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Sales Force Behavior, Pricing Information, and Pricing Decisions

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This paper focuses on salespeople behavior in business-to-business transactions. The paper investigates how salespeople use the information provided to them to set prices; of particular interest is how salespeople use price recommendations from a decision support tool. The investigation builds reduced-form models and tests them on a data set obtained by a grocery products distributor. The analysis shows that salespeople's decisions are explained well by a two-stage decision model whereby salespeople make an initial decision on whether or not to change the price (a binary decision) and then decide on the magnitude of change (a continuous response). We find that salespeople in our data set do not blindly adopt the recommended price change generated by the pricing tool. Rather, our two-stage model allows for us to uncover a nuanced association between the recommended price and the actual price change by identifying customer-specific and salesperson-specific market factors that moderate the influence of price recommendations.

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1. Introduction

> In business-to-business transactions, pricing decision making continues to be one of the least-understood levers influencing a company's ability to achieve high performance.... The most sophisticated price optimization models mean little if they are not manifested in the decisions made by salespeople every day.
>
> (Cudahy et al. 2012, p. 893)

Revenue management and pricing optimization tools have been successfully implemented in a wide range of sectors, such as airlines, hotels, and car rentals. Pricing and revenue management research has complemented the growth of these tools by developing models to help decision makers optimally determine prices. Almost without fail, the setting assumed in academic papers is one where the recommended price is adopted. (We refer the reader to Elmaghraby and Keskinocak 2003, Bitran and Caldentey 2003, and Talluri and van Ryzin 2004 for an in-depth review of revenue management and pricing optimization.) Adoption of the recommended price is a relatively innocuous assumption in settings where price determination is far removed from the actual salesperson, such as the case in business-to-consumer (B2C) markets. However, business-to-business (B2B) markets are very different. Although posted prices are the prevalent norm in B2C settings, pricing in B2B markets generally falls under the purview of salespeople, who manage sales by quoting prices, engaging in informal negotiations, and often quoting prices on a case-by-case basis (Boyd 2007).

In a growing number of B2B settings, salespeople are provided with pricing recommendations derived from price optimization decision support tools. The price recommendations are exactly that: recommendations to the salespeople, with the salespeople determining the final transaction prices. At first blush, it might seem that there is little harm in assuming away the "salesperson effect" and treating B2B and B2C environments as one and the same. This assumption would imply that salespeople would simply adopt the recommendations of the pricing tools, acting merely as the conveyer of the price to the customer, rather than as the helmsman of the pricing process. We will demonstrate that this assumption is wrong and misleading.

We have been given access to sales and pricing data for one of the largest grocery products distributors (GPDs) in the United States. As is customary in B2B sales transactions, sales are managed by salespeople who interact with customers on a regular basis. Interested customers contact their designated salesperson to place an order. Products are sold on a transaction-by-transaction basis, with prices frequently changing between transactions across time, customers, and salespeople. In our data set, the salespeople were provided with new price recommendations generated by a price optimization decision support tool. We use the data to investigate how the variation in salespeople's pricing decisions can be explained by the transaction context and, in particular, the price recommendations provided by a price optimization tool.

Given the lack of external manipulation of the field data, we abstain from putting forth a causal model. Using a proprietary data set from the GDP, we comb the data for relevant associations between the pricing transaction context, namely, the characteristics of the customer order and salesperson's experience, as well as underlying cost changes in the pricing environment and the resulting price changes. In fact, our goal is not so much explanatory modeling for causal theory development than descriptive—and in particular predictive—modeling (see e.g., Shmueli 2010), because of the large size of the data set and hence the less informative nature of statistical significance tests.

As in Bruno et al. (2012), we adopt a reference price framework to model salespeople's pricing decisions: we posit that the last price at which a salesperson sold a product to a customer serves as the salesperson's internal reference price (Winer 1986) for the current transaction and that current pricing decisions are evaluated vis-à-vis this reference point. We further posit that the recommended price from the pricing tool, and hence the recommended price change from the last transaction price, serves as an external reference price and influences the final transaction price change.

Through our empirical analysis, we find that the recommended price change is associated to varying degrees with the final transaction price change. The actual impact of the pricing tool is moderated by the transaction context, i.e., the environment in which the salesperson is making the pricing decision. Our main findings are summarized below.

• *Modeling decision making.* We find that a two-stage decision model to estimate price changes outperforms a benchmark (single) linear regression model. Under the two-stage model, the salesperson first decides whether to keep the price the same as it was in the last transaction or to change it in Stage 1. If the salesperson decides to change the price, then he or she decides on the magnitude of the change in Stage 2.

• *Recommended price as an external reference price.* Salespeople in our data set do not blindly adopt the recommended price change generated by the pricing tool. Our two-stage model allows for us to uncover a nuanced association between the recommended price and the actual price change. We find that a recommended price increase reduces the odds of a price change slightly (the odds decrease by 5%); if the decision to change the price is made, the recommended price increase has a sizable economic impact on the eventual price change ($1 recommended price increase is associated with a $0.15 increase in price). Conversely, a $1 recommended price decrease increases the odds of a price change (the odds increase by 56%) and is associated with a $0.96 decrease in price. These results illustrate the asymmetric association of the recommended price with eventual price changes in both the probability of changing the price and the actual price change.

• *Moderating influence of recommended price.* Given that over 94% of the transactions in our data set corresponded to recommended price increases, we investigate factors that may moderate the effectiveness of the tool. We find that the recommended price change is moderated by many factors in the salesperson's environment, characteristics of the customer's order, and the underlying cost environment. For example, we find that a salesperson facing a cost increase or decrease is less likely to pass along a recommended price increase to the customer (Stage 1). We also find that the odds of a salesperson changing the price (Stage 1) when facing a recommended price increase are highest when the salesperson handles few customers, is presented with few new recommended price changes within a week, and handles or sells many products across his or her customer base.

Few studies examine the role of decision support tools and their users in more traditional operational settings. Motivated by the work of Bowman (1963) on managerial coefficient theory, van Donselaar et al. (2010) empirically study orders placed by managers and the deviations of the order quantities from what was recommended by a decision support system. In van Donselaar et al. (2010), managers frequently adjusted away from the recommended order quantity to account for environment-specific considerations that were not considered by the tool, for example, in-store handling costs and incentives for managers to keep shelves full to ensure a higher service level. Their study, as our own, is motivated by interest in understanding what drives employees' decisions, in particular their deviations from automated decision support tool recommendations. To the best of our knowledge, this is the first study to bring these types of research questions to the realm of pricing decisions.

