HERNAN A. BRUNO, HAI CHE, and SHANTANU DUTTA*

The authors study the role of reference price in a setting in which both the price and the quantity are set through personal interaction during the transaction process, such as in business-to-business markets. Most studies on reference price in the marketing research literature focus on consumer packaged goods, for which prices are typically fixed during the shopping trip and the transaction does not involve personal interaction with a salesperson. In this study, the authors study the effect of reference price on the quantity purchased and also on the pricing outcome of the transaction. They estimate a simultaneous equation system of both pricing and quantity purchased. The findings are as follows: (1) Reference price effects exist on quantity purchased and on the transaction pricing outcome in business-to-business market transactions, (2) business customers react asymmetrically to price increases and price decreases, and (3) salespeople have their own reference prices that affect the transaction price. The authors also find that customer experience with the salesperson might exacerbate the loss aversion effect. They conclude by discussing the underlying reasons behind these findings and their managerial implications.

*Keywords*: reference price, business-to-business, pricing, loss aversion, salesperson role

# Role of Reference Price on Price and Quantity: Insights from Business-to-Business Markets

The extant marketing and economics literature has reported consistent empirical evidence that consumers evaluate products and make purchase decisions by comparing prices against an internal standard, usually referred to as "reference price" (Briesch et al. 1997; Kalyanaram and Winer 1995; Mazumdar, Raj, and Sinha 2005; Putler 1992; Winer 1986). Reference prices are formed from experience of previous prices either through purchase (i.e., paying the price) or observation. Researchers have found that a discrepancy between the reference price and the observed price affects choices in choice-based demand models using secondary data as well as in laboratory experiments.

This study investigates the role of reference price in situations in which both price paid and quantity purchased are determined during the transaction process. The existing literature, in contrast, demonstrates the effect of reference price in contexts in which the price is fixed during the transaction. In particular, the extensive evidence of reference price effects is based on consumer purchase data of grocery products, conditional on observed price (e.g., Chang, Siddarth, and Weinberg 1999; Erdem, Mayhew, and Sun 2001; Lattin and Bucklin 1989). However, there are many contexts in which the price is an outcome of the transaction and is determined through the interaction between a buyer and a seller. Despite the extensive evidence that reference prices affect choices, it is not directly evident that the effects found in the consumer packaged goods context can be generalized to situations in which the price paid is also an outcome of the transaction. This article extends the literature on refer-

*Hernan A. Bruno is Assistant Professor of Marketing, INSEAD (e-mail: hernan.bruno@insead.edu). Hai Che is Associate Professor of Marketing, Kelley School of Business, Indiana University in Bloomington (e-mail: haiche@indiana.edu). Shantanu Dutta is Dave and Jeanne Tappan Professor of Marketing, Marshall School of Business, University of Southern California (e-mail: sdutta@marshall.usc.edu). The authors are listed in alphabetical order. They thank Anthony Dukes and Haipeng Chen for helpful comments. Russ Winer served as guest editor for this article, and Yuxin Chen served as associate editor for this article.


ISSN: 0022-2437 (print), 1547-7193 (electronic)

ence prices by simultaneously modeling the effect of reference prices of buyers and sellers on observed prices and quantity demanded.

Marketing researchers have studied the role of reference price on price setting using laboratory experiments. Kahneman (1992) suggests that a reference point is used to determine how an offer is perceived in negotiation and subsequently could affect the final price outcome. Since then, several studies have explored the effects of reference price in pricing games in laboratory settings (Bottom and Studt 1993; Neale, Huber, and Northcraft 1987). Also using experimental data, Ho and Zhang (2008) find evidence of reference price effects in a three-part tariff pricing model between manufacturer and retailer. Our model and hypotheses build on this literature by exploring the roles of both customer reference price and salesperson reference price in the price-setting process. We contribute to the literature by providing evidence from actual market transactions that past transactions that were framed as a gain or a loss in relation to a reference price affect the price setting.

Many business-to-business (B2B) transactions fit the characteristics outlined here—namely, the price and quantity are agreed upon through the interaction between a buyer and a seller. In many industries, industrial purchasers buy a particular product repeatedly to fulfill production needs of the buying company. Transactions usually take place between a buying agent and a salesperson from the supplying firm. In these cases, the buyers are likely to use their past price experience (i.e., a reference price) to evaluate the current price of products. Similarly, salespeople who sell products to a vast number of buyers may also rely on their own reference prices when negotiating with a buyer. Given that B2B transactions constitute approximately 80% (86% in Asia, 82% in Europe, and 72% in North America) of the volume of payments in the global economy (Agicha et al. 2010), it is imperative to understand the role of reference prices in this context.

Using a data set constructed from the transactional record of industrial customers of a B2B company, we model a simultaneous system of regression equations in which price and quantity are endogenously determined through the interaction between buyer and seller. This modeling approach enables us to characterize the effects of reference price on the price paid and the quantity transacted as a joint outcome of the transaction. We focus on the internal reference price (IRP) and therefore operationalize reference price as a function of the previous transaction prices a customer experiences. In the spirit of Kahneman and Tversky (1979), we distinguish transactions in which the price is higher than the reference price (a "LOSS" from the customer's point of view) and lower than the reference price (a "GAIN").

Our estimation approach takes into account the key features of B2B transactions. First, we test the existence of reference price effects on the quantity purchased. Second, we investigate the role of the customer's reference price on the unit price paid in a given transaction. Third, we investigate the key role of the salesperson by incorporating the role of the salesperson's reference price on the price outcome of the transaction. Last, we assess the interaction effect of the buyer's past experience with the salesperson and the reference price.

Our estimates provide strong evidence that reference price effects exist in B2B transactions. The results from the quantity model show that business customers who purchase at a higher (lower) price than the reference price are more likely to purchase lower (higher) quantities beyond the decrease in magnitude that would be predicted by the price level alone. Furthermore, our findings indicate that customers react more strongly to losses than to gains. This result is consistent with the predictions of prospect theory (Kahneman and Tversky 1979) and with the findings from the empirical reference price literature using choice models.

We also investigate how the customer's past losses and gains affect the current pricing decision. Our results suggest that previous transactions influence the pricing outcome of the current transaction. We find that a buyer's losses in the past transaction lead to lower prices while a buyer's gains in the past transactions lead to higher prices. We show that this relationship between past price and current price is consistent with the prediction of prospect theory, in which past losses play a relatively stronger role than past gains. In addition, our estimation results from the pricing model also provide evidence of the existence of a salesperson reference price (i.e., an internal reference point that influences a salesperson's pricing behavior). Because salespeople handle many transactions a day with many different products and customers, it is likely that they also rely on simplifying heuristics (i.e., a reference point) when they set prices. This effect is stronger in cases in which previous prices were unfavorable (i.e., a LOSS) for the salesperson in a previous transaction.

Our finding of the effect of buyer and seller reference prices on pricing outcome using the B2B transaction data is new to the literature on reference prices and has important implications for managing B2B buyer–seller relationships. To our knowledge, our study is the first to report these reference price effects on pricing outside laboratory settings, which have reported mixed results (Neale, Huber, and Northcraft 1987; Northcraft and Neale 1987).

Moreover, we find that the effects of reference price on quantity and price are affected by the buyer's experience with the salesperson. The larger the number of transactions a customer has with a salesperson, the stronger is the effect of a perceived loss, and the weaker is the effect of a gain. Ceteris paribus, the effect of a loss on the quantity purchased by a customer who has extensive experience with a salesperson is likely to be greater than that of a customer with little experience with the salesperson. Similarly, experience with a salesperson also leads to a smaller increase in quantity purchased as a result of a "gain" in price because customers are likely to expect a beneficial relationship from a salesperson they know well. These results are consistent with the idea that a customer expects favorable deals (lower prices in this case) from salespeople with whom he or she interacts frequently.

In general, we show that the behavior of the customers in our study is consistent with reference-dependent preferences. In contrast to customers in consumer markets, B2B customers are firms that have their own customers (either end consumers or other firms). Their preferences are most likely the result of the reference-dependent behavior of the industrial buyer (i.e., the person(s) making the purchase decisions). However, this preference could also include or be influenced by the industrial buyer's understanding of the reference-dependent behavior of their own downstream customers (other firms or end consumers). This interdependence of the downstream value chain is one of the most important characteristics of B2B marketing.

To our knowledge, the current study is the first to measure and characterize the effect of reference prices on the behavior of industrial customers embedded in a value chain of B2B companies. Kalyanaram and Winer's (1995) study on reference prices as an empirical generalization suggests that further research should explore the role of reference price in contexts other than consumer packaged goods, particularly industrial markets, and whether customers' experience with salespeople affects the magnitude of reference price effects. The current study is an attempt to begin filling this gap and to shed light on the behavioral effects of prices in a B2B context using transactional data.

We organize the rest of the article as follows: In the next section, we provide a stylized theory model of reference price effects on transactions in the B2B markets. The following section provides the econometric model that is built on the theory model. Then, we describe the data and the empirical results together with the managerial implications of our findings. The final section discusses directions for further research.

## *THEORETICAL BACKGROUND*

Given that we are modeling the outcome of a transaction between a buyer and a seller with reference-dependent preferences, we need a theoretical framework to describe and analyze a B2B transaction in which quantity and pricing decisions are determined endogenously and influenced by reference price. In this section, we develop a stylized model of a B2B transaction that provides a framework for the empirical specification and the choice of variables.

In our model setup, the transaction takes place when a customer inquires about a product and the seller offers a selling price p. After observing the price, the customer decides whether to accept the price p for a quantity q(p) to maximize his or her transaction utility or to walk away if a minimum reservation utility level is not met. The seller knows the customer's utility function and decision rules when he or she offers a price for the requested product. The model is spelled out in detail in the Web Appendix (www.marketingpower.com/jmr_webappendix) and is based on the following general assumptions: (1) The buyer's utility function has a comparative utility term that is a function of the reference price, (2) the buyer's reservation utility $U_{min}$ is a function of experienced prices, and (3) the seller's payoff function includes a term $\sigma$ that embodies the psychological cost or benefit of the transaction and is influenced by previous transactions.

