency.

The conducted experiments yield a reduction of the BWE for the first tier of the retailer (in our scenario: wholesaler) of about 44% and for the third tier of the retailer (here: supplier) of about 13%.

The simulation of decisions in multi-tier SCs calls for complex models that consider local goals, inventory management, and the respective costs and revenues for each participant. Our current simulation assumes that some of these considerations are equal for all participants, i.e., standard (s, S) inventory policy, lead time, forecast technique, and the type of demand and supply function. Another limitation of the current model is that our inventory policy (algorithm 1) calculates the order quantity independently from costs incurred by ordering and stocking goods.

Considering the reverse pricing model, we assumed linear supply and demand curves. This assumption is coherent with basic concepts of microeconomics, though it has to be noted that other types of functions are more suitable to reflect actual supply and demand behavior. Hence, we plan to adopt other functions in future work in order to assess the impact of our proposal in different settings.

From the perspective of SC management, the shape of supply and demand functions has a great impact on both supplier's revenues and buyer's costs, because even a marginal change in demand leads to a change of the price. In many actual SCs, prices are being settled for a longer period of time. A potential alternative way of implementing our model could be using the mechanism for determining the allowed order quantity only, while the price remains fixed as defined in a procurement contract between buyer and supplier. This option could also limit the danger of strategic behavior (i.e., reconstructing the supply function by a set of bids over time).

With regard to the limitations described, we aimed at proofing first that reverse pricing can support SC coordination and reduce the BWE in specific settings. In our future work, we plan to release selected constraints, i.e., other SC configurations which would also require extending the product model.

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