The remainder of this paper is organized as follows. We describe the B2B pricing environment, reference-dependent preferences, and reference prices as an appropriate framework for evaluating pricing decisions and our data and choice of predictors in §2.

In §3 a two-stage statistical framework is developed to characterize price changes. We identify moderators of the recommended price change in §4 and conclude with our main findings and discuss the managerial implications for the future of B2B pricing in §5.

2. Salespeople and the Pricing Environment

Grocery product distributors are wholesale food and nonfood distributors that connect farmers and manufacturers of food service products with restaurants, caterers, grocery stores, churches, and other business buyers. The GPD relies on salespeople to quote prices to business customers, who come to the GPD to purchase a wide variety of items, including highly perishable food items, such as fresh produce and vegetables, and nonperishable items, such as napkins and toothpicks. As noted in the introduction, we have been given access to the sales and pricing data for one of the largest GPDs in the United States.

As is common in many B2B settings (Phillips 2012), there are no list prices for products; interested business buyers must contact their designated salesperson to place an order. Typically, customers request a range of items in any given order. A representative sample of product types includes eggs; frozen potatoes; oils and shortenings; fresh, canned, and dry vegetables; bakery sugar, flour, and mixes; tabletop disposables; ketchup, mustard, and vinegar; and snacks, cookies, crackers, etc. Items are priced and sold on a transaction-by-transaction basis, with prices frequently changing between transactions across time, customers, and salespeople. In general, salespeople conduct business with a wide range of customer types. That is, salespeople do not specialize in a particular type of customer, resulting in each salesperson transacting over a wide portfolio of products. Although each salesperson manages multiple customer accounts, individual customers interact with only one salesperson. The customer base is highly diverse: Depending on the nature of his needs, a customer can have multiple transactions during a month or only a few transactions in a year.

Similar to other B2B companies, the GPD's salespeople have pricing authority. This practice allows the salesperson to customize prices based on customer- and product-specific information. However, the practice has a major drawback: decision making is not scientific, leading to inconsistencies in prices across product families, and may not even be rational, given potential biases or the heuristics used in decision making. In fact

> Many sales executives express the opinion that price latitude causes sales personnel to take the path of least resistance, for example, discounting rather than overcoming objections. (Stephenson et al. 1979, p. 26)

To make the pricing process more scientific and help nudge salespeople toward a higher price point (to combat eroding profit margins), a decision support tool was implemented at GPDs. The pricing tool was designed to identify a small(er) set of products that would benefit from price optimization and have the highest impact on gross margins. Each Friday evening, the pricing tool creates a list of new price recommendations for selected products: The tool suggests an "optimal" price for each product in the set, based on predictive analytics, optimization, and business rules set forth by the GPD. Although we cannot provide additional information regarding the scientific methods employed by this tool, we can report that the pricing tool optimizes current margins based on current costs and demand estimates. That is, the tool tracks historical sales (what was purchased, how much, and at what price) and aggregates the data to create a forecast of future demand per item or product. Based on this aggregate demand estimate, the tool identifies a short list of "high priority" products for which it recommends a profit margin and associated recommended price. In our data set, the tool recommended an increase in price from the last transaction price in over 94% of the transactions, where a transaction is defined at the salesperson-customer-product level. On average, 30% of the transactions had new price recommendations.

When an interested buyer calls, requesting to purchase several distinct products, a few of the items on the customer's purchase list may have new price recommendations. When quoting a price in response to a new customer order, a salesperson at the GPD has information about the list of requested products (and quantities), each item's current salesperson-specific unit cost, the customer's purchase history, the last price at which the customer purchased the item, and the new price recommendation.

It is important to note that the salespeople were under no obligation to accept the recommended price change. Furthermore, since the final transaction price is determined by the salesperson at the customer-item level, prices can differ across customers for the same product. This implies that, although the salespeople may be seeing the same new price recommendation, the actual recommended change in price (recommended price minus last transaction price) may be different for each customer for the same product.

Salespeople typically negotiate with customers over prices until a mutually agreed price is reached. Although there is no ceiling on the price a salesperson can offer a customer, there is a natural floor price, the salesperson's unit cost, which includes the GPD's own procurement cost as well as relevant overhead costs for that salesperson. We learned from our discussions with salespeople that, as a result of the negotiation process, salespeople rarely lost a customer's sale because of an uncompetitive price. The interviewed salespeople indicated that they lost less than 5% of customers' orders and that, when they did, the customer had asked them to price below cost. Salespeople have access to inventory levels across products; however, our (informal) interviews with salespeople indicate that stock-outs were rare; salespeople typically operate under the assumption that inventory is not a constraint in sales. The typical salesperson is compensated based on his or her earned gross profit (difference between transaction price and salesperson's unit cost). Salespeople who have a tenure under one year earn a fixed salary. While we do not have detailed tenure information on the salespeople in our data set, we were informed that those with tenure under one year represented a small fraction of the sales force (less than 10%).

2.1. Reference Prices

Our informal interviews with salespeople in the grocery products industry reveal a rich fabric of issues considered during the pricing process. "Obviously, one of the biggest factors in setting prices overall is what the cost of the product is, but in terms of day to day pricing, it can depend on a number of other things. In general, we try to maintain a steady price in the face of small shocks ... we do base our price today on what we charged last time'' (interview with GPD sales manager, June 8, 2012).

This quote reveals an important factor that looms in the salesperson's mind when quoting a price: the *last* price charged to the customer serves as a *reference price* from which salespeople consider changing the price. Reference prices are standards or benchmarks against which the purchase or bid price of a product is judged (Mazumdar et al. 2005). Prior work in B2C marketing has identified two main categories of reference prices that affect consumer decision making: internal reference prices (IRPs) and external reference prices (ERPs). An IRP is based on prices or behavior that the consumer has observed in the past; the IRP is primarily self-generated from memory and dynamic. As new prices are observed and assimilated, the IRP is updated appropriately (Yadav and Seiders 1998). In addition to the IRP, consumers also encounter contextual or environmental information that may provide additional reference points for price expectations. These could include prices offered for other products in the same category, prices in competing stores, or the presence of advertised sales or promotions (Yadav and Seiders 1998, Adaval and Monroe 2002). These are collectively called ERPs since they provide an alternative standard for the price of the product that is rooted in the specific context.

The role of past prices as reference prices and their ability to shape choices for decision makers with reference-dependent preferences has begun to receive attention in the operations literature in B2C settings. Popescu and Wu (2007) undertake a theoretical exploration of reference price effects in a monopolistic setting. In their paper, the monopolist faces a consumer market whose aggregate demand is a function of the current price as well as past prices (influencing demand via a reference price effect). Popescu and Wu (2007) find that the optimal prices must consider short-term profits as well as longer-term effects of prices on reference points.

