In: Proceedings of the 10th IEEE International Conference on E-Commerce Technology (CEC 2008), Washington, D.C., USA, July 21-24, 2008, pp. 68-75.

Reverse Pricing in Supply Chains: An Assessment of Sourcing Strategies

Yll Mujaj, Joerg Leukel, Stefan Kirn
University of Hohenheim, Information Systems II, Stuttgart, Germany
{yll.mujaj | joerg.leukel | stefan.kirn}@uni-hohenheim.de

Abstract

Reverse pricing as a special form of dynamic pricing has become a growing interest in e-commerce. It gives buyers an active role: The price of a transaction is not given by the supplier, but is mainly determined by the buyer's bid. This paper extends the coverage of current reverse pricing models to sourcing. The reason is that sourcing strategies, such as global, local, and multiple sourcing, greatly determine both structure and behavior of supply chains. The contribution is a new coordination mechanism that integrates reverse pricing and sourcing strategies. Our simulation study shows that this mechanism helps reducing order and inventory variances.

1. Introduction

Pricing plays a decisive role in matching supply and demand. In the past years, e-commerce research has studied this role and subsequently developed dynamic pricing mechanisms that can both be automated fully and improve allocation efficiency. Reverse pricing is such a mechanism. Recently, it has been studied in the context of supply chains [1].

An important phenomenon often observed in supply chains, known as bullwhip effect (BWE), implies that order variability increases when moving up the supply chain [2]. The main approaches to countering this phenomenon are information sharing and collaboration; their implementation, however, has to overcome strong economic, social, political, and technical barriers. Bearing these limitations in mind, this paper solely considers supply chains in which each participant decides based on local information only. In such a supply chain (SC) without global vision, the price plays a dominating and in many cases an exclusive role for coordinating supply and demand.

The objective of our work is to design and validate a new coordination mechanism that adopts reverse pricing and aims at reducing the BWE. We investigate supply chains from a procurement perspective, which provides a rich theory on sourcing strategies.

The contribution of this research is a new coordination mechanism that integrates reverse pricing and sourcing strategies and thus extends the reverse pricing to more realistic supply chain scenarios. In our previous work [1], we have developed a preliminary coordination mechanism which did not consider sourcing. Here, we extend its coverage to competitive supply chains. Technical details on the agent-based simulation system can be found in [3].

The remainder of this paper is structured by the design-science paradigm. In section 2, we *review* existing work and relate it to our research. Section 3 provides a *basic model* that captures sourcing strategies and operational procurement. In section 4, we *design* a reverse pricing model that integrates concepts of sourcing strategies and operational procurement. In section 5, we *evaluate* this artifact by simulation. In the final section, we *discuss* our findings and motivate avenues of future research.

2. Related work

The related work to this research can be grouped in (1) approaches aimed at reducing the BWE, (2) dynamic pricing in supply chains, and (3) the problem of BWE with regard to sourcing.

1. Approaches aimed at reducing the BWE can be separated into information sharing and coordination.

Information sharing has received a lot of attention [2, 4, 5]. Mason-Jones investigates several variations of the information enrichment strategy and determined that information sharing is beneficial for reducing BWE [6]. The rationale is that historical data about the final customer demand can help aligning demand forecasts in preceding SC tiers. For instance, in [5] 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, cannot be achieved even if all demand information is shared [2]. Lee et al. [4] and Dejonckheere et al. [7] provide similar findings.

Coordination of SC activities aims at harmonizing local plans, or even a single centralized plan for ordering and production respectively. Lack of coordination is, in general, a major cause for the BWE [8, 9]. A wealth of research exists on respective coordination mechanisms. With regard to the BWE, negotiation-based approaches for synchronizing local plans between independent SC participants have been explored [10]. This is also subject to collaborative multiagent planning, e.g., [11].

2. Dynamic pricing has been a subject of extensive research. Various mechanisms have been adopted for improving procurement and inventory management, e.g., [12, 13]. Dynamic pricing for time-limited goods can increase the profit of the supplier by estimating the demand curve and maximizing the gross returns when the buyer's demand curve is unknown [14]. It has to be stated though, that the integration of these mechanisms in supply chains is still at an early stage. In particular, applications in multi-tier and competitive supply chains have rarely been studied. Most researchers address simple two-tier supply chains only.