### *Buyer's Quantity Decision*

Buyers choose a quantity q of a product. At a price p, conditional on their reference price R, a buyer purchases an amount q that maximizes the utility function U(p, q; R). The function U is the sum of two terms: a transaction utility V (p, q) and a comparative utility term proportional to the difference of the transaction utility and a reference utility. Specifically, we define the buyer's utility as follows:

$$(1)\quad U(p,q;R) = \underbrace{V(p,q)}_{\text{Transaction Utility}} + \delta\overbrace{\left[V(p,q) - \underbrace{V(R,q)}_{\text{Reference Utility}}\right]}^{\text{Comparative Utility}}.$$

The transaction utility is increasing in quantity ($V_q > 0$) and concave ($V_{qq} < 0$); that is, there are diminishing returns to quantity, and it is decreasing in price ($V_p < 0$).[1] We also assume a regularity condition to ensure the existence of a solution, namely, that $V_{qq}$ should remain bounded (see the Web Appendix at www.marketingpower.com/jmr_webappendix). Finally, we assume that $V_{qp} < 0$.

The second term in the right-hand side of Equation 1 is the comparative utility. It is the difference between the transaction utility V(p, q) and a reference utility, V(R, q), defined as the transaction utility at price p = R. In other words, given a transaction quantity q, the buyer is comparing the value obtained in the current transaction with the hypothetical value that would have been obtained at price R. The positive proportionality constant $\delta$ measures how much the comparative utility influences the buyer's utility function. Let $\delta = \delta_G$ if V(p, q) > V(R, q) and $\delta = \delta_L$ if V(p, q) < V(R, q). In line with prospect theory (Kahneman and Tversky 1979), we expect that $\delta_G < \delta_L$, implying that buyers will react asymmetrically to the price discrepancy depending on whether this discrepancy is perceived as a gain or a loss. Finally, we assume that buyers have a reservation utility $U_{min}$ that captures all the outside options and general attitude toward the purchase. If $\max_q[U(p, q; R)] < U_{min}$, the buyer walks away and the purchase quantity q = 0.

The optimal quantity q*(p; R) maximizes U(p, q; R) and solves the first-order condition. Differentiating Equation 1, equating it to zero, and rearranging the terms, we obtain the optimality condition:

$$(2)\qquad V_q(p,q^*) = \frac{\delta}{1+\delta}V_q(R,q^*).$$

Equation 2 says that at the optimal quantity q*, the ratio of the slopes of the transaction utility (at price p) to the slope of the reference utility (at price R) equals the constant $\delta/(1 + \delta)$. In our model, there is a trade-off between the utility increase or decrease and the concomitant change in comparative utility. In the case of a loss, for example, every unit of quantity not only changes the transaction utility but also provides an amount of loss that is subtracted from the buyer's total utility. Thus, buyers optimize their utility by decreasing quantity purchased relative to that of the optimum without reference dependence to a point at which the marginal transaction utility equals the marginal comparative utility. A similar argument can be made for a gain. Panel A in Figure 1 illustrates a loss ($p_0 > R$), and Panel B illustrates a gain ($p_1 < R$).

From Equation 2, we can solve for the optimal quantity q*(p; R), which is a function of the transaction price p and the reference price R. The optimal quantity q* is monotonically decreasing in price p. In addition, the relationship between q* and p is influenced by the comparative utility

[1]We use subscripts q and p to refer to the derivative of a function with respect to quantity and price, respectively.

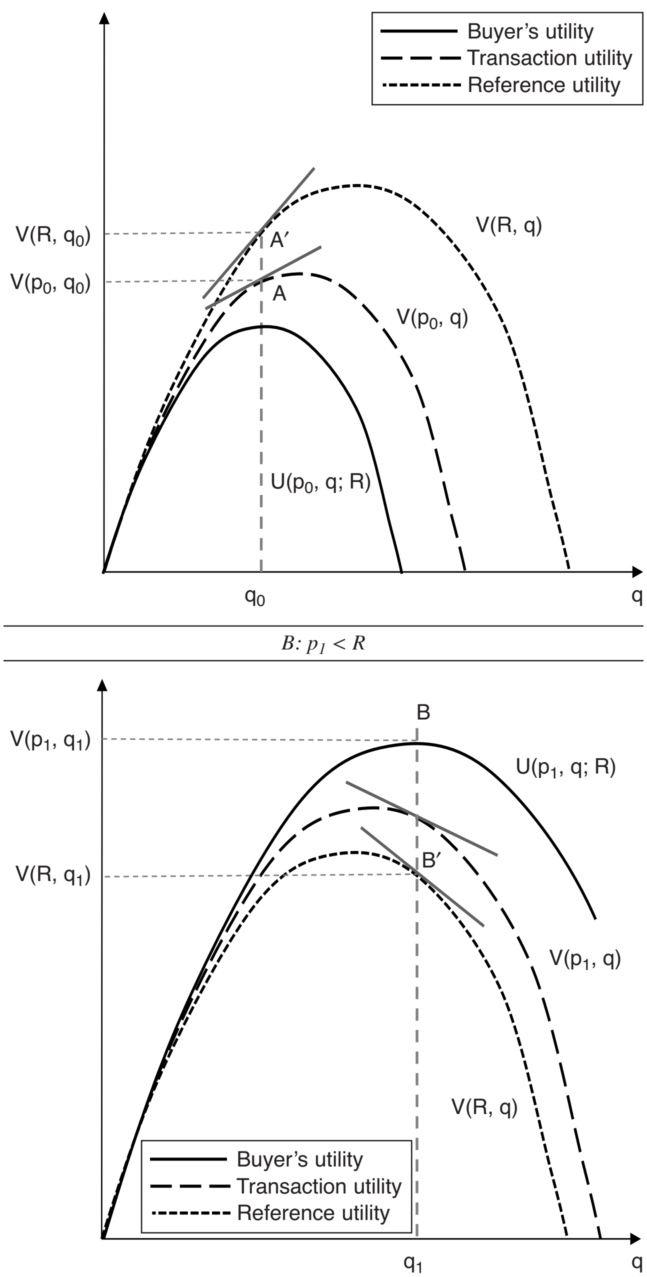
term in Equation 1. For example, a transaction that is viewed as a loss leads to a lower quantity purchased than a similar transaction at the same price that is perceived as neither a loss nor a gain.[2] The optimal quantity under our assumptions is as follows:

$$(3)\qquad q^{**} = \begin{cases} q^{*}(p; R) & \text{if } U\left(p, q^{*}; R\right) \geq U_{min} \\ 0 & \text{if } U\left(p, q^{*}; R\right) < U_{min} \end{cases}.$$

Figure 1

TRANSACTION UTILITY, REFERENCE UTILITY, AND TOTAL BUYER'S UTILITY

*A: $p_0 > R$*




Notes: Panel A shows the transaction utility $V(p_0, q)$, the reference utility $V(R, q)$, and the total buyer's utility $U(p_0, q; R)$ in a case in which the price is below the reference price (i.e., $p_0 > R$). Note that $U(p_0, q; R) < V(p_0, q) < V(R, q)$ for all q. In addition, note that at the maximum buyer's utility, the slopes of $V(p_0, q)$ and $V(R, q)$ are positive (points A and A' in the curve) and the slope of the reference utility is larger than the slope of the transaction utility, as per Equation 2. Analogously, Panel B shows the same curves for a $p_1 < R$, in which $V(R, q) < V(p_0, q) < U(p_0, q; R)$. The slope of the reference utility in this case is also larger in magnitude than the slope of the transaction utility.

*Seller's Pricing Decision*

The seller's decision is to set the price p. We assume that the seller has perfect information about the buyer's utility function and reference price and sets the price such that it maximizes the following payoff function:

$$(4)\qquad V^{s} = [p - (c + \sigma)]q.$$

The parameter c represents the marginal cost of the product. In addition to the marginal cost c, we introduce the effects of the seller's experience in previous transactions into the pricing equation. Although there are several possible ways of introducing such effects, we do so by including an additional parameter $\sigma$, defined as the net cost (or benefit) that is beyond the product cost that occurred in the transaction. The behavioral and experimental economics literature of pricing (Al-Najjar, Baliga, and Besanko 2008; Ho, Lim, and Cui 2010) has adopted such specification of modeling the psychological costs, and it is the most parsimonious way that we can capture the reference price effects from the seller's past experience. In our model, the parameter s is not an economic fundamental but a reduced-form variable that captures shifts in the perceived cost of the transaction. The net cost term $\sigma$ could be affected by the seller's previous transaction outcomes because the seller will try to raise the price when past transactions were viewed as losses in value. Therefore, the seller's past losses could impose a cost on the seller in setting prices. The opposite (benefit, instead of cost) could be argued for the seller's past transactions that are framed as gains.

The seller's problem is to find the best price that maximizes Equation 4 and provides a level of utility to the customer such that the purchase takes place.[3] Recall that cus-

[2]We should also point out that our model is a general version of standard utility models used in the reference price literature. Typically, the comparative utility is modeled as the difference between price and reference price (e.g., $\delta[R - p]q$) (Briesch et al. 1997; Kalyanaram and Winer 1995; Putler 1992). The approach followed in the reference price literature is a special case of our model in which the transaction utility has the additive separable form $V(p, q) = f(q) - pq$. Substituting this utility specification into Equation 1, we obtain $U(p, q; R) = f(q) - pq + \delta(R - p)q$. This implies that the customer is comparing values, but under some assumptions, values are directly proportional to prices; therefore, comparing values and prices is equivalent (for a detailed explanation of the boundary conditions, see the Web Appendix at www.marketingpower.com/jmr_webappendix). The specific relationship between q* and prices depends on the functional form, particularly on the way the slopes change as we change q. The Web Appendix discusses particular functional form examples to provide further intuition. The Web Appendix also discusses a more general situation when buyers use a quantity different from the transaction quantity in the comparative utility.

[3]This optimality condition implicitly assumes that sellers only maximize current-period profits. In our empirical setting, the salesperson has little incentive to set a dynamically optimal price that takes into consideration the impact of the current price in the future reference price. This is because the next customer transaction may occur with a different salesperson or may occur again in another few months. In addition, the main effect of a dynamic optimal pricing policy would be a higher price than the static pricing policy (see Popescu and Wu 2007) and would not bias our estimates.

tomers purchase only if $U(p, q^*[p; R];R) > U_{min}$. Therefore, we can state the seller's decisions as finding p such that

$$p^* = \text{argmax}\{p < \bar{p}\}[p - (c + \sigma)]q,$$

where $\bar{p}$ is the price above which the buyer's utility falls below $U_{min}$; that is, if $p > \bar{p}$, then $U(p, q^*[p; R]; R) < U_{min}$. As we explained previously, $U_{min}$ captures the state of mind and the outside options the customer has when he or she enters the transaction. If the customer experienced a recent transaction that was framed as a loss in price or value, he or she may have a higher utility threshold $U_{min}$, and thus a lower $\bar{p}$, and is more likely to walk away from a transaction. Analogously, the customer who experienced a recent transaction that was framed as a gain will have a higher $\bar{p}$ and could be willing to accept higher prices. Thus, $\bar{p}$ represents the upper price threshold above which the customer rejects the offer and ends the transaction, and it depends on the customer's past price experiences with the seller.[4]

When $p < \bar{p}$, we can find the optimal price $p^*$ by solving the first-order conditions and rewriting as follows:

$$p^* = c + \sigma - \frac{q}{\frac{\partial q}{\partial p}}.$$

In general, we can then write the seller's price as follows:

$$p^{**} = \min\{p^*, \bar{p}\}.$$

*Implications for the Empirical Model*

Our model captures the reference-dependent transaction in a general and parsimonious way. From the buyer's and seller's first-order conditions, which are two equations and two unknowns (quantity and pricing), we can solve for the equilibrium quantity and price $\{q^{**}, p^{**}\}$. The properties of the buyer and seller utility functions ensure that there is a unique equilibrium. The exact relationships depend on the specific functional (for examples, see the Web Appendix at www.marketingpower.com/jmr_webappendix).