In our B2B salesperson pricing context, we can interpret the last transaction price at which the salesperson sold a product to a customer as an IRP and the recommended price as an ERP, for it may help to form salespeople's expectations as to a reasonable transaction price. To the best of our knowledge, the only other papers that investigate the role of reference pricing in the salesperson pricing process in B2B markets are Elmaghraby et al. (2012), Bruno et al. (2012), and Zhang et al. (2014). Bruno et al. (2012) develop a parsimonious theoretical model to describe and evaluate B2B transactions in which industrial buyers (e.g., furniture manufacturers) contact salespeople for timber products. The final quantities and prices are determined endogenously and are influenced by reference prices and corresponding perceived loss and gain effects in utility. The authors posit that buyers have reference-dependent preferences and decide on what quantity to purchase after being quoted a price from a salesperson; the salesperson has perfect information regarding buyer utility and reference prices and sets the price to maximize expected payoff. Bruno et al. (2012) use data on B2B timber sales to provide empirical evidence that reference prices shape the framework within which buyers and salespeople evaluate gains and losses and the current pricing and quantity decisions. Furthermore, the authors find evidence that the number of times the salesperson and customer have interacted moderates reference price effects.

Zhang et al. (2014) study the sequential pricing decisions of an aluminum retailer's salespeople and the types of price quotes initiated by its industrial buyers. The authors posit that the B2B relationship is governed by latent states of trust. As in Bruno et al. (2012) and this paper, the authors study the impacts of IRPs and ERPs on salespeople's pricing decisions. Zhang et al. (2014) find strong empirical evidence that buyers operate in two states of trust, where buyers in the weakened state of trust are more sensitive to reference price effects and exhibit amplified asymmetric reference price effects. The authors conclude with recommendations on how salespeople can manage pricing dynamics to control buyers' transition between the states of trust and improve profitability. Exploring alternative price change models to the one developed in this paper, Elmaghraby et al. (2012) provide evidence that asymmetric price responses to cost changes originate at the salesperson level.

Motivated by these papers and management concerns, we build a reduced-form model that explicitly considers price *changes* from one transaction to the next with the same customer on the same product, that is, a salesperson-customer-item triplet. This model takes the last transacted price as the internal reference price and considers deviations away from the reference price. With our reduced-form model, we are interested in uncovering correlations between the actual price change from the last transaction price and the recommended price change at the salesperson-customer-item level.

2.2. Data and Model-Free Observations

We were given data on sales transactions that occurred between individual salespeople and customers across all products sold between January 2007 and August 2008. For each transaction, the salesperson identification number (ID), customer ID, and item purchased are recorded. In addition, we have information on the product category, date of transaction, unit cost, recommended price, quantity sold, and final transaction price. The records also indicate whether the item sold in a transaction is a "commodity," that is, a highly perishable item such as fruit, or a "noncommodity." From these data, we are able to construct, for each transaction, the cost and price changes from one transaction to the next and the recommended price change from the last transaction at the salesperson-customer-item level as well as the total number of times the salesperson and customer have interacted in the data setup to that transaction point.

Our focus is the pricing decision and the transaction context at the time of the last (observed and recorded) transaction of a triplet. We use the two most recent transactions of a triplet in our data set. The pricing decision support tool was introduced to the sales force shortly before January 2007. To highlight the role of the price recommendation system after it had been integrated into the company's operations and was familiar to the salespeople, we limited our analysis to the last transaction for each triplet. We are interested in the factors that affect price changes, $\Delta P_{ijk} = P_{ijk} - \tilde{P}_{ijk}$, for salesperson i, customer j, and item k, where P_{ijk} denotes the current price, $\tilde{P}_{ijk}$ denotes the last transaction price, and ΔP_{ijk} denotes the change in price from the last transaction price. In our data set, we have a total of 1,184 salespeople and 14,401 customers. There are 43,857 items and 88 product categories over a period of 18 months, resulting in a total of 207,942 triplets.

Salespeople have flexibility in their pricing decisions and can charge different prices across customers and over time for a given item, regardless of the product type. A reasonable educated guess about pricing behavior would be that price changes follow underlying cost changes. Table 1 shows the direction of price changes (price increase, price decrease, and no change in price) broken down by three types of cost changes (cost increase, cost decrease, and no change in cost) in our data. For those transactions with no change in the cost, 19.34% of the transactions resulted in an *increase* of price while only 6.24% led to a price decrease. Furthermore, whereas over 83% of all the transactions with a cost increase resulted in a price increase, only 54.53% of cost decreases led to price decreases. In many instances cost and price move in opposite directions.

Table 1 **Percentage of Consecutive Triplet Transactions with Price and Cost Change**

		Price change frequency conditioned on cost change (%)		
Cost change	Frequency (%)	Price decrease	No change in price	Price increase
Decrease	8.84	54.53	31.06	14.41
No change	68.69	6.24	74.43	19.34
Increase	22.47	5.53	11.40	83.07
Frequency		10.35	56.43	33.22

In those instances where the price changes are asynchronous with underlying cost changes, it is possible that the salespeople are following the advice of the price recommendation system. The pricing tool was introduced to guide salespeople to higher price levels. The pricing tool recommended a price that was higher than the last recorded transaction price in over 94% of the triplets in our data. Table 2 reports on the movements of the recommended price changes and actual price changes. We find that for the transactions when the tool recommends an increase in price, the salespeople decrease the price or do not change the price 65% of the time. When the tool recommends a price decrease, the salespeople follow that recommendation 56.97% of the time.

All in all, these preliminary investigations suggest that transaction price changes are not merely a (sign-preserving) transformation of the underlying costs,

Table 2 **Percentage of Consecutive Triplet Transactions with Recommended and Actual Price Change**

		Price change frequency conditioned on change in recommended price (%)		
Change in recommended price	Frequency (%)	Price decrease	No change in price	Price increase
Decrease	5.67	56.97	39.28	3.75
No change	0.07	21.83	54.93	23.24
Increase	94.26	7.53	57.47	35.00
Frequency		10.35	56.43	33.22

nor do they blindly mimic the recommended price path. Instead, a more nuanced landscape of influential factors should be considered to predict actual price changes better.