3. The problem of the BWE combined with sourcing strategies has received little attention. Marshall et al. investigate the concept of accurate response from the perspective of forecasting [15], which is indirectly related to the BWE. Another approach is undertaken by Maltz et al. who describe the automotive industry's sourcing strategies and its trend towards introducing multiple versions of the same car model each year [16]. In [17], a simulation model is used in a case study; it shows how the best sourcing strategy for fashion products should combine local suppliers. The conclusion is that that many standard operations commonly found in some US industries are inadequate for international supply chains operating in countries such as Mexico, because they induce the BWE [17].

The review of related work points to the fact that (1) information sharing and coordination have a high impact on the BWE, although their application is often restricted due to barriers and lack of trust between SC participants, and (2) dynamic pricing provides a rich set of mechanisms to support coordination between suppliers and buyers. To the best of our knowledge, an assessment of sourcing strategies and their impact on the BWE phenomenon has not been made so far.

3. Basic model of procurement decisions

In this section, we introduce a basic model of procurement decisions based on sourcing strategies.

A procurement decision consists of three steps: (1) selecting one or more suppliers, (2) calculating order quantity, and (3) determining the time of order. Respective decision models can get very complex in terms of parameters, thus we look at a single-product SC only (also in [2, 9]), in which each participant j adds value to the good. As shown in figure 1, we consider competitive supply chains with multiple suppliers by distinguishing multiple branches; it allows the implementation of various sourcing strategies, since each branch represents a specific type of supply.

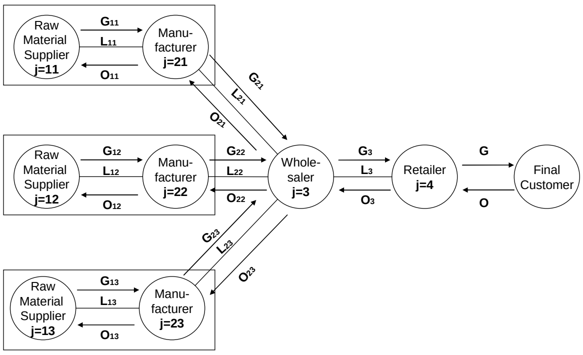

Figure 1. Competitive supply chain (G: goods; O: order; L: lead time)

The SC is characterized as follows:

The lead time L_i is variable for each participant; it is defined as the duration between receipt of the order by participant j and delivery of the ordered goods to the buyer.

The SC is subject to a stochastic customer demand $D_{t,C}$. The aim of the entire 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. There is no lead time between retailer and final customer because the retailer is a stationary one.

3.1 Supplier selection by sourcing strategies

In a competitive SC, the wholesaler can place orders by one or more suppliers as represented by each branch. Assume that price and lead time are the two criteria being used to evaluate potential suppliers. Further, assume that: (1) the first supplier of the wholesaler (here: $j = 21$) has a favorable lead time, e.g., denoted by $L_{21} = 1$, but a high price, (2) the second supplier ($j = 22$) has a standard price and a favorable lead time, e.g., denoted by $L_{22} = 2$, and (3) the last supplier ($j = 23$) has a moderately favorable lead time, e.g., denoted by $L_{23} = 3$, but a low price.

One strategy[1] for supplier selection is local sourcing. This strategy takes advantage of short lead times, but does not exploit potentially lower prices of competitors. Thus, the supplier very close to the wholesaler will provide goods ($j = 21$).

A complementary strategy is global sourcing. If low costs are more important than lead time, the wholesaler will select the supplier with the lowest price ($j = 23$).

Particularly when lead times are different, the simultaneous use of two or more suppliers tends to reduce the uncertainty in lead times and offers savings in inventory holding costs. In the strategy of dual sourcing, the order quantity is split between two suppliers. In this strategy, lead time and costs are important, thus the suppliers close to the wholesaler with the shortest lead time ($j = 21$) and the lowest price ($j = 23$) will both be contracted.

The remaining basic strategy is multiple sourcing. This strategy aims to balance risks and opportunities. An order is split between three or more suppliers.