The general approach for the empirical model described in the next section is a simultaneous system of equations in which price and quantity are endogenous variables. From our analysis of the customer quantity decision, we expect that an increase in price (i.e., a customer loss) or a decrease in price (i.e., a customer gain) relative to the reference price would have a negative or positive effect, respectively, on the quantity purchased, and they should enter the empirical specification explicitly.

Our theoretical framework assumes that customers compare the value of the transaction to the value of a hypothetical transaction at the reference price. This allows consumers to adjust the quantity purchased to match the marginal effect of the transactional utility to the marginal effect of the comparative utility. In contrast, empirical choice models on reference price assume that quantity is fixed, so comparing values is equivalent to comparing prices. In our empirical model, we use a more flexible empirical specification (i.e., we use higher-order terms in GAIN and LOSS, as explained in the next section) that accounts for this theory implication and enables consumers to compare transaction value with reference value.

Our theoretical framework also assumes that past transactions have an effect on the buyer's reservation price $\bar{p}$ and the seller's psychological cost $\sigma$. In the empirical specification for the pricing model with respect to the reference price, we include the lagged terms of the LOSS and GAIN variables for the customer to capture the customer's recent price experience with the selling firm. A customer who comes from a recent loss (gain) would have a lower (higher) reservation price, $\bar{p}$, and we should expect lower (higher) prices on average. Analogously, in the empirical specification of the pricing model, we can include the lagged LOSS and GAIN variables of the salesperson to account for the effect of a seller's psychological cost on the current price.

## EMPIRICAL MODEL

The theory model presented in the previous section suggests that the transaction quantity is a function of transaction price, namely, the perceived loss or gain from the transaction price with respect to reference price for the buyer. The theory also suggests that transaction price is a function of transaction quantity, cost, and the lagged LOSS or GAIN of transaction price with respect to reference price for the buyer as well as for the seller.

*Reference Price*

We expect that the observed transaction price should depend on the customer reference price as well as on the departures from the reference price. There are several ways of specifying the reference price terms (Erdem, Mayhew, and Sun 2001), and we use two in our study. The first reference price specification uses the customer's last transaction price as the reference price for the current transaction, $RP_{ijt} = p_{ij, t-1}$. The reference price specifications are in the realm of IRPs and have been widely used (Bell and Bucklin 1999; Kalyanaram and Little 1994; Krishnamurthi, Mazumdar, and Raj 1992; Lattin and Bucklin 1989; Mayhew and Winer 1992; Winer 1986).[5] Briesch et al. (1997) find that even in a consumer goods setting, IRP provides the best fit. The lack of competitors' price information also makes it impossible for us to assess the role of external reference price as Hardie, Johnson, and Fader (1993) suggest. However, as discussed subsequently, we include external price indexes and a set of customer-, product-, and time-specific fixed effects to capture the effects of competitors' price on the quantity demand and pricing outcome. Empirically, past prices that influence the reference price can be either the records of past transactions in a data management system or the memory of the purchasing and selling agent.

*LOSS and GAIN Variables*

In the theory model, the reference price effect is modeled using the comparative utility term. The comparative utility

[4]Our definition of $\bar{p}$ is similar to the reservation price concept. In reference price consumer behavior literature, researchers have found that reservation prices and reference prices are often highly correlated (Janiszewski and Cunha 2004; Lichtenstein and Bearden 1989) and that reservation prices are sometimes higher than reference prices (Lichtenstein and Bearden 1989). Therefore, we hypothesize that the customer's past price experience can be highly correlated with $\bar{p}$ and therefore affect the pricing outcome.

[5]We also test a second reference price specification, which is a weighted average of the customer's last transaction price and last reference price (for the results, see the Web Appendix at www.marketingpower.com/jmr_webappendix).

term is a function of the difference between price and reference price (p – R) and affects the transaction quantity and price. Empirically, we only observe how far the paid price departs from the reference price. Following the current literature in empirical models (Krishnamurthi, Mazumdar, and Raj 1992; Winer 1986), we can specify the LOSS and GAIN variables in the quantity equation to capture the departure of the current price from the reference price upward and downward, respectively. More specifically, for a given buyer i who buys product j from seller s during transaction t,

$$(5)\qquad \begin{aligned} GAIN_{isjt} &= \left[R_{ijt} - p_{ijst}\right] \times 1\left\{R_{ijt} > p_{ijst}\right\} \\ LOSS_{isjt} &= \left[p_{ijst} - R_{ijt}\right] \times 1\left\{p_{ijst} > R_{ijt}\right\}, \end{aligned}$$

where either the GAIN or the LOSS term will hold depending on the sign of $p_{ijst} - R_{ijt}$, and we specify the difference term (between R and p) inside the bracket in Equation 5 to be always positive. Here, LOSS and GAIN work as proxies for the comparative utility term: The larger the LOSS or GAIN variable, the larger is the comparative utility and its effect on the transacted quantity. In line with prospect theory, we expect GAIN to have a positive effect on the quantity purchased and LOSS to have a negative effect. Additionally, we expect the absolute effect of GAIN to be smaller than the absolute effect of LOSS.

Our theoretical framework assumes that buyers are comparing values, not merely comparing the transaction price with the reference price. Mathematically, this is equivalent to saying that the optimal quantity $q^*$ is not necessarily a linear function of LOSS or GAIN in price (i.e., p – R or R – p). For the general model, the derivative of the optimal quantity $q^*$ with respect to price ($\partial q^*/\partial p$) is a function of price and depends on the optimal quantity itself (see the Web Appendix at www.marketingpower.com/jmr_webappendix). A change in price p changes the optimal quantity $q^*$; in addition, the size of this effect ($\partial q^*/\partial p$) could decrease or increase as LOSS or GAIN become larger. To account for this and better approximate the effect of comparative utility on quantity purchased, we estimate additional models to include linear as well as higher-order variables of LOSS and GAIN, such as $(LOSS)^2$ and $(GAIN)^2$, in our empirical model of buyer's quantity decision.

In the empirical specification of the pricing decision, we include lagged LOSS and GAIN variables for both the buyer and the seller. As we discussed in the "Theoretical Background" section, the past reference price effects for both the buyer and the seller can also affect the pricing outcome. More specifically, the buyers' reservation price can be correlated with their past experience of reference price effects (Janiszewski and Cunha 2004; Lichtenstein and Bearden 1989). For the seller, past experiences of reference price effects may affect the *net* cost (of benefit) $\sigma$ that is beyond the product cost c and can be conceptualized as a representation of the psychological cost (Al-Najjar, Baliga, and Besanko 2008; Ho, Lim, and Cui 2010). Therefore, we include the buyer's and the seller's lagged LOSS and GAIN variables as independent variables in the estimation of the pricing equation. These variables are exogenous to the current transaction and capture the buyer and the seller's reference price effects on the pricing outcome. For the buyer, the LOSS and GAIN variables in the pricing equation are specified as in Equation 5. For the seller, the LOSS or GAIN variables are also specified as the difference between the transaction price and the salesperson reference price. Specifically, for a salesperson who sells product j in transaction t,

$$(6)\qquad \begin{aligned} GAIN^S_{jt} &= \left[p_{ijst} - R^S_{jt}\right] \times 1\left\{p_{ijst} > R^S_{jt}\right\} \\ LOSS^S_{jt} &= \left[R^S_{jt} - p_{ijst}\right] \times 1\left\{R^S_{jt} > p_{ijst}\right\}. \end{aligned}$$

Similar to Equation 5, we specify the difference term between R and p inside the brackets to be positive. We also estimate models that include higher-order powers of the buyer's and seller's lagged LOSS and GAIN variables, such as $(\text{lagged LOSS})^2$ and $(\text{lagged GAIN})^2$, in the pricing equation to investigate diminishing effects as lagged LOSS and lagged GAIN become larger.

In line with the theory model prediction, we include price and customer's GAIN and LOSS terms as key independent variables in the quantity equation; in the pricing equation, we include quantity, cost, and the customer's as well as the seller's lagged GAIN (denoted as $GAIN_{t-1}$) and lagged LOSS (denoted as $LOSS_{t-1}$) terms as independent variables. Specifically, a customer i's purchase from salesperson s of product j of quantity q and transaction price paid p at transaction t can be estimated simultaneously with the following two equations[6]:

$$(7)\qquad \begin{aligned} q_{isjt} = {} & \alpha_q + \gamma_p p_{isjt} + \gamma_{G1} GAIN_{isjt} + \gamma_{G2}(GAIN_{isjt})^2 \\ & + \gamma_{L1} LOSS_{isjt} + \gamma_{L2}(LOSS_{isjt})^2 + Z^q_{isjt}\gamma + \phi_{ij} + \phi_{sj} \\ & + \tau_t + \varepsilon^q_{ijt}, \text{ and} \end{aligned}$$

$$(8)\qquad \begin{aligned} p_{isjt} = {} & \alpha_p + \beta_q q_{isjt} + \beta_c c_{jt} + \beta_{G1} GAIN_{isj,\,t-1} \\ & + \beta_{G2}(GAIN_{isj,\,t-1})^2 + \beta_{L1} LOSS_{isj,\,t-1} \\ & + \beta_{L2}(LOSS_{isj,\,t-1})^2 + \beta^s_{G1} GAIN^s_{j,\,t-1} \\ & + \beta^s_{G2}(GAIN^s_{j,\,t-1})^2 + \beta^s_{L1} LOSS^s_{j,\,t-1} \\ & + \beta^s_{L2}(LOSS^s_{j,\,t-1})^2 + Z^p_{isjt}\beta + \eta_{ij} + \eta_{sj} + \tau_t + \varepsilon^p_{ijt}. \end{aligned}$$

For variable Z in the preceding quantity and pricing equations, we include the inventory and recency variables, the effect of customer–salesperson experience, the effect of cost change, and variables and fixed-effect variables, as detailed in the following subsections.