2.3. Hypotheses Development

As noted by the salespeople, the last price the salesperson charged a customer for a product serves as a natural reference point at the time of determining a new price. If salespeople do assess the focal transaction with the last transaction serving as a reference point (with its corresponding last price, cost, and associated profits), then it is plausible that salespeople's reactions to cost changes and resulting price changes are in line with *prospect theory*. Through a series of experiments, Kahneman and Tversky (1979) posited that decision makers are not expected utility maximizers but rather have preferences that follow the predictions of prospect theory. In particular, decision makers are risk averse over prospects involving gains, whereas they become risk-loving over prospects involving losses (i.e., their preferences over gains and losses are asymmetric). Through framing or history-dependence, decision makers (implicitly) define a reference point for these asymmetrical preferences: all outcomes to the left of the reference point are viewed as losses, whereas those to the right are viewed as gains. In our context, if the cost of the product has increased since the last time the salesperson and customer transacted, then the salesperson would find himself in the realm of loss (of profits) if he were not to change the price. Alternatively, if the cost of the product were to decrease, then the salesperson would find himself in the realm of gains (of profit) if he were not to change the price.

Hypothesis 1. *Salespeople are more likely to change price when confronted with a cost increase than a cost decrease.*

From the vantage point of reference prices, we posit that the recommended price change serves as an external reference price and positively influences the actual price change in all transaction environments.

Hypothesis 2. *The actual price change is positively associated with the recommended price change.*

In the next section, we present a regression model by which we can tease out the impact of the information present in the sales environment on the salesperson's pricing decision.

2.4. Choice of Predictors

Based on the data that are available to us, as well as the discussion in §2.3, we include the following variables in our regression analyses. We define $\tilde{C}_{ijk}$ to be the unit cost to salesperson i of product k the last time the salesperson and customer j transacted over product k, and C_{ijk} to be the unit cost of the current transaction. We define the *cost environment* characteristics to include (i) the magnitude of a cost change a salesperson faces from the previous transaction for the same triplet, represented by $Cost.Inc_{ijk} = \max(C_{ijk} - \tilde{C}_{ijk}, 0)$ and $Cost.Dec_{ijk} = \max(\tilde{C}_{ijk} - C_{ijk}, 0)$ and (ii) the potential nonlinearities in the impact of the cost change, represented by $Cost.Inc^2_{ijk} = \max(C_{ijk} - \tilde{C}_{ijk}, 0)^2$ and $Cost.Dec^2_{ijk} = \max(\tilde{C}_{ijk} - C_{ijk}, 0)^2$.

To reflect *customer sales characteristics*, we include (i) the cumulative number of times salesperson i and customer j have transacted across all products over the 18-month period to serve as a proxy for the intensity of the customer-salesperson relationship (T_{ij}), (ii) a binary flag indicating whether item k is a commodity ($CO_k = 1$) versus a noncommodity, and (iii) the relative size of customer j's spending on product k vis-à-vis customer j's total purchases with salesperson i that day:

$$Frac_{ijk} = \frac{\$\text{ spent on purchasing item } k}{\begin{array}{c}\text{total }\$\text{ spent by customer } j \text{ across all}\\ \text{products purchased that day}\end{array}}.$$

To reflect the *salesperson's environment*, we include (i) the total number of customers salesperson i has in his business portfolio ($N.Cust_i$), (ii) the total number of products that salesperson i sells across all of his or her customers ($N.Item_i$), and (iii) the total number of new price recommendations salesperson i encounters that day across all transactions ($N.New.RPC_i$).

Finally, to reflect the nature of the recommended price for item k (RP_k), we include the recommended price change measured by $RPC.Inc_{ijk} = \max(RP_k - \tilde{P}_{ijk}, 0)$, reflecting a recommended price increase over the price paid in the previous transaction of the triplet, and $RPC.Dec_{ijk} = \max(\tilde{P}_{ijk} - RP_k, 0)$, reflecting a recommended price decrease. Table 3 reports the summary statistics for these variables (at the level of the triplet).

Table 3 Summary Statistics for Predictor Variables

	Cost.Inc	*Cost.Dec*	*Cost.Inc*^{2}	*Cost.Dec*^{2}	*RPC.Inc*	*RPC.Dec*
Min	0.00	0.00	0.00	0.00	0.00	0.00
Mean	1.48	1.67	16.91	21.75	1.62	1.12
Median	0.84	0.75	0.71	0.56	1.04	0.26
Max	320.64	262.42	102,810	68,864	328.78	436
Std. dev.	3.84	4.35	831.93	668.86	3.39	4.79

	Frac	*CO*	*T*	*N.Cust*	*N.Item*	*N.New.RPC*
Min	0.00	0.00	3.00	1.00	1.00	1.00
Mean	0.13	0.36	25.86	22.27	268.49	5.79
Median	0.06	0.00	17.00	22.00	253.00	3.00
Max	1.00	1.00	428	55.00	716.00	101.00
Std. dev.	0.19	0.48	25.42	9.46	144.31	8.87

3. Pricing Decision Models

The objective of this paper is to explore our data and identify associations between the transaction context (customer order characteristics, salespeople's environment, cost environment, recommended price change) and the resulting price change. To that end, we initially employ a benchmark random effects linear regression model:

$$\begin{aligned}\Delta P_{ijk} = {} & \alpha_0 + \beta_1 \mathit{Cost.Inc}_{ijk} + \beta_2 \mathit{Cost.Dec}_{ijk} \\ & + \beta_3 \mathit{Cost.Inc}^2_{ijk} + \beta_4 \mathit{Cost.Dec}^2_{ijk} + \beta_5 \log(T_{ij}) \\ & + \beta_6 \mathit{CO}_k + \beta_7 \mathit{Frac}_{ijk} + \beta_8 \mathit{N.Cust}_i \\ & + \beta_9 \mathit{N.Item}_i + \beta_{10} \mathit{N.New.RPC}_i + \beta_{11} \mathit{RPC.Inc}_{ijk} \\ & + \beta_{12} \mathit{RPC.Dec}_{ijk} + u_i + \epsilon_{ijk}, \qquad (1)\end{aligned}$$

where ΔP_{ijk} denotes the change in price *from* the last transaction price (as defined in §2.2), i denotes salesperson i, j denotes customer j, k denotes item k, and ϵ_{ijk} is residual error. Note that u_i denotes the random effect, which is specific to salesperson i. Using random effects instead of fixed effects is well established as a tool when we are more interested in the population of salespeople (rather than a specific, individual salesperson); for example, see Agresti et al. (2000). The random effects model captures salesperson-specific behavior that is otherwise unobservable to us (such as salesperson-specific biases, experience, or attitudes toward taking risks) and hence allows us to account for possible correlation among observations because of (unobservable) salesperson characteristics. Although some of that correlation could be explained by the inclusion of suitable salesperson-specific predictor variables (such as attitude toward taking risks in a transaction, attitude toward biases, or experience and training), these variables were unavailable to us.