3.2 Calculating order quantity and time

Calculating order quantity 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 T periods.
2. *Inventory policy*: The inventory is managed by an inventory policy. In the following, we consider the standard (s, S) inventory policy only, which is a periodic review, order-up-to policy with a fixed review time [2]. It determines the order-up-to point $q_{t,j}$ for the next period by:

$$q_{t,j} = L_i \hat{D}_{t,j} + z\sqrt{L_i}\hat{\sigma}_{t,j} \tag{1}$$

The constant z denotes the α-service level that has to be met [2].

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

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

Note that $y_{t,j}$ may be negative [2, 9], in which case we assume, analogue to [2, 9], that this excess inventory is returned without costs. We formalize supplier selection and calculating order quantity in algorithm 1.

```
Algorithm 1: Procurement decision with sourcing strategies
Input:
  $D_{t,j}$, …, $D_{t-n,j}$ : Customer demand in $t$ and in previous periods
                with $n = 1,...,T$ ; $T$ = Number of periods.
  $L_i$ : Lead time for $\forall i \in \{1,...,I\}$ .
  $\tau$ : Number of suppliers depending on sourcing strategy.
  $z$ : $\alpha$ -service level.
  $\hat{D}_{t,j}$ : Estimated demand received by participant $j$ in $t$.
  $\hat{\sigma}_{t,j}$ : Estimated standard deviation of forecast error.
Output:
  $y_{t,j}$ : Order placed by participant $j$ in $t$ at $\tau$ suppliers.
Process:
  Switch (sourcing){
   case local or global or dual or multiple sourcing:
    $q_{t,j} \leftarrow (L_i \hat{D}_{t,j} + z\sqrt{L_i}\hat{\sigma}_{t,j})$ : Order-up-to point in $t$.
    $y_{t,j} \leftarrow (1/\tau\,(q_{t,j} - (q_{t-1,j} - D_{t-1,j})))$ : Order quantity in $t$.
  break;}
```

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 $D_{t,C}$ [2].

4. Adoption of reverse pricing

In this section, we design a reverse pricing model for operational procurement decisions. For a comprehensive reasoning about reverse pricing in supply chains from a microeconomics perspective and a detailed specification see [1].

4.1 Reverse pricing basics

In recent years, reverse pricing as popularized by marketplaces such as priceline.com has become a reality in e-commerce. As a special form of dynamic pricing, reverse pricing is similar to auction pricing in that customers explicitly state their willingness to pay for a given product. In auctions, there is often a clearly defined reference price such as asking price whereas in reverse pricing, customers are asked to name their

---

[1] Operations management literature addresses diverse sourcing strategies. An overview can be found in [18].

price without an explicitly available reference point [19, 20, 21]. Reverse pricing gives potential customers an active role: The price of a transaction is not given by the seller, but determined by the buyer's bid. The process of 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, the transaction will take place with the bid price. Otherwise, the buyer cannot bid for the same good for a predefined time.

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 [19, 21].

4.2 Reverse pricing model for supply chains

The adaptation of reverse pricing for procurement decisions calls for specifications of the three steps of reverse pricing. We look at the inter-relation between order behavior on the buyer's side and supply behavior on the supplier's side. Both can be represented formally by demand respectively supply functions. These functions describe how demand respectively supply depends 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.

Due to their independency, 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 [22]:

$$Q_d = a - bP,\ where\ a > 0\ and\ b > 0 \qquad (3)$$

In this equation, the constant a embodies the effect of the price. The coefficient b, which is the slope of the demand curve, reflects how the price of the good affects the quantity demanded. 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 [22]:

$$Q_s = c + dP,\ where\ c < 0\ and\ d > 0 \qquad (4)$$

In this equation, the constant c embodies the effect of the price. The coefficient d represents the responsiveness of supply to price changes.

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. 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 demand[2] E_d and the price elasticity of supply[3] E_s are available. Then we can determine the parameters a and b from the demand function as well as c and d from the supply function. Figure 2 shows the relationship between demand and supply as described.