### *Inventory and Recency Variables*

We add an inventory variable (Bucklin and Gupta 1992) and a recency variable to control for possible buyer inventory dynamics. If customers are building inventories when prices are low and then using them up when prices are high, we could observe an effect similar to the one studied in the current research: higher (lower)-than-expected purchases for decreases (increases) in price. We compute the inventory variable as in Bucklin and Gupta (1992) but use a smoothed average of product purchases during the previous quarter as consumption rate. We operationalize the recency variable as number of weeks since last purchase.

[6]In the estimation, we specify quantity as the logarithm of the quantity transacted; similarly, we specify price as the logarithm of the price transacted. The quantity purchased for the average transaction varies markedly across products. Using logarithms alleviates the potential effect of heteroskedasticity that could result from these large variations across observations.

*The Effect of Customer–Salesperson Experience*

The role of customer and salesperson interaction is an important characteristic in business markets. In addition to our base model, we also explore whether the customer experience with the salesperson has an impact on the relationship between GAIN/LOSS and the quantity and price decisions. In particular, we explore how the reference price effects on quantity purchased and transaction price are affected by the customer's previous experience with the salesperson. We operationalize the customer–salesperson experience by defining a frequency variable, $F_{isjt}$, representing the number of purchases a customer made from a salesperson in the most recent quarter (lower quartile = 4, median = 30, upper quartile = 70). A higher number of purchases during the previous month implies a higher number of interactions with a given salesperson and a higher experience between the customer and the salesperson. We also add the interaction terms between the corresponding frequency variable and reference price variables, GAIN, and LOSS to investigate whether the relationship between the salesperson and the customer affects the transaction price. *Ex ante*, we do not have a prediction on the direction of this effect. On the one hand, a stronger buyer–seller relationship could lead to a higher observed price because the salesperson may be taking advantage of customer loyalty and/or switching costs (Palmatier, Scheer, and Steenkamp 2007). On the other hand, a stronger buyer–seller relationship could lead to lower prices because salespeople may favor their long-term relationship with a customer (Bagozzi 1995) or customers use their familiarity with the salesperson to push down the price.

*The Effect of Cost Change*

As we explained previously, we observe the cost of the product sold and include the cost variable $c_{jt}$ (log of reported cost of the item sold) in the pricing equation with coefficient $\beta_c$. In addition, we are interested in how changes in cost affect the GAIN and LOSS effects because of potential fairness concerns. Fairness feelings can be rule based; business consumers, for example, could judge the social acceptability of the price in relation to rules such as cost (Kahneman, Knetsch, and Thaler 1986). Rule-based fairness could be an induced feeling underlying the observed reference price effect, especially loss aversion. When the transaction price is higher than the reference price and not associated with a cost increase, buyers might deem it to be unfair and exhibit strong loss aversion, but when the price increase is associated with a cost increase, buyers could perceive it as fair and exhibit less loss aversion or none at all. We include two interaction terms between increase in cost (actual cost change in the previous transaction) and GAIN and LOSS to capture possible fairness effects related to changes in cost.

*Control Variables and Fixed Effect Variables*

In addition to the key variables shown in Equations 7 and 8, we include a lag-quantity variable $q_{ij,\,t-1}$ in the quantity equation to account for serial correlation in quantity purchase. This variable captures the effect of the most immediate past transaction, whereas the inventory variable described previously captures a more long-term trend. We include both the customer and the salesperson reference prices (R and $R_{sp}$, respectively) in the pricing equation to control for the effect of reference points on pricing.

To account for downstream demand and other unique features of B2B transactions, we include additional control variables and fixed-effect variables. Both the quantity and pricing equations contain several fixed effects, including customer-, salesperson-, and product-specific fixed effects. In addition, we include four weekly price indexes that capture the spot prices in commodity exchanges markets for lumber, framing lumber, and structural panels and boards.[7] As a set of variables, these indexes capture the market perception of what the prices for raw timber materials and semiprocessed products will be in the medium term. We expect the salespeople and customers (e.g., purchasing managers in firms such as appliance manufacturers) in our data set to be aware (even if the knowledge is imperfect) of price trends and that this awareness may affect their purchase and pricing behavior.

Our data set also contains location information for each customer, enabling us to use a dummy variable to control for relevant economic and industry characteristics in the particular customer's region. We focus on the construction industry, given that the customers in the data set are either directly or indirectly related to construction. We use the number of new buildings approved (Construction Approvals) and the number of construction employees (Construction Employment) as two proxy variables for construction activity. Finally, we compute the total sales observed in our data set (across products and customers) in each postal area. This variable is constructed from the overall transaction database; that is, it includes products and customers that are not part of our estimation. These variables control for market structure and different degrees of business activity and competition that the customer (the buying firm in our model and estimation) faces with respect to its own customers. High levels of downstream competition would change the pricing behavior of the seller's buyers, who in turn can change the way they interact with their suppliers (i.e., the customer or buyer in our model). We also include quarterly dummies to account for seasonal changes in the market environment that may be affecting purchasing or selling behavior. Table 1 summarizes the fixed effects we include and the specific reason to have them in each of the two simultaneous equations.

This completes our discussion of the empirical specification of our simultaneous equation system model. By including all the key variables, control variables, fixed-effect variables, and variables in our extended models into the equations, the most complete model can be rewritten as follows:

$$(9)\quad q_{isjt} = \alpha_q + \gamma_p p_{isjt} + \gamma_q q_{ij,\,t-1} + \gamma_G \mathrm{GAIN}_{isjt} + \gamma_L \mathrm{LOSS}_{isjt} + \gamma_F F_{isjt} + \gamma_{FG}\left(F_{isjt}\mathrm{GAIN}_{isjt}\right) + \gamma_{FL}\left(F_{isjt}\mathrm{LOSS}_{isjt}\right) + \gamma_I \mathrm{INV}_{ijt} + \gamma_R \mathrm{Recency}_{ijt} + \sum_{r=1}^{R}\mathrm{Regional\_Dummies}_r + \phi_i + \phi_j + \phi_s + \tau_t + \varepsilon^q_{ijt},\ \text{and}$$

[7]We used weekly indexes for the Chicago Mercantile Exchange Lumber Future, the Framing Lumber Composite Price, the Structural Panel Composite Price, and the OSB 7/16″ Northern Central Price. These data are publicly available.

Table 1
DESCRIPTION OF FIXED EFFECTS

| *Fixed Effects* | *Quantity Equation* | *Pricing Equation* |
|---|---|---|
| Product-specific | Some products are typically bought in larger quantities than others. | This accounts for the specific unit price level for a product. |
| Customer-specific | Some customers buy larger volumes than others, affecting the quantity observed for the customer. | Customers have different willingness to pay or different negotiating ability, which may affect the overall price level at which their transactions occur. |
| Salesperson-specific | Some salespeople may be better than others at selling larger volumes. | Some salespeople have different negotiating ability or perhaps a tendency to offer lower prices. |
| Regional dummies | The type and number of competitors and downstream customers varies by region. This dummy variable accounts for changes in quantity purchased that may result for these different market conditions across geographies. | The competitive landscape varies by region. Including a regional dummy allows us to control for higher price competition (there are more firms selling timber) or higher competition downstream (the customer's customers make lower margins and are more price sensitive) across geographic regions. |
| External price indexes | Changes in international prices for the basic commodities may lead to changes in the quantity purchased. Customers may buy higher quantities if stockpiling when they perceive international prices to be low. Alternatively, they may buy lower quantities when waiting for the price to come down. | The pricing decision may be influenced by the current prices in the marketplace. A change in one of these indexes may lead to accepting higher prices or negotiating harder for a lower price. |
| Seasonal dummies | This dummy variable controls for changes in the total demand for the end products that may be occurring over time, affecting customer's purchased volumes. | This dummy variable controls for changes in the competitive environment that may lead to different price-taking behavior from customers. |

$$
\begin{aligned}
(10)\quad p_{isjt} = {} & \alpha_p + \beta_p q_{isjt} \\
& + \beta_R RP_{ijt} + \beta_G GAIN_{isj,\,t-1} + \beta_L LOSS_{isj,\,t-1} \\
& + \beta_R^s RP_{jt}^s + \beta_G^s GAIN_{j,\,t-1}^s + \beta_L^s LOSS_{j,\,t-1}^s \\
& + \beta_F F_{isjt} + \beta_{FG}\left(F_{isjt} GAIN_{isj,\,t-1}\right) + \beta_{FL}\left(F_{isjt} LOSS_{isj,\,t-1}\right) \\
& + \beta_c c_{jt} + \beta_{cG}\left(c_{jt} GAIN_{isj,\,t-1}\right) + \beta_{cL}\left(c_{jt} LOSS_{isj,\,t-1}\right) \\
& + \beta_I INV_{ijt} + \beta_R Recency_{ijt} + \sum_{k=1}^{K} \beta_k Market\_Prices_{jt} \\
& + \sum_{r=1}^{R} Regional\_Dummies_r + \eta_i + \eta_j + \eta_s + \tau_t + \varepsilon_{ijt}^p.
\end{aligned}
$$

We can also write a similar model with the added quadratic effects described in Equations 7 and 8.

We estimate the model using three-stage least squares (3SLS). Specifically, we use the costs as instruments for the endogenous variables, price, and reference price in the first-stage regression of 3SLS. The cost of the product serves as the instrument for the price variable in our model. We observe the cost that the selling firm assigns to the product. This accounting cost is based primarily on the cost of the raw materials purchased and sometimes minor inputs that went into machining the product. Salespeople use it to compute their sale margin, and it is correlated with the selling price. This internal accounting cost is material specific and is uncorrelated to the market price indexes, which mostly capture broad industry trends and expectations. Thus, we can consider it exogenous to the transaction and thus serving as a good instrument. As Hausman (1975, 1983) shows, 3SLS has the same asymptotic distribution as the full-information maximum likelihood estimator, which is asymptotically efficient among all estimators.

## *DATA OVERVIEW*

Our data come from a customer transaction database of a European (U.K.) company selling processed timber to industrial customers (e.g., furniture manufacturers, window manufacturers, decking contractors). Two sets of factors make this industry an ideal setting for studying reference price: product–service homogeneity and product usage.