Equation (1) investigates all the factors listed above and has an adjusted R^2 of 0.79, which suggests a very reasonable data fit. Despite the fact that the model in Equation (1) explains a little over 79% of the variability in price changes, there is reason to believe that this benchmark model could be improved. We observe that, whereas over 56% of all transactions have no cost change, the benchmark model severely underpredicts the occurrence of no cost change (a histogram plotting the frequency of actual versus predict price changes can be found in the online appendix, available as supplemental material at http://dx.doi.org/10.1287/msom.2015.0537). Thus, we set out to improve our model by exploring and statistically testing the suitability of a two-stage decision model.

Gensch (1987), one of the earliest papers in the marketing literature that discusses two-stage models, finds empirical support for the theory that an individual uses multiple stages in the decision process and that the information and rules used at each stage may differ. We develop a two-stage model for the decision process of salespeople: At the first stage of the decision process, salespeople make a binary decision—*whether or not* to change the price quoted to the customer. Once the salesperson decides to change the price, the salesperson enters the second stage of the decision process, where he or she has to decide exactly *by how much* the price should change.

Gensch (1987) points out that, although there has been considerable hypothesizing about the existence of two-stage choice decisions, his model was one of the first in the marketing literature to empirically formalize the process. Bronnenberg and Vanhonacker (1996) point to the relative void of two-stage decision models in the literature. In Gensch (1987) and earlier theoretical work (e.g., Bettman 1979), individuals are assumed to possess a hierarchical attribute-screening process to reduce the feasible set of alternatives to a final choice set, whereas the final choice set uses a more compensatory decision rule in which alternatives are fully evaluated and then compared. There is additional evidence that individuals first use elimination-type rules to simplify the decision process, only to use more comparative models in the second stage once irrelevant alternatives have been ruled out (e.g., Payne 1976, Einhorn 1970). We are not aware of any two-stage decision models in the context of B2B decision making and salesperson decisions. Although the increasing availability of B2C data has fostered research on consumer choice models (e.g., Moe 2006), seller behavior is rarely analyzed using empirical research.

A sequential decision process, in which the first stage chooses an action from a binary or countable set of alternatives and the second stage chooses actions from a continuous set, is in line with the statistical methods appropriate for our zero-inflated data. There are different approaches for dealing with zero-inflated or, more generally, *semicontinuous* data (see, e.g., Shmueli et al. 2008). The most viable approach is to model the data in two steps: the first step employs a logit model for the probability of a price change; the second step employs linear (i.e., least-squares) regression, conditional on a nonzero price change. We adopt these two steps in this paper.

3.1. Two-Stage Model

The first stage of our two-stage model starts with the decision of whether or not to change price: the binary decision is modeled using logit. We use the same set of predictors introduced in §2.4; the response variable is now the probability of a price change. As defined in §2.2, let ΔP_{ijk} be the price change in two consecutive triplet transactions, and define $\rho_{ijk} = \text{Prob}(\Delta P_{ijk} \neq 0)$. The results from our Stage 1 regression can be viewed as the odds (i.e., the probability of success divided by the probability of failure) or the probability of a price change. We can interpret the *incremental odds or probability* related to a regression coefficient η_i via its exponential, that is, $\exp^{\eta_i}$. The model in Stage 1 is then

$$\begin{aligned}\log\left(\frac{\rho_{ijk}}{1-\rho_{ijk}}\right)\\ &= \eta_0 + \eta_1\, Cost.Inc_{ijk} + \eta_2\, Cost.Dec_{ijk}\\ &\quad + \eta_3\, Cost.Inc^2_{ijk} + \eta_4\, Cost.Dec^2_{ijk} + \eta_5 \log(T_{ij})\\ &\quad + \eta_6\, CO_k + \eta_7\, Frac_{ijk} + \eta_8\, N.Cust_i + \eta_9\, N.Item_i\\ &\quad + \eta_{10}\, N.New.RPC_i + \eta_{11}\, RPC.Inc_{ijk}\\ &\quad + \eta_{12}\, RPC.Dec_{ijk} + u_i + \epsilon_{ijk}. \qquad (2)\end{aligned}$$

In the second stage of our model, we fit the direction and magnitude of the price change, on transactions for which there was an *actual* price change (90,596 transactions had actual price changes of a total of 207,942 transactions). Since price change is a continuous variable, we now employ a linear model identical to the benchmark model in Equation (1).

We are confident that the two-stage model leads to more accurate conclusions (compared with the benchmark model): The values of the Bayesian information criterion (BIC) are significantly smaller (711,335 for the benchmark model, 237,700 for Stage 1 and 373,190 for Stage 2 of the two-stage model). Furthermore, the value of the adjusted-R^2 in the second stage of our model (81%) has improved over that of the benchmark model (79%). In addition, we also conduct a holdout sample analysis to gauge its predictive performance. To that end, we trained our model on the transaction data from 2007; this results in a total of 84,932 transactions. Then, to test the ability of the model to predict future transactions, we apply it to the data from 2008, in which there are a total of 123,010 transactions.

In the holdout sample analysis, we first use the Stage 1 model to predict whether or not an observation has a price change (for all observations in the holdout sample). Then, using only the instances where the Stage 1 model predicts a price change (using a threshold of 0.5), we apply the Stage 2 model and predict the amount of the price change for these values. We estimate the coefficients of the Stage 2 model on the training sample using the observations that actually had a price change in the training sample; this is conceptually sound since, consistent with the data mining literature, we assume that all the information inside the training set is known to us. We then compare the predicted price changes against the true price changes. Table 4 shows the results: We find that the two-stage model improves the *prediction accuracy* by over 32% (benchmark model mean absolute percentage error (MAPE) of 27.13% versus a two-stage MAPE of 18.19%); that is, the model is able to anticipate the true price change of a salesperson's future transaction with significantly higher accuracy.