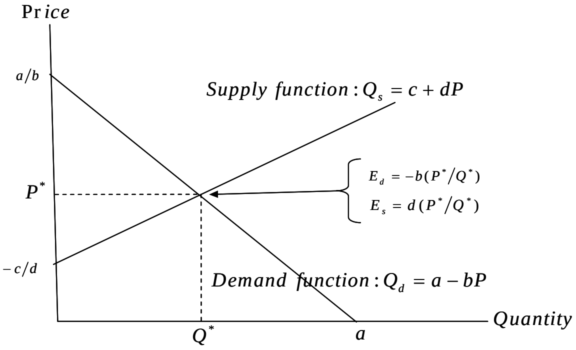

Figure 2. Demand and supply function

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

4.2.1 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. As shown in [1], we arrive at the price that the buyer is willing to pay for $D_{t,j}$ which we denote by $B_{t,j}$:

$$B_{t,j} = (a_{t,j}/b_{t,j}) - (1/b_{t,j})D_{t,j} \qquad (5)$$

In algorithm 2, we summarize the determination of the buyer's bid.

---

[2] Price elasticity of demand measures how much the quantity demanded changes when its price changes.

[3] Price elasticity of supply tells us the percentage change in quantity supplied for each percent change in price.

```
Algorithm 2: Demand curve and buyer's bid
Input:
    $D_{t,j}$ : Customer demand in $t$.
    $E_d$ : Price elasticity of demand.
    $P^*_{t,j}$ : Equilibrium price.
    $Q^*_{t,j}$ : Equilibrium quantity.
Output:
    $B_{t,j}$ : Bid price in $t$.
Process:
    $b_{t,j} \leftarrow (-E_d(Q^*_{t,j} / P^*_{t,j}))$ : Coefficient $b$ of the demand curve.
    $a_{t,j} \leftarrow ((1-E_d)Q^*_{t,j})$ : Coefficient $a$ of the demand curve.
    $B_{t,j} \leftarrow ((a_{t,j} / b_{t,j}) - (1/b_{t,j})D_{t,j})$ : Bid price.
```

4.2.2 Step 2: Seller's minimum price. Similarly to section 4.2.1, we determine the seller's minimum price (see [1] again) and get the following definition:

$$P_{t,j} = -(c_{t,j} / d_{t,j}) + (1/d_{t,j})D_{t,j} \tag{6}$$

In the following, we denote this price by $\underline{p}_{t,j}$. Algorithm 3 contains the formal specification.

```
Algorithm 3: Supply curve and seller's minimum price
Input:
    $D_{t,j}$ : Customer demand in $t$.
    $E_s$ : Price elasticity of supply.
    $P^*_{t,j}$ : Equilibrium price.
    $Q^*_{t,j}$ : Equilibrium quantity.
Output:
    $\underline{p}_{t,j}$ : Seller's minimum price in $t$.
Process:
    $d_{t,j} \leftarrow E_s(Q^*_{t,j} / P^*_{t,j})$ : Coefficient $d$ of the supply curve.
    $c_{t,j} \leftarrow ((1-E_s)Q^*_{t,j})$ : Coefficient $c$ of the supply curve.
    $\underline{p}_{t,j} \leftarrow (-(c_{t,j} / d_{t,j}) + (1/d_{t,j})D_{t,j})$ : Seller's minimum price.
```

4.2.3 Step 3: Matching. In our reverse pricing model, the supplier receives an incoming bid including bid price and quantity. The decision whether the demand is valid is solely up to the supplier. When matching supply and demand, the supplier will not accept any order quantity, but limit it in view of its own capabilities. In particular, these capabilities are determined by (1) the inventory level, (2) the delivery time of its own suppliers, and (3) the service level that needs to be met.

Therefore, we define a heuristic that results in a potential reduction of the demand. We consider the following two cases:

- The bid price is equal or higher than the seller's minimum price $(B_{t,j} \geq \underline{p}_{t,j})$. In this case, the transaction takes place with the bid price for the order quantity, which was calculated by the buyer according to algorithm 1.
- The bid price is lower than the seller's minimum price $(B_{t,j} < \underline{p}_{t,j})$. The order quantity calculated by the buyer using algorithm 1 needs to be modified to $y^{new}_{t,j}$. The product of bid price and order quantity is interpreted as the *total willingness to pay* in the current period. It will be divided by the seller's minimum price and leads to the allowed order quantity; hence the proportion of bid price to minimum price expresses the reduction:

$$y^{new}_{t,j} = (B_{t,j} / \underline{p}_{t,j})y_{t,j} \tag{7}$$

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
Input:
    $y_{t,j}$ : Order quantity from algorithm 1.
    $B_{t,j}$ : Bid price from algorithm 2.
    $\underline{p}_{t,j}$ : Seller's minimum price from algorithm 3.
Output:
    $y^{new}_{t,j}$ : Allowed order quantity in $t$.
Process:
    if $(B_{t,j} \geq \underline{p}_{t,j})$ then return $y^{new}_{t,j} \leftarrow y_{t,j}$ : No modification.
    if $(B_{t,j} < \underline{p}_{t,j})$ then return $y^{new}_{t,j} \leftarrow (B_{t,j} / \underline{p}_{t,j})y_{t,j}$ : Modification.
```

5. Simulation

This section describes the simulation study and its results. We have developed an agent-based simulation system called HoPIX[4], which is specifically designed for simulating multi-tier supply chains. For more details about HoPIX see [3].

5.1 Simulation setting

We define a competitive SC as shown in figure 1. We apply our reverse pricing model to all participants and compare it to conventional procurement. Only the last tier $(j = 4)$ knows the final customer demand $D_{t,C}$. We conduct experiments for all four sourcing strategies. We set the following parameters:

---

[4] Hohenheimer Process Integrator eXtension

- Final customer demand $D_{t,C}$: normally distributed with expected value $\mu = 100$ and standard deviation $\sigma = 10$.
- Forecast technique: moving average [2], 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 $T = 10$ periods:

  $$\hat{D}_{t,j} = (1/T)\sum_{n=1}^{T} D_{t-n,j} \tag{8}$$

  For estimating standard deviation of the forecast error $\hat{\sigma}_{t,j}$ see [2].
- α-service level: 99% thus, z in formula (1) equals 2.33 [2].
- Equilibrium price: we calculate $P^*_{t,j}$ for each SC participant based on bid price $B_{t,j}$ from the preceding $n = 52$ periods:

  $$P^*_{t,j} = (1/n)\sum_{t=1}^{n} B_{t,j} \tag{9}$$
- Equilibrium quantity: we calculate $Q^*_{t,j}$ for each SC participant based on demand data $D_{t,j}$ from the preceding $n = 52$ periods:

  $$Q^*_{t,j} = (1/n)\sum_{t=1}^{n} D_{t,j} \tag{10}$$
- Price elasticity for all tiers: $E_d = -0.8$, $E_s = 1.6$ (taken from [22]).
- Lead times: $L_4 = 1$, $L_3 = 1$, $L_{21} = 1$, $L_{22} = 2$, $L_{23} = 3$, $L_{11} = 1$, $L_{12} = 1$, $L_{13} = 1$

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

5.2 Metrics

The evaluation is based on standard metrics that quantify the BWE (see table 1). For each metric we calculate both the mean and standard deviation.

Table 1. Metrics

Metric	Definition	Interpretation
Order BWE	Quotient of the variance of order quantity y in tier j and the variance of final customer demand $D_{t,C}$ [2]: $O_j^{BWE} = Var(y_j)/Var(D_C),\ where\ j = 1...J$	Values greater than 1 indicate the BWE.
Inventory BWE	Quotient of the variance of inventory q in tier j and the variance of final customer demand $D_{t,C}$ [23]: $I_j^{BWE} = Var(q_j)/Var(D_C),\ where\ j = 1...J$	Values greater than 1 indicate the BWE.

5.3 Results

In the first set of experiments, we determine the BWE for local and global sourcing. Table 2 and 3 present the data for order and inventory BWE (see also figure 3 and 4). We calculate the order and inventory BWE for j=3 and j=11 (local sourcing) as well as for j=3 and j=13 (global sourcing).