For customers to compare prices, it is important that the purchases are comparable. Products in this industry are unambiguously defined by a few characteristics (e.g., species of the raw material, finishing, environmental certification, dimensions of each piece, country of origin), and these product specifications do not vary over time. In addition, the level of service offered is fairly constant across these products. For example, delivery is included in the final paid price for all these purchases. As a result, customers can compare purchases for a given product and construct an IRP over time. From our perspective, it enables us to identify each product (not always possible in B2B settings) and ensure that our comparisons are valid. Our analysis would not be possible in industries in which a higher level of product or service customization is common or service variability is high across customers or over time, because it would result in too many unobserved drivers of the transaction price.

The type of usage of the products in our studies is also conducive to study reference prices. First, it is a frequently purchased manufacturing input (in contrast, for example, to machinery that is purchased yearly). It is typical for customers to place several orders a month for different materials and sometimes for exactly the same material. Customers use this product to manufacture furniture or in construction. The product constitutes between 20% and 30% of the cost of the final product (depending on the particular industry). This means that changes in prices are not likely to result in significant changes in downstream prices. Consider a simple channel structure in which the buyer in our model is a furniture manufacturer who wants to maintain its absolute margins. Therefore, a 10% increase in the price paid for timber would translate into approximately a 3% change in the downstream price if we assume complete pass-through.[8]

Because we are studying a seller that sells a frequently purchased standardized product used as one of many inputs in the manufacture of customized infrequently purchased products, our assumption that the reference effect is happening at the customer decision point is likely to be justified. Taken together, these factors enable us to estimate the reference price effect and suggest that we are measuring the customer's (e.g., industrial's buyer's) reference-dependent preferences.

Transactions originate from the customer purchasing agent who calls in to the in-house sales center of the firm. A typical transaction involves the request for a price quote for a given quantity and product specifications. The salespeople have authority to set the price and are observed by the sales manager, who evaluates them according to their sales performance (volume, margin, and other subjective metrics). The quantity the customer requests may change during the transaction. The company also deals with large-volume customers through a separate channel (usually a dedicated account manager). These large-scale customers may have long-term contracts. Because the company identified these customers to us, we excluded them from our analysis. The analysis of the effects of pricing on these large key accounts is beyond the scope of this study.

We observe two years of transactions (2002–2003). For each customer transaction, we observe the price paid, cost of the product to the selling firm, and the salesperson responsible for the transaction. The firm computes the cost to monitor their margins and is based on the recent wholesale purchase of raw timber at market prices.

We perform the estimations using the 55 most frequently purchased products. This enables us to observe repeated transactions involving the same product for a given customer and infer how previous prices are affecting behavior as well as have a suitable variation in prices paid. Using frequently purchased categories with few different stockkeeping units (e.g., tuna, ketchup, orange juice) is also a typical approach in reference price studies in consumer packaged goods categories. For each product, we select customers who have purchased the product at least ten times in the two-year period. The average interpurchase time for a given product is 3.3 weeks, though sometimes customers purchase the same product twice or more in a given month.

The number of customers in our final data set is 135, and the number of salespeople is 33. We use a total of 10,614 transactions in our model estimation. Table 2 summarizes the customer and salesperson activity of our focal products. The table also shows that there is a large variability in the customer and salesperson activity (relatively large standard deviations).

[8]Considering how competitive industries such as kitchen and furniture manufacturers are, pass-through rates (how much a firm increases its price for a given increase in cost) are likely to be less than unity; in other words, furniture manufacturers are likely to absorb most of the price increase, lowering their margins somewhat. More intermediaries (e.g., furniture retailers) can lead to further margin absorption.

Price discrimination across customers results in different customers paying markedly different prices for the same product. In our study, we are concerned with the price variation experienced by a given customer for a given product over time. As we show in Table 3, approximately 60% of the transactions involve a customer obtaining the same price as the price paid in the previous transaction. For the remaining transactions (approximately 40%), the price increases or decreases. Last, we complement our data set with publicly available market indexes for timber and lumber prices and futures, as described in the previous section.

## *RESULTS*

In this section, we present and discuss the results from the estimation of the simultaneous system of equations. We estimate four versions of the general model (Models 1–4). Model 1 accounts for reference price effects on both quantity and pricing. This base model does not include variables such as experience between the customer and the salesperson or changes in cost. Model 2 is similar to Model 1 but with the addition of variables that capture salesperson–customer experience, namely frequency $F^{SalesP}$ (we drop the subscripts

Table 2
SUMMARY STATISTICS

| | *M* | *SD* |
|---|---|---|
| *Customer* | | |
| Number of items purchased per customer | 93 | 126 |
| Number of distinct products purchased per customer (of top 20) | 3.8 | 4.2 |
| Average sale monetary volume per item (€) | 317 | 282 |
| Number of distinct salespeople | 7.9 | 4.0 |
| Average interpurchase time for a given product type (weeks) | 3.3 | .8 |
| *Salesperson* | | |
| Number of items sold by a salesperson | 321 | 426 |
| Number of distinct products sold by a salesperson (out of top 20) | 22 | 16 |
| Average yearly sale (€) | 290 | 133 |
| Number of distinct customers (of the 270 considered) | 27 | 23 |
| *Customer–Salesperson Dyad* | | |
| Number of items for a customer–salesperson dyad | 11.7 | 37.5 |
| Number of distinct products for a customer–salesperson dyad | 2.5 | 2.7 |
| Monetary sales per customer–salesperson dyad (€) | 2891 | |

| | *Total* |
|---|---|
| Number of products | 55 |
| Number of customers | 114 |
| Number of salespeople | 33 |
| Number of customer–salesperson dyads | 909 |

Table 3
PRICE AND QUANTITY CHANGES

| | *Quantity Increase* | *Quantity Same* | *Quantity Decrease* | *Total* |
|---|---|---|---|---|
| Price increase | 8.3% | .2% | 10.7% | 19.1% |
| Same price | 28.4% | 3.9% | 30.0% | 62.3% |
| Price decrease | 10.6% | .2% | 7.8% | 18.6% |
| Total | 47.3% | 4.2% | 48.5% | 100.0% |

Notes: Each cell in this table indicates the proportion of all transactions that correspond to a price increase, the same price, or a price decrease and its relationship to changes in quantity purchased.

here and in the following text for ease of exposition), and its interactions with the LOSS and GAIN terms. Model 3 extends the base model by including a variable that describes the changes in cost in the previous transaction and the corresponding interactions with the GAIN and LOSS variables. Finally, Model 4 is the most complete specification, including both variables that capture salesperson–customer interaction and cost changes. In addition, we estimate a basic model (labeled Model 0) without reference effects for comparison purposes.

We specify the reference price as $RP_{ijt} = p_{ij,\,t-1}$—that is, a customer's last transaction price as the reference price.[9] In the "Theory Background" section, we suggest that the relationship between quantity and reference price can be either linear or nonlinear depending on whether the customer is comparing prices or comparing values. Therefore, we estimate two versions of the empirical model, Equations 9 and 10. In the first version, we only include linear reference price variables, which capture the reference price effects on quantity and price (see Tables 4 and 5, respectively). Our theoretical analysis suggests that the relationship between the observed quantity and prices need not be linear in general. In the second version (see Tables 6 and 7), we include both linear and quadratic reference price variables to better capture the potential diminishing (or increasing) reference price effects on quantity and price when customers are comparing the transaction value with the reference value. For ease of exposition, we only provide selected estimates of the model with quadratic effects because the results are qualitatively the same as those in the regression with only linear terms (for complete tables, see the Web Appendix at www.marketingpower.com/jmr_webappendix).

[9]We also estimated the models using another specification of the reference price, $RP_{ijt} = \theta p_{ij,t-1} + (1-\theta)RP_{ij,t-1}$—that is, the weighted average of last transaction price and past reference price as the current reference price. We set $\theta = .5$. The results are similar to the case in which $RP_{ijt} = p_{ij,t-1}$ and are presented in the Web Appendix (www.marketingpower.com/jmr_webappendix).

*Endogenous Variables and Instruments*

The price coefficient is negative and significant, as customers generally buy lower quantities at higher prices. Similarly, the quantity coefficient in the pricing equation is also negative and significant. The coefficient on the lagged quantity variable in the quantity equation is positive, showing some level of state dependence in purchases. (Recall that we accommodated customer heterogeneity in quantity purchased using the fixed effects.) The estimates of the cost coefficient are also positive and significant, an expected result given that salespeople rely on the cost information to set price.

*The Effect of Reference Price on Quantity Purchased*

The estimated coefficients of the variables GAIN and LOSS in the quantity measures the reference price effect on the quantity purchased. We find that the GAIN variable has a positive and significant coefficient across all models and both reference price specifications. In contrast, the LOSS variable has a negative and significant coefficient across models and reference price specifications. In other words, when the current transaction price is higher than the customer's reference price and consequently there is a perceived LOSS, the customer tends to buy less of the product than the amount he or she would have purchased without the LOSS effect. Analogously, when the current price is lower than his reference price, the perceived GAIN results in a higher quantity purchased than the one without the GAIN effect. Another important point to note is the size of the main effects of GAIN and LOSS in the base model

Table 4

ESTIMATION RESULTS FOR QUANTITY EQUATION USING LAST TRANSACTION PRICE AS REFERENCE PRICE ($R = P_{-1}$)

| *Quantity Equation* | *Model 0* | *Model 1* | *Model 2* | *Model 3* | *Model 4* |
|---|---|---|---|---|---|
| Price | **–.778** | **–1.195** | **–1.176** | **–1.177** | **–1.222** |
| | (.184) | (.197) | (.198) | (.197) | (.197) |
| Lagged quantity | **.205** | **.206** | **.206** | **.206** | **.205** |
| | (.009) | (.009) | (.009) | (.009) | (.009) |
| Loss | | **–1.324** | **–1.045** | **–1.320** | **–.994** |
| | | (.175) | (.229) | (.175) | (.228) |
| Gain | | **.349** | **.519** | **.342** | **.565** |
| | | (.150) | (.199) | (.150) | (.199) |
| $F^{salesp}$ | | | 1.35E-04 | | 9.68E-05 |
| | | | (2.86E-04) | | (2.86E-04) |
| $F^{salesp}$ × LOSS | | | **–.007** | | **–.008** |
| | | | (.003) | | (.003) |
| $F^{salesp}$ × GAIN | | | *–.004* | | *–.004* |
| | | | (.002) | | (.002) |
| Weekgap | .013 | .018 | .017 | .018 | .018 |
| | (.012) | (.012) | (.012) | (.012) | (.012) |
| Inventory | .002 | .001 | 1.00E-03 | .001 | .001 |
| | (.005) | (.005) | (.005) | (.005) | (.005) |
| Post area sales | **–.210** | **–.195** | **–.282** | **–.195** | **–.196** |
| | (.077) | (.076) | (.087) | (.076) | (.076) |
| Construction approvals | **8.31E-05** | **8.39E-05** | 6.62E-05 | **8.40E-05** | *8.01E-05* |
| | (4.21E-05) | (4.20E-05) | (6.19E-05) | (4.20E-05) | (4.20E-05) |
| Construction employment | –.002 | *–.003* | 8.24E-04 | *–.003* | *–.003* |
| | (.001) | (.001) | (.003) | (.001) | (.001) |
| Fit (BIC relative to Model 0) | 0 | 61.1 | 50.4 | 60.3 | 34.3 |

Notes: Estimates in boldface are significant at the $p < .05$ level. Estimates in italics are significant to the $p < .10$ level.