Table 4 Holdout Sample Analysis of Models

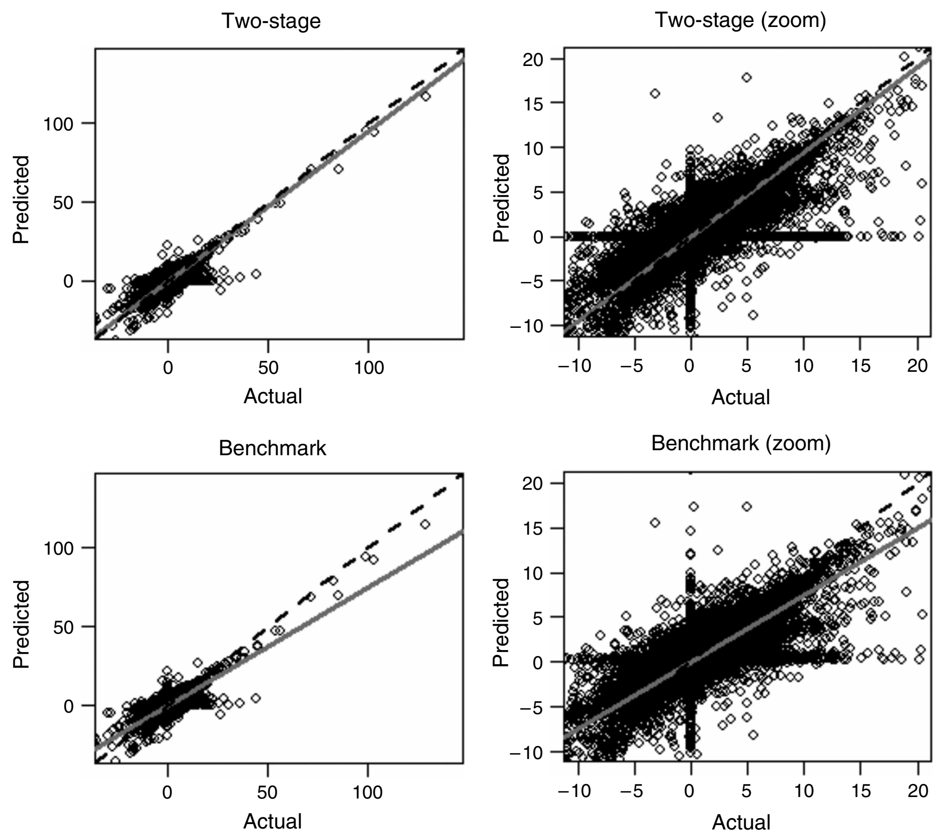
Model	MAPE
Benchmark	0.2713
Two stage	0.1819
Relative improvement	32.95%

Although Table 4 shows the improvement in prediction accuracy with the two-stage model, it does not directly reveal the origin of the improvement. Figure 1 shows a prediction plot for the two-stage model (top) versus the benchmark model (bottom). In particular, each graph plots the actual values (x axis) versus the predicted values (y axis) for the holdout sample. The left panel shows the plots on the entire data; the right panel shows a zoom into the center of the data.

On a graph of actual versus predicted values, we would expect a perfect model (i.e., one that reproduces each observation perfectly) to yield a scatter of points that fall perfectly on the diagonal. Since in reality no model can be perfect (and since data are usually observed with noise), we look for models that produce a scatter of actual versus predicted that approximates the diagonal as closely as possible. In Figure 1, the diagonal is represented by the dashed lines. The grey lines show a linear fit through the data; that is, the grey lines represent the linear trend of the scatter of the actual versus predicted observations. We can see that in the two-stage model, the grey line traces the diagonal very closely; that is, the two-stage model produces predicted values that are almost identical to the actual values, at least on average. In contrast, in the benchmark model, the linear fit through the scatter (i.e., the grey line) deviates significantly from the diagonal. This suggests that the benchmark model systematically overpredicts for the lower values but systematically underpredicts for the larger values.

Another insight revealed by the two-stage model is with respect to the impact of the salesperson random effect. In Stage 2 of the model, the salesperson's random effect variance (0.48) is much larger compared with that of the benchmark model (0.11); the variance differs by over a factor of four. A large variance in the random effects is desirable because it implies that the random coefficient manages to account for a large proportion of the residual noise and hence results in a better model. The regression results from the benchmark model, as well as an extended discussion and comparison of benchmark versus two-stage models, can be found in the online appendix.

Figure 1 Actual vs. Predicted Values on the Holdout Set



3.2. Two-Stage Model Results

We now discuss whether the two-stage model supports our hypotheses; the two-stage regression is presented in Table 5. We report the pseudo-R^2 for the Stage 1 model and adjusted-R^2 for Stage 2. In all the tables, standard errors are given in parentheses, bold numbers indicate significance levels greater than 0.1, and all other numbers are significant at less than 0.01.

From our two-stage model, we find support for Hypothesis 1. We find that salespeople are more likely to change the price (Stage 1) when there is a cost increase (2.232) than when there is an equivalently sized cost decrease (0.4993). Hence, for each \$1 increase in cost, the odds of a price change increase by exp(2.232) = 9.31; whereas for each \$1 cost decrease, the odds of a price change increase by only exp(0.4993) = 1.65, which implies an approximately 5–1 ratio in terms of the odds. Hence, salespeople's decisions follow in line with prospect theory, with preferences over gains and losses (from the reference point) being evaluated asymmetrically. We find that the odds of changing the price decrease slightly as the relative magnitude of the cost change increases (represented by $Cost.Inc^2$ and $Cost.Dec^2$).

If the decision to change the price has been made, then the coefficients in Stage 2 are aligned with standard intuition; salespeople increase price when confronting a cost increase (0.8189) and decrease price, albeit to a smaller degree, when facing a similarly sized cost decrease (−0.7430). In both cases, the salespeople pass along less than the full cost change, resonating with observed price stickiness in industrial markets, such as steel, petroleum, paper, and chemicals (Carlton 1986). In addition, the price change is increasing in the relative size of the cost change; a larger cost increase (decrease) results in a larger price increase (decrease) captured by the positive (negative) coefficient for $Cost.Inc^2$ ($Cost.Dec^2$).