In general, the BWE increases with an increase of lead time [2]. The comparison of the conventional procurement decision and the reverse pricing model yields a reduction in the order BWE of 14.3% to 52.8% (local sourcing) and 21.3% to 42.1% (global sourcing). In the inventory BWE we observed a reduction of 43.8% to 50.2% (local sourcing) and 29.7% to 52.1% (global sourcing). This observation was confirmed by a reduction in the standard deviation of 18.4% to 51.7% respectively.

Table 2. Local sourcing

j=3 (Wholesaler)						
	Without RP		With RP		Change	
BWE	M	SD	M	SD	M	SD
Order	4.72	0.26	2.23	0.20	-52.8%	-21.3%
Inventory	2.70	0.33	1.34	0.17	-50.2%	-47.7%
j=11 (Raw Material Supplier)						
	Without RP		With RP		Change	
BWE	M	SD	M	SD	M	SD
Order	7.52	0.55	6.44	0.43	-14.3%	-21.5%
Inventory	3.22	0.31	1.81	0.15	-43.8%	-51.2%

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

Table 3. Global sourcing

j=3 (Wholesaler)						
	Without RP		With RP		Change	
BWE	M	SD	M	SD	M	SD
Order	5.55	0.31	3.22	0.16	-42.1%	-48.6%
Inventory	4.73	0.58	2.26	0.28	-52.1%	-51.7%
j=13 (Raw Material Supplier)						
	Without RP		With RP		Change	
BWE	M	SD	M	SD	M	SD
Order	16.10	3.49	12.68	1.66	-21.3%	-52.3%
Inventory	9.18	0.61	6.45	0.50	-29.7%	-18.4%

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

In the second set of experiments, we assess dual sourcing. In this case, the order quantity is split between two suppliers. Table 4 shows the results on the order BWE and inventory BWE. We observe a reduction by reverse pricing in the order BWE for j=3, j=11 and j=13 of 12.8% to 50.8%. With regard to the inventory BWE, we observe a reduction for j=3, j=11, and j=13 of 14.9% to 48.3% (see also figure 3 and 4).

In the third set of experiments, we study multiple sourcing (table 5). An order is split between three suppliers. We observe a reduction by reverse pricing in the order BWE for j=3, j=11, j=12, and j=13 of 22.4% to 42.3%. Regarding the inventory BWE, the experiments yield a reduction for j=3, j=11, j=12, and j=13 of 22.4% to 42.7% (see also figure 3 and 4).

Table 4. Dual sourcing

j=3 (Wholesaler)						
	Without RP		With RP		Change	
BWE	M	SD	M	SD	M	SD
Order	5.38	0.26	2.65	0.12	-50.8%	-52.9%
Inventory	2.71	0.22	1.40	0.15	-48.3%	-33.9%
j=11 (Raw Material Supplier)						
	Without RP		With RP		Change	
BWE	M	SD	M	SD	M	SD
Order	3.82	0.22	3.18	0.17	-16.7%	-23.0%
Inventory	2.05	0.27	1.27	0.14	-37.8%	-45.5%
j=13 (Raw Material Supplier)						
	Without RP		With RP		Change	
BWE	M	SD	M	SD	M	SD
Order	4.43	1.36	3.86	0.66	-12.8%	-51.3%
Inventory	3.48	0.67	2.97	0.34	-14.9%	-49.7%

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

Table 5. Multiple sourcing

j=3 (Wholesaler)						
	Without RP		With RP		Change	
BWE	M	SD	M	SD	M	SD
Order	5.42	0.52	3.13	0.37	-42.3%	-30.0%
Inventory	6.41	1.36	3.67	1.00	-42.7%	-26.5%
j=11 (Raw Material Supplier)						
	Without RP		With RP		Change	
BWE	M	SD	M	SD	M	SD
Order	5.25	0.60	4.07	0.36	-22.4%	-40.0%
Inventory	3.19	1.03	2.31	0.84	-27.4%	-18.0%
j=12 (Raw Material Supplier)						
	Without RP		With RP		Change	
BWE	M	SD	M	SD	M	SD
Order	6.11	0.42	4.59	0.25	-24.9%	-40.5%
Inventory	4.24	0.54	2.88	0.42	-32.0%	-20.9%
j=13 (Raw Material Supplier)						
	Without RP		With RP		Change	
BWE	M	SD	M	SD	M	SD
Order	6.50	0.51	4.86	0.29	-25.1%	-42.4%
Inventory	5.72	0.96	4.44	0.82	-22.4%	-14.8%

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

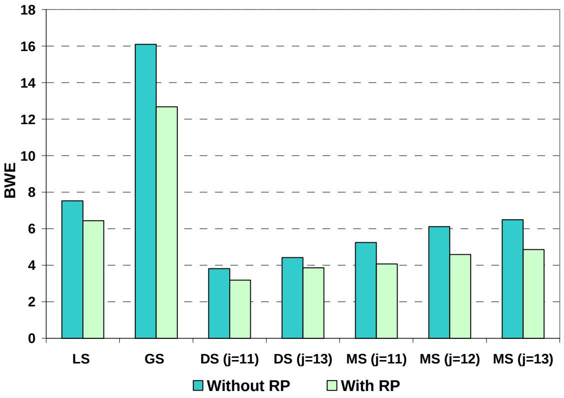

Figure 3. Assessment of sourcing strategies with regard to order BWE

(RP: reverse pricing; LS: local sourcing; GS: global sourcing; DS: dual sourcing; MS: multiple sourcing)