Table 5

ESTIMATION RESULTS FOR *PRICING* EQUATION USING LAST TRANSACTION PRICE AS REFERENCE PRICE ($R = P_{-1}$)

| *Pricing Equation* | *Model 0* | *Model 1* | *Model 2* | *Model 3* | *Model 4* |
|---|---|---|---|---|---|
| Quantity | –.005 | **–.071** | **–.071** | **–.057** | **–.070** |
| | (.003) | (.003) | (.003) | (.003) | (.003) |
| Cost | **.207** | **.155** | **.154** | **.159** | **.139** |
| | (.016) | (.016) | (.016) | (.016) | (.014) |
| Lag of increase in cost | | | | –.018 | –.014 |
| | | | | (.014) | (.012) |
| RP | **.471** | **.580** | **.579** | **.576** | **.498** |
| | (.007) | (.009) | (.009) | (.009) | (.008) |
| Lagged_Loss | | **–.273** | **–.236** | **–.264** | **–.058** |
| | | (.013) | (.016) | (.013) | (.017) |
| Lagged_Gain | | **.082** | **.104** | **.083** | **.045** |
| | | (.010) | (.013) | (.010) | (.014) |
| $RP_{sp}$ | | **.014** | **.016** | **.016** | **.019** |
| | | (.005) | (.005) | (.005) | (.005) |
| $Lagged\_Loss_{sp}$ | | **.002** | *–.008* | –.007 | *.005* |
| | | (.002) | (.004) | (.004) | (.003) |
| $Lagged\_Gain_{sp}$ | | 1.59E-04 | –.004 | –.005 | *.003* |
| | | (.002) | (.003) | (.003) | (.002) |
| $F^{salesp}$ | | | –8.66E-06 | | –2.11E-05 |
| | | | (2.12E-05) | | (2.16E-05) |
| $F^{salesp}$ × Lagged_Loss | | | **–8.21E-04** | | **–8.41E-04** |
| | | | (1.96E-04) | | (2.35E-04) |
| $F^{salesp}$ × Lagged_Gain | | | **–4.66E-04** | | *–3.16E-04* |
| | | | (1.81E-04) | | (1.92E-04) |
| Lag of increase in cost × Lagged_Loss | | | | .188 | **.919** |
| | | | | (.305) | (.335) |
| Lag of increase in cost × Lagged_Gain | | | | –.133 | .089 |
| | | | | (.302) | (.295) |
| Weekgap | .001 | .001 | .001 | .001 | *.002* |
| | (9.24E-04) | (8.87E-04) | (8.83E-04) | (8.90E-04) | (9.05E-04) |
| Inventory | –3.32E-04 | **.001** | **.001** | **8.14E-04** | **9.36E-04** |
| | (3.59E-04) | (3.44E-04) | (3.42E-04) | (3.44E-04) | (3.51E-04) |
| Post area sales | .008 | –.008 | –.010 | –.005 | –.007 |
| | (.006) | (.006) | (.007) | (.006) | (.006) |
| Construction approvals | *–6.36E-06* | 9.99E-07 | 1.42E-07 | –3.76E-07 | 2.55E-07 |
| | (3.30E-06) | (3.16E-06) | (4.64E-06) | (3.16E-06) | (3.22E-06) |
| Construction employment | **–2.93E-04** | **–4.33E-04** | **–6.99E-04** | **–4.08E-04** | **–4.01E-04** |
| | (1.07E-04) | (1.03E-04) | (2.43E-04) | (1.03E-04) | (1.05E-04) |
| Chicago Mercx | 5.02E-05 | 3.32E-05 | 2.53E-05 | 2.95E-05 | 3.71E-05 |
| | (6.35E-05) | (6.08E-05) | (6.05E-05) | (6.11E-05) | (6.21E-05) |
| Fralum | –1.45E-04 | –1.03E-04 | –9.12E-05 | –8.81E-05 | –1.21E-04 |
| | (9.34E-05) | (8.95E-05) | (8.90E-05) | (8.99E-05) | (9.13E-05) |
| Structpan | *1.30E-04* | **1.52E-04** | **1.47E-04** | **1.42E-04** | **1.45E-04** |
| | (7.05E-05) | (6.76E-05) | (6.72E-05) | (6.78E-05) | (6.89E-05) |
| Osb | –9.62E-05 | *–1.24E-04* | *–1.18E-04* | *–1.25E-04* | –1.14E-04 |
| | (7.51E-05) | (7.19E-05) | (7.16E-05) | (7.22E-05) | (7.34E-05) |
| Fit (BIC relative to Model 0) | 0 | 980 | 1023.1 | 884.1 | 944.4 |

Notes: Estimates in boldface are significant at the $p < .05$ level. Estimates in italics are significant to the $p < .10$ level.

(Model 1 in Table 4). The absolute magnitude of the LOSS variable is significantly larger than that of the GAIN variable. For example, for Model 1, the coefficients for LOSS and GAIN are –1.32 (SE = .17) and .348 (SE = .15), respectively. Because these variables are standardized, this difference in magnitude suggests that customers in these markets exhibit loss aversion. This result is similar to the findings from studies in consumer packaged goods industries (Kalyanaram and Winer 1995).[10]

[10]Note that we obtained these results from a transaction data set that records purchases that did occur, and we do not have information on customer–salesperson interactions that did not lead to a purchase. However, the effects of reference price could be even larger than what we would find if we had such data because a higher price (compared with reference price) could drive customers to go to a competitor or decide not to buy. Therefore, the extent of loss aversion may plausibly be stronger than our results suggest.

The results for the quantity equation of the models when both linear and quadratic coefficients are included appear in Table 6. In this case, the coefficients for LOSS and GAIN are –2.47 (SE = .39) and .57 (SE = .21) when we include both linear and quadratic terms of LOSS and GAIN. We find that Tables 4 and 6 show the same pattern for the coefficients for all the models estimated.

The quadratic LOSS and GAIN coefficient estimates are significant, as we show in Table 6. The estimates suggest that the reference price effects have diminishing effects as the magnitudes of losses and gains increase. Consider the LOSS variable. The estimates of the quadratic term, $(LOSS)^2$, are positive; this suggests that as price increases, the magnitude of the LOSS effect increases but at a decreasing rate. An explanation for this result is that higher prices lead to higher LOSS. However, a higher LOSS leads to a

Table 6
ESTIMATION RESULTS FOR *QUANTITY* EQUATION WITH QUADRATIC TERMS USING LAST TRANSACTION PRICE AS REFERENCE PRICE ($R = P_{-1}$)

| *Quantity Equation* | *Model 1* | *Model 2* | *Model 3* | *Model 4* |
|---|---|---|---|---|
| Price | **–1.062** | **–1.083** | **–1.046** | **–1.085** |
| | (.197) | (.197) | (.196) | (.197) |
| Lagged quantity | **.207** | **.207** | **.207** | **.207** |
| | (.009) | (.009) | (.009) | (.009) |
| Loss | **–2.477** | **–2.171** | **–2.471** | **–2.172** |
| | (.385) | (.433) | (.385) | (.433) |
| $(\text{Loss})^2$ | **3.716** | **3.526** | **3.707** | **3.527** |
| | *(1.041)* | (1.053) | *(1.041)* | (1.053) |
| Gain | **.571** | **.773** | **.568** | **.774** |
| | (.212) | (.245) | (.212) | (.245) |
| $(\text{Gain})^2$ | *–.474* | *–.457* | **–.478** | *–.457* |
| | (.243) | (.243) | (.243) | (.243) |
| $F^{salesp}$ | | 7.45E-05 | | 7.43E-05 |
| | | (2.86E-04) | | (2.86E-04) |
| $F^{salesp}$ × LOSS | | *–.006* | | *–.006* |
| | | (.003) | | (.003) |
| $F^{salesp}$ × GAIN | | *–.004* | | *–.004* |
| | | (.002) | | (.002) |
| Weekgap | .019 | .019 | .019 | .019 |
| | (.012) | (.012) | (.012) | (.012) |
| Inventory | .001 | .001 | .001 | .001 |
| | (.005) | (.005) | (.005) | (.005) |
| Post area sales | **–.191** | **–.193** | **–.191** | **–.193** |
| | (.076) | (.076) | (.076) | (.076) |
| Construction approvals | **8.44E-05** | *8.12E-05* | **8.45E-05** | *8.12E-05* |
| | (4.20E-05) | (4.20E-05) | (4.20E-05) | (4.20E-05) |
| Construction Employment | *–.003* | *–.003* | *–.003* | *–.003* |
| | (.001) | (.001) | (.001) | (.001) |
| Fit (BIC relative to model 0) | 73.6 | 44.3 | 72.9 | 44.5 |

Notes: Estimates in boldface are significant at the $p < .05$ level. Estimates in italics are significant to the $p < .10$ level.

smaller optimal quantity, making the comparative utility smaller. This reduces the effect of LOSS (per “unit” of loss). The significance of the quadratic LOSS and GAIN variables also suggests that the buyer is comparing the transaction utility and the reference utility in quantity decision rather than just the prices.

In the last row of Tables 4 and 6, we provide the Bayesian information criterion (BIC) for the model, relative to the BIC of Model 0 (in which higher numbers imply better fit). All models with reference effects have a better fit than the base Model 0, and the quadratic terms improve the overall fit in most cases.

### *The Effect of Reference Price on Price Paid*

We first analyze the main effect of both customers and salesperson reference prices on the pricing outcome of the transaction and then the effects of the customer’s and salesperson’s perceived losses and gains. The variable RP in this model is the previous price the customer paid. It captures the main effect of the reference price on the quantity purchased. The coefficient estimate for RP is positive across all models, essentially capturing the dependence of pricing on reference points. (The fixed effects accommodate customers having different intrinsic willingness to pay.) This is consistent with the idea that prices are fairly sticky, and often customers pay similar or identical prices to their previous purchase prices. The variable $RP_{sp}$ is the previous price the salesperson charges. We find that its coefficient estimates are also positive and significant across all models. This implies that salespeople may be relying on previous prices charged to other customers when setting or negotiating the prices with the customer.