With regard to the recommended price change, our results provide partial support for Hypothesis 2. We find that, in Stage 1, a recommended price increase (*RPC.Inc*) decreases the odds of a price change (−0.0443); *RPC.Inc* = \$1 decreases the odds of a price change by 5% (= exp(−0.0443)). On the other hand, a recommended price decrease (*RPC.Dec*) increases the odds of a price change (0.4458); *RPC.Dec* = \$1 increases the odds of a price change by 56% (= exp(0.4458)). We find that *RPC.Inc* has a positive association with price changes in Stage 2 (0.1479), whereas *RPC.Dec* has a strong negative association with price changes in Stage 2 (−0.9571). Given that less than 6% of the recommended price changes are negative, these results indicate that a salesperson passes along the recommended price decrease almost in its entirety but follows a recommended price increase only modestly; a \$1 recommended price increase results

Table 5 Two-Stage Model

	Two-stage	
	Stage 1	Stage 2
α	−0.4883	0.2897
	(0.0152)	(0.0195)
Cost.Inc	2.2320	0.8189
	(0.0196)	(0.0045)
Cost.Dec	0.4993	−0.7430
	(0.0108)	(0.0051)
Cost.Inc^2	−0.0068	0.0002
	(0.0001)	(0.0000)
Cost.Dec^2	−0.0019	−0.0015
	(0.0001)	(0.0000)
RPC.Inc	−0.0443	0.1479
	(0.0033)	(0.0026)
RPC.Dec	0.4458	−0.9571
	(0.0183)	(0.0037)
Frac	−0.1826	0.3302
	(0.0267)	(0.0331)
CO	0.5640	−0.1976
	(0.0104)	(0.0128)
T	−0.0050	0.0014
	(0.0002)	(0.0003)
N.Cust	0.0027	*0.0003*
	(0.0007)	(*0.0009*)
N.Item	−0.0008	*0.0000*
	(0.0000)	(*0.0001*)
N.New.RPC	−0.0122	−0.0106
	(0.0007)	(0.0009)
BIC	237,700	373,190
Pseudo and adj. R^2	0.39	0.81
Std. dev. random effects	0.7	0.48

in a \$0.14 increase in the price, but a \$1 recommended price decrease results in a \$0.95 decrease in price on average.

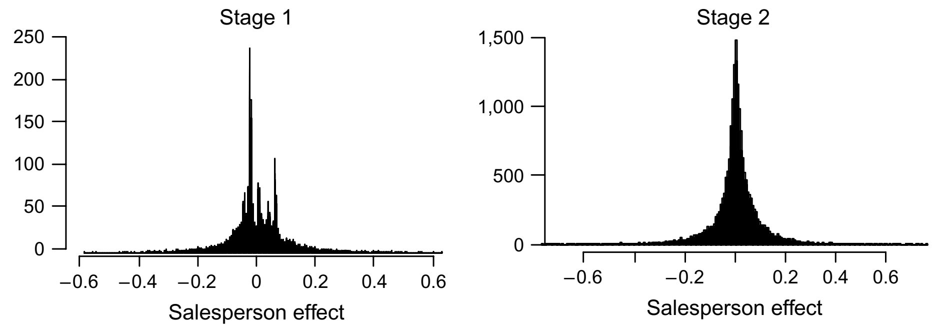
We find that, whereas T, the total number of times the salesperson and customer have transacted, has a negative correlation with the probability of a price change (−0.0050), it has a positive association on any realized price change (0.0014). One question raised by this variable may be whether salespeople tend to charge lower (or higher) prices to more frequent customers (higher T) and that the relative price changes do not take into account the baseline price from which the salesperson is changing the price. Further exploration of the data did not uncover any systematic relationships between T and the actual prices charged to customers across product categories. This finding suggests that the decreased probability of changing the price and the increase in the magnitude of the price change counteract each other to yield a price level that is invariant with respect to T. Similarly, we find that the relative amount of money that the customer is spending on the particular item (when evaluated relative to other items purchased that day), *Frac*, has a negative association with the decision to change the price (−0.1826) but has a positive association with the actual price change (0.3302). This finding implies that salespeople are less likely to change the price for larger expenditure categories, but once the decision to change the price has been made, they pass along a larger price change for larger expenditure items. Finally, whether or not the item is a commodity is associated with the decision to change the price and the resulting price change. The odds of a salesperson changing the price are 75% higher if pricing a commodity (0.5640); however, price changes are almost \$0.20 less for commodity products (−0.1976).

We find that the number of customers with whom a salesperson interacts across his portfolio ($N.Cust$) has a positive association with the odds of a price change in Stage 1 (0.0027). By contrast, we find that the number of items a salesperson prices across his customer portfolio ($N.Item$) has a negative association (−0.0008) with the likelihood of a change in the price (Stage 1). Neither variable is statistically significant in Stage 2. Finally, we find that the variable $N.New.RPC$, which captures the number of new price recommendations a salesperson faces that day across all of his customers, has a negative association with the probability of changing the price (−0.0122) *and* the magnitude of price change (−0.0106).

Furthermore, we find that salespeople demonstrate heterogeneity in the pricing process, as seen in the distributions of the salesperson-specific random effects in Figure 2. Salespeople demonstrate idiosyncratic heterogeneity in the likelihood of a change in the price (Stage 1) but are relatively homogeneous in the manner in which they determine the size of the price change (Stage 2).

One potential problem with modeling data in two stages is selection bias; that is, since price changes can only occur if the salesperson decides to alter prices, any unobservables that affect the first binary decision could be correlated with unobservables in the second-stage regression. This could cause bias in the estimates. One method to detect possible selection bias is via the Heckman (1979) correction (using the inverse Mill ratio). Using the Heckman approach (results omitted), we find little to no evidence that selection bias exists in our data. We hypothesize that, unlike the canonical examples in the literature on sample selection bias, our data cannot be segmented into "price changers" versus "no price changers." In fact, salespeople do not systematically either change or not change a price; such behavior would be considered economically unwise, and it would also be corrected very quickly by management. In that sense, the data entering the second stage of our model are likely a random draw from the population without any selection bias.

Figure 2 Random Effects Model in Stages 1 and 2



4. Moderators of Recommended Price Change

The regression results in the previous section indicate that the price recommendation is associated with the final price change (Hypothesis 2). That is, our results suggest that the price recommendation serves as an external reference price in Stage 2, with a recommended price increase associated with a price increase and a recommended price decrease associated with a price decrease. Within our B2B pricing setting, we might expect the transaction context of a salesperson-customer interaction, namely that the customer-salesperson's prior purchase experience, the current purchase context, and individual characteristics of the customer-salesperson, to moderate the influence of recommended price changes. This expectation is premised on extant literature in consumer purchasing behavior and the formation of reference prices. The framework proposed by Mazumdar et al. (2005, p. 85) summarizes research on expectation-based reference prices. The framework proposes that "consumers' prior purchase experiences, the current purchase context, and individual characteristics of customers influence certain aspects of reference price formation, retrieval and effects either directly or indirectly." In this section we investigate the moderating effect of transaction context on the recommended price change. Given that management's stated goals for the recommendation system were to nudge salespeople to a higher price point (the recommendation system suggested an increase in price in over 94% of the transactions), we specifically wish to explore if the association of the recommended price *increase* with actual price change is moderated by any (or all) attributes of the transaction context.