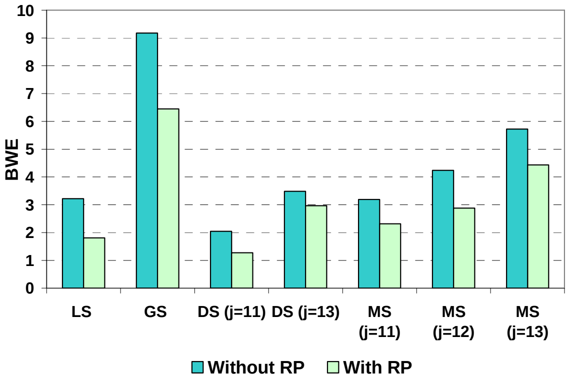

Figure 4. Assessment of sourcing strategies with regard to inventory BWE

(RP: reverse pricing; LS: local sourcing; GS: global sourcing; DS: dual sourcing; MS: multiple sourcing)

6. Discussion and conclusions

This paper contributes to the advancement of reverse pricing in supply chains. By referring to sourcing and procurement theory, we have extended the scope of such a coordination mechanism to more complex and thus more realistic supply chain models.

In particular, we have (1) designed a new coordination mechanism for competitive supply chains, (2) evaluated this mechanism by simulating selected sourcing strategies, and (3) provided a mean for assessing sourcing strategies with regard to the BWE in general. The set of experiments yielded a reduction of both the order and inventory BWE for all sourcing strategies as indicated by reductions in mean and standard deviation. We find that our coordination mechanism with heuristic and reverse pricing reduce the order BWE for the first tier of the retailer (in our scenario: wholesaler) of about 52.8% for local sourcing, 42.1% for global sourcing, 50.8% for dual sourcing and 42.3% for multiple sourcing. For the third tier of the retailer (here: row material supplier) of about 14.3% for local sourcing, 21.3% for global sourcing, 16.7% for dual sourcing and 25.1% for multiple sourcing.

Modeling supply chains for the purpose of evaluating a new artifact has to consider that the scope of such a model and thus the validity of simulation as a mean for evaluation are constrained. This is also true for our current model as specified in section 3 and 4. In particular, we have limited the SC complexity with respect to, e.g., inventory policy, forecast technique, and distribution of order quantities to multiple suppliers. In addition, our evaluation is purely based on two BWE metrics which do not reflect costs. Without considering cost factors, the simulation results are not valid in the real application. We plan to extend the scope of the current simulation by using costs factors and real-world data instead of artificially generated data. With respect to the representation of supply and demand by functions, the limitation is that we use linear functions only; we do acknowledge that other types of functions better represent actual behavior of suppliers and buyers.

References

[1] Y. Mujaj, J. Leukel, and S. Kirn, “A Reverse Pricing Model for Multi-Tier Supply Chains”, *Proceedings of the 9th IEEE International Conference on E-Commerce Technology (CEC’07)*, Tokyo, Japan, 2007, pp. 331-338.

[2] F. Chen, Z. Drezner, J.K. Ryan, and D. Simlich-Levi, “Quantifying the Bullwhip Effect in a Simple Supply Chain, The Impact of Forecasting, Lead Time, and Information”, *Management Science*, vol. 46, 2000, pp. 436-443.

[3] Y. Mujaj and J. Leukel, “An Agent-based Reverse Pricing Model for Reducing Bullwhip Effect in Supply Chains”, *Proceedings of the 13th Americas Conference on Information Systems (AMCIS 2007),* Keystone, Colorado, USA, 2007.

[4] H.L. Lee and S. Whang, “Information Sharing in a Supply Chain”, *Informational Journal of Technology Management Science*, vol. 43, 2000, pp. 546-558.

[5] C. Carlsson and R. Fuller, “Reducing the Bullwhip-Effect by Means of Intelligent, Soft Computing Methods”, *Proceedings of the 34th Annual Hawaii International Conference on System Sciences (HICSS-34)*, 2001.