### *The Effect of Customers’ Perceived Losses and Gains on Price Paid*

Across the four models (Table 5), we find that the customer’s Lagged_Loss coefficients are significant and have a negative sign. This implies that if the previous transaction was a loss in utility (as well as in price) for the customer, the current price is likely to be lower. Analogously, we find that the customer’s Lagged_Gain coefficient is positive and significant, which means that previous transactions that are perceived as gains (in utility and price) explain higher transaction prices. In addition, we find that the Lagged_Loss coefficient is larger than the Lagged_Gain coefficient, which is consistent with the prediction from prospect theory of loss aversion. Regarding the quadratic effects of the lagged reference dependent variables Lagged_Loss and Lagged_Gain for the buyer, as Table 7 shows, we observe a similar pattern to that in the quantity equation. The estimates imply a concave effect; that is, there are diminishing effects as Lagged_Loss and Lagged_Gain become larger. In summary, we find that the customer’s reference price has an effect on both quantity purchased and price outcome and that the LOSS effect is larger than the GAIN effect.

### *The Effect of Salespeople’s Perceived Losses and Gains on Price Paid*

The coefficient estimates for the salesperson loss variable ($\text{Lagged\_Loss}_{sp}$) are negative and 95% significant in the full model (Tables 5 and 7), as our theory predicts. However, we find that the coefficient estimates for the salesperson gain variable ($\text{Lagged\_Gain}_{sp}$) are insignificant. These results are consistent with our hypothesis that reference price effects, especially loss aversion, exist and play an important role in salespeople’s price-setting behavior. This is a unique feature in our model because we allow the pricing outcome to be influenced by both customer and salesperson reference price effects. The existence of the salesperson reference price effect is also a unique characteristic of the B2B transactions as compared with the B2C transactions. The quadratic terms of the seller’s lagged reference price variables (i.e., the quadratic terms of $\text{Lagged\_Loss}_{sp}$ and $\text{Lagged\_Gain}_{sp}$ terms in Table 7) are not significant.

### *The Effect of Customer Experience with Salesperson on Price Paid and Quantity Purchased*

We suggest that the experience customers have with a salesperson affects the customer’s transactional behavior. We measure customer experience with a salesperson using a variable that captures the recent frequency of interaction between the customer and the salesperson. Higher frequency of interaction often implies a closer relationship between buyer and seller that may moderate the effect of GAIN and LOSS.

In the quantity equation, interaction coefficients between frequency $F^{Salesp}$ and the variables GAIN and LOSS ($F^{Salesp}$ × GAIN and $F^{Salesp}$ × LOSS variables) are negative and significant (see Tables 4 and 6; also note that $F^{salesp}$ × GAIN variables are 90% significant). This implies that a higher

Table 7

ESTIMATION RESULTS FOR *PRICING* EQUATION WITH QUADRATIC TERMS USING LAST TRANSACTION PRICE AS REFERENCE PRICE ($R = P_{-1}$)

| *Pricing Equation* | *Model 1* | *Model 2* | *Model 3* | *Model 4* |
|---|---|---|---|---|
| Quantity | **–.068** | **–.068** | **–.055** | **–.068** |
| | (.003) | (.003) | (.003) | (.003) |
| Cost | **.156** | **.156** | **.162** | **.159** |
| | (.016) | (.015) | (.016) | (.016) |
| Lag of increase in cost | | | –.019 | –.018 |
| | | | (.014) | (.014) |
| R | **.574** | **.574** | **.571** | **.573** |
| | (.009) | (.009) | (.009) | (.009) |
| Lagged_Loss | **–.364** | **–.321** | **–.359** | **–.320** |
| | (.017) | (.019) | (.017) | (.019) |
| $(\text{Lagged\_Loss})^2$ | **.146** | **.152** | **.151** | **.152** |
| | (.017) | (.017) | (.017) | (.017) |
| Lagged_Gain | **.108** | **.126** | **.107** | **.125** |
| | (.016) | (.017) | (.016) | (.017) |
| $(\text{Lagged\_Gain})^2$ | **–.050** | **–.043** | **–.049** | **–.043** |
| | (.017) | (.018) | (.018) | (.018) |
| $R_{sp}$ | **.017** | **.017** | **.017** | **.017** |
| | (.005) | (.005) | (.005) | (.005) |
| Lagged_Loss_Sp | –.009 | –.008 | –.008 | –.007 |
| | (.010) | (.010) | (.010) | (.010) |
| $(\text{Lagged\_Loss\_Sp})^2$ | –.003 | –.002 | –.003 | –.002 |
| | (.007) | (.007) | (.007) | (.007) |
| Lagged_Gain_Sp | 5.35E-04 | –1.84E-04 | 4.93E-04 | –3.52E-04 |
| | (.007) | (.007) | (.007) | (.007) |
| $(\text{Lagged\_Gain\_Sp})^2$ | –3.90E-04 | –5.45E-04 | –2.70E-04 | –5.55E-04 |
| | (.001) | (.001) | (.001) | (.001) |
| $F^{salesp}$ | | –1.06E-05 | | –1.12E-05 |
| | | (2.12E-05) | | (2.12E-05) |
| $F^{salesp}$ × Lagged_Loss | | **–9.93E-04** | | **–9.90E-04** |
| | | (1.97E-04) | | (1.97E-04) |
| $F^{salesp}$ × Lagged_Gain | | **–4.90E-04** | | **–4.82E-04** |
| | | (1.82E-04) | | (1.84E-04) |
| Lag of increase in cost × Lagged_Loss | | | .237 | .158 |
| | | | (.304) | (.303) |
| Lag of increase in cost × Lagged_Gain | | | –.173 | –.096 |
| | | | (.302) | (.303) |
| Weekgap | .001 | .001 | .001 | .001 |
| | (8.84E-04) | (8.84E-04) | (8.88E-04) | (8.84E-04) |
| Inventory | **.001** | **.001** | **8.56E-04** | **.001** |
| | (3.43E-04) | (3.43E-04) | (3.44E-04) | (3.43E-04) |
| Post area sales | –.008 | –.008 | –.005 | –.008 |
| | (.006) | (.006) | (.006) | (.006) |
| Approvals | 8.71E-07 | 6.74E-07 | –4.62E-07 | 6.95E-07 |
| | (3.15E-06) | (3.14E-06) | (3.15E-06) | (3.14E-06) |
| Construction employment | **–4.36E-04** | **–4.32E-04** | **–4.12E-04** | **–4.31E-04** |
| | (1.03E-04) | (1.03E-04) | (1.03E-04) | (1.03E-04) |
| Chicago Mercx | 2.48E-05 | 2.13E-05 | 2.32E-05 | 2.29E-05 |
| | (6.06E-05) | (6.06E-05) | (6.09E-05) | (6.06E-05) |
| Fralum | –9.17E-05 | –8.72E-05 | –8.16E-05 | –8.94E-05 |
| | (8.92E-05) | (8.91E-05) | (8.96E-05) | (8.92E-05) |
| Structpan | **1.48E-04** | **1.50E-04** | **1.43E-04** | **1.51E-04** |
| | (6.74E-05) | (6.73E-05) | (6.76E-05) | (6.73E-05) |
| Osb | *–1.22E-04* | *–1.27E-04* | *–1.25E-04* | *–1.27E-04* |
| | (7.17E-05) | (7.17E-05) | (7.20E-05) | (7.17E-05) |
| Fit (BIC relative to model 0) | 1018.2 | 995.4 | 931.8 | 989.6 |

Notes: Estimates in boldface are significant at the $p < .05$ level. Estimates in italics are significant to the $p < .10$ level.

level of interaction between buyers and sellers strengthens the effect of LOSS but weakens the effects of GAIN. These results are consistent with the idea that customers expect salespeople with whom they interact frequently to provide favorable deals in the transaction. For example, a lower price (i.e., a GAIN) may be taken for granted by the customer who purchases from a familiar salesperson, so the reaction to a GAIN is attenuated. Conversely, a customer may react more strongly to a higher price (i.e., a LOSS) from a salesperson with whom he or she interacts often, strengthening the effect of a LOSS and purchasing a lower amount than if the higher price had come from an unfamiliar salesperson. For a customer who has a moderately high number of interactions (in the upper quartile), the magnitude of this interaction effect is approximately 30% of the main effect.

We observe a similar situation in the pricing equation, in which the coefficients for the interactions between the frequency variable $F^{salesp}$ and Lagged_Loss and Lagged_Gain are both negative and significant. This implies that higher values of $F^{salesp}$ lead to lower prices and strengthen the effect of Lagged_Loss (whose main effect is negative and significant) and weaken the effect of Lagged_Gain (whose main effect is positive and significant).

From these results, we can conclude that higher purchase frequency of a buyer with a seller leads to more favorable outcomes for customers. These results are consistent with the results suggesting that familiarity between buyers and sellers leads to a more lenient price outcome, which could be realized through higher mutual trust (Morgan and Hunt 1994), reciprocity (Bagozzi 1995), and mutual knowledge.

### *The Effects of Changes in Cost on Price Paid*

We estimate the interaction between the Lagged_Loss and Lagged_Gain and increases in cost. Our aim is to test the hypothesis that changes in cost may affect the perceptions of gains and loss on the basis of ideas of fairness (Kahneman, Knetsch, and Thaler 1986). We do not find these interactions to be significantly different from zero. This could be the result of customers being aware of costs but not necessarily of those changes as soon as they happen.

### *Inventory and Recency Variables*

The inventory level (Inventory) and the recency (Weekgap) variables do not seem to have a significant effect on the quantity purchased. In the pricing model, however, we find that higher inventory level explains higher prices paid, which could indicate some product seasonality factor.

## *GENERAL DISCUSSION AND CONCLUSION*

The results from our estimation characterize reference price in a new empirical context and provide some new insights to the reference price literature. Specifically, we show that reference price effects do exist in B2B transactions, not only in quantity purchased but also in the transaction pricing outcome. In terms of quantity purchased, we find that business buyers respond negatively to increases in prices and positively to decreases in prices. Consistent with findings from the choice model literature, we find that business buyers respond more strongly in magnitude to the former (LOSS) than to the latter (GAIN). With regard to pricing outcome, we find that customers' and salespeople's past gains and losses affect the transaction price, and these effects are also in agreement with prospect theory. Last, we find the reference price effects interact with buyers' experiences with salespeople. Overall, we provide rich evidence that reference price effects exist in both quantity demand and pricing outcome in repeated interactions in B2B markets. These results fill an important gap in the literature on reference prices and our understanding of pricing in B2B transactions.

From a managerial perspective, our results have important implications for the field's understanding of the customer and salesperson pricing behavior in repeated transactional interactions. Particularly, we find that customers are likely to adjust their quantity decisions according to their transaction-specific perception of how good the price is by comparing it with their IRP.

Our results show that the customers' reaction to price depends on the previous prices paid. In the quantity log-log equation, the LOSS and GAIN variables are additive shifts to the elasticity represented by the price coefficient. Consider the case of Model 1 for the reference price specification. We infer from the model that a transaction that is perceived as a LOSS would have an elasticity of –2.50, and a transaction that is perceived as a GAIN would have an elasticity of –.85.[11] Therefore, a price reduction of 10% would lead to an 8.5% increase in quantity purchased, whereas a price increase of 10% would lead to a 25% reduction in quantity purchased. Thus, we can think of price elasticity for the transaction as being composed of the main pricing effect plus a reference point effect that magnifies or attenuates it. This effect is consistent with prospect theory and the concept of loss aversion, in that price increases contribute to the elasticity to a larger extent than price decreases. In terms of the magnitude, our results show the reference price effect contributes up to one-fourth of the price elasticity in quantity demand.

The effect of reference price on the pricing equation is smaller in magnitude but still substantial enough to be managerially relevant. Consider the coefficient of –.27 of the variable Lagged_Loss, which is the effect of the price increase in the previous transaction. This means that a 20% price increase (a typical price jump in our data set) in a previous transaction would result not only in a decrease in quantity demand but also in a 5% price decrease on average in the current transaction. This can have a substantial impact on profits when margins are slim.

Our research has direct implications for sales force management. We show that salespeople are influenced by their own reference prices. We believe that salespeople are using past prices as a heuristic to set the terms of the transaction. Even though salespeople charge a wide range of prices, they seem to rely on their most recent prices when they set a price during a transaction. This could be because they lack immediate decision support information and rely on their own heuristics to set prices. Given that all customers are different in terms of their willingness to pay, this result implies that suboptimal outcomes may result if the judgment on the current transaction is contaminated with reference effects from previous transactions that may have occurred under different conditions.

The finding that customers exhibit reference-dependent reactions to prices has implications on the way salespeople behave. Salespeople should be trained to understand that customers have reference points and price discount may have significant consequences beyond the current transaction. Salespeople who lower prices to close a sale may face a more price-sensitive customer next time.

Finally, our results have important implications for the management of buyer–seller relationships. We show that the effects of reference price on quantity are affected by the experience the customer has with the salesperson and the product. These results imply that cultivating strong salesperson–buyer relationships may lead to higher sensitivities to price increases (relative to the reference point). Conversely, strong salesperson–buyer relationships may reduce the effectiveness of a price discount, possibly because customers take price discounts for granted as part of their high frequency of transactions. Sales force managers may use this knowledge to advise salespeople on pricing strategies. In particular, our results suggest that monitoring the strength of the buyer–seller relationship (e.g., by keeping track of the frequency of interaction over a given period of time) may yield important insights into optimizing pricing policies.

Several directions exist for further research. First, our analysis focuses on IRP and its effects on quantity and price. It would also be worthwhile to determine whether external reference prices also have similar effects in B2B transactions. Second, our data set is transactional and does not include information on customer transactions that did not lead to a purchase. We argue that the effects we uncovered could be even stronger than suggested here if we had data on nonpurchase occasions. Having no-purchase data as well as competitor information could help test this hypothesis. Third, it would be worthwhile to investigate further how reference price effects interact with other buyer, seller, or category characteristics that are unique to B2B transactions. Finally, it would be worthwhile to investigate whether our results hold with a more structural version of the price negotiation model.

[11]Because we standardized the variables LOSS and GAIN before the estimation, computing the contribution to elasticity of a change in price (a loss or a gain) requires destandardizing the coefficients of the variables LOSS and GAIN by dividing them by their corresponding standard deviation.

## REFERENCES


Agicha, Vijay, Oliver Denecke, Yran Dias, and Gien Sarvady (2010), "The McKinsey Global Payments Map: A Global Eye on Local Opportunities," a McKinsey & Company report, (October), (accessed July 9, 2012), [available at http://www.mckinsey.com/App_Media/Reports/Financial_Services/MoP9_Global%20Payments%20Map.pdf].

Al-Najjar, Nabil, Sandeep Baliga, and David Besanko (2008), "Market Forces Meet Behavioral Biases: Cost Misallocation and Irrational Pricing," *RAND Journal of Economics*, 39 (1), 214–37.

Bagozzi, Richard P. (1995), "Reflections on Relationship Marketing in Consumer Markets," *Journal of the Academy of Marketing Science*, 23 (Fall), 272–77.

Bell, David R. and Randolph E. Bucklin (1999), "The Role of Internal Reference Points in the Category Purchase Decision," *Journal of Consumer Research*, 26 (September), 128–43.

Bottom, William P. and Amy Studt (1993), "Framing Effects and the Distributive Aspects of Integrative Bargaining," *Organizational Behavior and Human Decision Processes*, 56, 459–74.

Briesch, Richard, Lakshman Krishnamurthi, Tridib Mazumdar, and S.P. Raj (1997), "A Comparative Analysis of Internal Reference Price Models," *Journal of Consumer Research*, 24 (2), 202–214.

Bucklin, Randolph E. and Sunil Gupta (1992), "Brand Choice, Purchase Incidence, and Segmentation: An Integrated Modeling Approach," *Journal of Marketing Research*, 29 (May), 201–215.

Chang, Kwangpil, Glenn Mayhew, and Baohong Sun (2001), "Understanding the Reference Price Sensitive Shopper: A Within and Cross-Category Analysis," *Journal of Marketing Research*, 38 (November), 445–57.

———, S. Siddarth, and Charles Weinberg (1999), "The Impact of Heterogeneity in Purchase Timing and Price Responsiveness on Estimates of Sticker Shock Effects," *Marketing Science*, 18 (2), 178–92.

Hardie, Bruce G.S., Eric J. Johnson, and Peter S. Fader (1993), "Modeling Loss Aversion and Reference Dependence Effects on Brand Choice," *Marketing Science*, 12 (Fall), 378–93.

Hausman, Jerry (1975), "An Instrumental Variable Approach to Full-Information Estimators in Linear and Certain Nonlinear Econometric Models," *Econometrica*, 43 (4), 727–38.

——— (1983), "Specification and Estimation of Simultaneous Equation Models," in *Handbook of Econometrics*, Vol. 1, Z. Griliches and M. Intriligator, eds. Amsterdam: North-Holland, 392–448.

Ho, Teck H., Noah Lim, and Tony Cui (2010), "Reference Dependence in Multilocation Newsvendor Models: A Structural Analysis," *Management Science*, 56 (11), 1831–1910.

——— and Juan J. Zhang (2008), "Designing Price Contracts for Boundedly Rational Customers: Does the Framing of the Fixed Fee Matter?" *Management Science*, 54 (4), 686–700.

Janiszewski, Chris and Marcus Cunha Jr. (2004), "The Influence of Price Discount Framing on the Evaluation of a Product Bundle," *Journal of Consumer Research*, 30 (4), 534–46.

Kahneman, Daniel (1992), "Reference Points, Anchors, Norms, and Mixed Feelings," *Organizational Behavior and Human Decision Processes*, 51 (2), 296–312.

———, Jack L. Knetsch, and Richard H. Thaler (1986), "Fairness as a Constraint on Profit Seeking: Entitlements in the Market," *The American Economic Review*, 76 (4), 728–41.

——— and Amos Tversky (1979), "Prospect Theory: An Analysis of Decision Under Risk," *Econometrica*, 47 (March), 263–91.

Kalyanaram, Gurumurthy and John D.C. Little (1994), "An Empirical Analysis of Latitude of Price Acceptance in Consumer Package Goods," *Journal of Consumer Research*, 21 (December), 408–418.

——— and Russell S. Winer (1995), "Empirical Generalizations from Reference Price and Asymmetric Price Response Research," *Marketing Science*, 14 (Part 2 of 2 in Issue 3), G161–69.

Krishnamurthi, Lakshman, Tridib Mazumdar, and S.P. Raj (1992), "Asymmetric Response to Price in Consumer Brand Choice and Purchase Quantity Decisions," *Journal of Consumer Research*, 19 (December), 387–400.

Lattin, James M. and Randolph. E. Bucklin (1989), "Reference Effects of Price and Promotion on Brand Choice Behavior," *Journal of Marketing Research*, 26 (August). 299–310.

Lichtenstein, Donald R. and William O. Bearden (1989), "Contextual Influences on Perceptions of Merchant-Supplied Reference Prices," *Journal of Consumer Research*, 16 (June), 55–66.

Mayhew, Glenn E. and Russell S. Winer (1992), "An Empirical Analysis of Internal and External Reference Prices Using Scanner Data," *Journal of Consumer Research*, 19 (June), 62–70.

Mazumdar, Tridib, S.P. Raj, and Indrajit Sinha (2005), "Reference Price Research: Review and Propositions," *Journal of Marketing*, 69 (October), 84–102.

Morgan, Robert M. and Shelby D. Hunt (1994), "The Commitment–Trust Theory of Relationship Marketing," *Journal of Marketing*, 58 (July), 20–38.

Neale, Margaret A., Vandra L. Huber, and Gregory B. Northcraft (1987), "The Framing of Negotiations: Contextual Versus Task Frames," *Organizational Behavior and Human Decision Processes*, 39 (2), 228–41.

Northcraft, Gregory B. and Margaret A. Neale (1987), "Expert, Amateurs, and Real Estate: An Anchoring-and-Adjustment Perspective on Property Pricing Decisions," *Organizational Behavior and Human Decision Processes*, 39 (1), 228–41.

Palmatier, Robert W., Lisa K. Scheer, and Jan-Benedict E.M. Steenkamp (2007), "Customer Loyalty to Whom? Managing the Benefits and Risks of Salesperson-Owned Loyalty," *Journal of Marketing Research*, 44 (May), 185–99.

Popescu, Ioana and Yaozhong Wu (2007), "Dynamic Pricing Strategies with Reference Effects," *Operations Research*, 55 (3), 413–29.

Putler, Daniel S. (1992), "Incorporating Reference Price Effects into a Theory of Consumer Choice," *Marketing Science*, 11 (3), 287–309.

Winer, Russell S. (1986), "A Reference Price Model of Demand for Frequently Purchased Products," *Journal of Consumer Research*, 13 (September), 250–56.