[6] R. Mason-Jones, *The holistic strategy of market information enrichment through the supply chain*, PhD Thesis, Cardiff University, UK, 1998.

[7] J. Dejonckheere, S.M. Disney, M.R. Lambrecht, and D. R. Towill, “The Impact of Information Enrichment on the Bullwhip-Effect in Supply Chains: A Control Engineering Perspective”, *European Journal of Operations Research*, vol. 153, 2004, pp. 727-750.

[8] C.F. Daganzo, *A Theory of Supply Chains*, Springer, Berlin et al., 2003.

[9] H.L. Lee, V. Padmanabhan, and S. Whang, “Information Distortion in a Supply Chain: The Bullwhip Effect”, *Management Science*, vol. 43, 1997, pp. 546-558.

[10] G. Dudek and H. Stadtler, “Negotiation-based collaborative planning between supply chains partners”, *European Journal of Operational Research*, vol. 163, 2005, pp. 668-687.

[11] T. Moyaux, B. Chaib-draa, and S. D’Amours, “Multi-Agent Simulation of Collaborative Strategies in Supply Chain”, *Proceedings of the 3rd International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS)*, New York, USA, 2004.

[12] D. Bertsimas and S. de Bore, “Dynamic Pricing and Inventory Control for Multiple Products”, *Journal of Revenue and Pricing Management*, vol. 3, 2005, pp. 303-319.

[13] S. Biller, L.M.A. Chan, D. Simchi-Levi, and J. Swann, “Dynamic Pricing and the Direct-to-Customer Model in the Automotive Industry”, *Electronic Commerce Research*, vol. 5, 2005, pp. 309-334.

[14] P. Dasgupta, L.E. Moser, and P.M. Melliar-Smith, “Dynamic Pricing for Time-Limited Goods in a Supplier-Driven Electronic Marketplace”, *Electronic Commerce Research*, vol. 5, 2005, pp. 267-292.

[15] L.F. Marshall, J. H. Hammond, W. R. Obermeyer and A. Raman, “Making Supply meet demand in an uncertain world”, *Harvard Business Review*, vol. 72, 1994, pp. 83-93.

[16] A. Maltz, P. Christiansen, O. Carranza, and G. Adegoke, “Integrating Developing Country Firms into Global Supply Chains: Preliminary Findings”, *North American Teaching Symposium*. Institute of Supply Chain Management, 2003.

[17] O.C. Torres and F. V. Moran, “Cross-Border Logistics and Sourcing: A Methodology to Analyze Planning Policies”, in O.C. Torres and F.V. Moran (Eds.), *The Bullwhip Effect in Supply Chains*, Palgrave Macimillan. New York 2006, pp. 187-214.

[18] R.B. Chase, N.J. Aquilano, and F.R. Jacobs, *Production and Operations Management: Manufacturing and Services*, Eight Edition, Irwin/McGraw-Hill, New York et al., 1998.

[19] O. Hinz and M. Bernhardt, “Scalable Business Models with Web Services in a Reverse Pricing Scenario”, *Proceedings of the 13th European Conference on Information Systems (ECIS 2005)*, 2005, pp. 1199-1210.

[20] M. Bernhardt and O. Hinz, “Creating Value with Interactive Pricing Mechanisms – a Web Service-Oriented Architecture”, *Proceedings of the 7th IEEE International Conference on E-Commerce Technology (CEC’05)*, 2005, pp. 339-346.

[21] I.H. Hann and C. Terwiesch, “Measuring the Frictional Costs of Online Transactions: The Case of a Name-Your-Own-Price Channel”, *Management Science*, vol. 49, 2003, pp. 1563-1597.

[22] D. Besanko and R.R. Braeutigam, *Microeconomics*, Second Edition, John Wiley & Sons, NJ, 2005.

[23] S.M. Disney and D.R. Towill, “On the bullwhip and inventory variance produced by an ordering policy”, *OMEGA: The International Journal of Management Science*, vol. 31, 2003, pp. 157-167.