Discussions with salespeople provide us with insights into the impact of transaction context. Although the pricing tool recommends a *single* per-unit price to all salespeople for distinct customer segments, the salespeople decide what price to offer a particular customer, and this decision is couched within their salesperson-customer-product history. The very reason why pricing in B2B sales is so often relegated to the salesperson is that a salesperson may possess customer-specific knowledge that allows him or her to assess a customer's willingness to pay, price sensitivity, and the least damaging ways to pass along cost increases to that customer. As noted in Bruno et al. (2012) and their study of B2B pricing in an industrial setting, if customers are averse to an increase in price (which would be viewed as a loss from the customer's viewpoint), salespeople may follow neither underlying cost changes nor the recommended price change for fear of damaging their customer relationship. Hence, the flexibility provided to salespeople to determine the final price offers them the latitude to circumnavigate the customers' negative reaction to an increase in price. From the perspective of building and sustaining a healthy (profitable) relationship, a salesperson may prefer to pass along less of the recommended price increase to a customer who has revealed himself to be a steady and frequent purchaser. Similarly, salespeople have hinted that they are more willing to pass along recommended price increases if the product represents a small fraction of the total dollars spent by a customer on that day or order, since price changes in smaller spend items are less likely to be closely monitored by customers.

Hypothesis 3. *The association of the recommended price increase* (*RPC.Inc*) *with the actual price change is negatively moderated by the frequency of the salesperson-customer interactions* (*T*) *and the relative size of the customer's spending on that product vis-à-vis the customer's total purchases* (*Frac*).

In addition, a salesperson may find himself facing anywhere from one to 101 new price recommendations (on distinct products) within a week, pricing anywhere from one to hundreds of items across all customers (*N.Item*) and handling orders from as few as one to as many as 55 customers (*N.Cust*). It takes time to reflect on a new price recommendation and consider the appropriateness of the recommended price change. The intensity of this mental task is exacerbated if the salesperson handles multiple products or multiple customers. A *bounded rationality* argument (Simon 1955) would suggest that salespeople may simply disregard the recommended price(s) if they are confronted with too many (i.e., are unable to process and evaluate all of the new information). Also, the impact of the recommended price changes will diminish as the salesperson handles more products and customers (implying an increased cognitive task load, since each triplet has a unique history;hence, a single recommended price may imply a unique recommended price change for each triplet).

Hypothesis 4. *The association of a recommended price change with the actual price change is negatively moderated by the number of new price recommendations* (*N.New.RPC*), *number of products within a salesperson's portfolio* (*N.Item*), *and number of customers a salesperson manages* (*N.Cust*).

We present below our more focused analysis to identify any moderating effects of (i) the cost environment ($Cost.Inc$, $Cost.Dec$, $Cost.Inc^2$, and $Cost.Dec^2$), (ii) the customer's demand characteristics (*Frac*, *CO*, and *T*), and (iii) the salesperson's environment ($N.Cust$, $N.Item$, and $N.New.RPC$) on $RPC.Inc$ (and $RPC.Dec$) in Stages 1 and 2. We run our regressions for each of the three context dimensions separately; this is done to highlight the interaction terms of interest, using the other variables as controls.

4.1. Results

Foreshadowing the results to be presented below, we find the correlation of $RPC.Inc$ with actual price changes (ΔP) to be moderated by almost all aspects of the transaction context. Our results do not support Hypothesis 3, whereas they provide partial support for Hypothesis 4. We present our results in Tables 6–8 and discuss the implications of each. As before, we report the pseudo-R^2 for the Stage 1 model and adjusted-R^2 for Stage 2. In Tables 6–8, standard errors are given in parentheses, bold numbers indicate significance levels greater than 0.1, and all other numbers are significant at less than 0.01.

When we examine how the cost environment moderates the relationship between $RPC.Inc$ and the price change (Table 6), we find that the influence of $RPC.Inc$ is more nuanced than the results from Table 5 would suggest. We find that a change in cost (either increase or decrease) will always decrease the effect of $RPC.Inc$ on the price change; however, the decrease of that effect is smaller when cost decreases (compared with when cost increases). Recall from Table 3 that the average $RPC.Inc$ in our data set is \$1.62, whereas the average actual price change is \$0.41. (Over 56% of all transactions have a zero change in price; 30% of the transactions have a price change that is greater than 4¢, whereas only 15% have a price change that is over \$1. Or, in terms of a price change relative to an

Table 6 Cost Environment Moderators

	Cost environment	
	Stage 1	Stage 2
α	−0.5279	0.3275
	(0.0152)	(0.0188)
Cost.Inc	2.6770	0.8464
	(0.0291)	(0.0050)
Cost.Dec	0.5706	−0.8000
	(0.0150)	(0.0075)
$Cost.Inc^2$	−0.0621	−0.0068
	(0.0160)	(0.0001)
$Cost.Dec^2$	−0.0044	−0.0026
	(0.0002)	(0.0001)
RPC.Inc	−0.0179	0.1230
	(0.0030)	(0.0025)
RPC.Dec	0.4527	−1.0170
	(0.0201)	(0.0037)
Frac	−0.1909	0.3406
	(0.0267)	(0.0318)
CO	0.5677	−0.2235
	(0.0104)	(0.0123)
T	−0.0049	0.0015
	(0.0002)	(0.0003)
N.Cust	0.0027	−0.0003
	(0.0007)	(0.0009)
N.Item	−0.0008	0.0000
	(0.0000)	(0.0001)
N.New.RPC	−0.0121	−0.0110
	(0.0007)	(0.0008)
$RPC.Inc * Cost.Inc$	−0.1808	0.0069
	(0.0056)	(0.0001)
$RPC.Inc * Cost.Dec$	−0.0327	−0.0031
	(0.0046)	(0.0018)
$RPC.Inc * Cost.Inc^2$	0.0067	0.0000
	(0.0006)	(0.0000)
$RPC.Inc * Cost.Dec^2$	0.0003	0.0001
	(0.0000)	(0.0000)
$RPC.Dec * Cost.Inc$	**−0.0381**	−0.6040
	(**0.2059**)	(0.0467)
$RPC.Dec * Cost.Dec$	**−0.0073**	0.1004
	(**0.0175**)	(0.0027)
$RPC.Dec * Cost.Inc^2$	**−0.0560**	0.0858
	(**0.0380**)	(0.0109)
$RPC.Dec * Cost.Dec^2$	**−0.0009**	−0.0028
	(**0.0007**)	(0.0001)
BIC	236,643.9	365,916
Pseudo and adj. R^2	0.39	0.82
Std. dev. random effects	0.7	0.47

associated change in cost, in 30% of all instances the price change is larger than the cost change, whereas in 16% of all instances it is more than two times larger than the cost change.)

Assume that $RPC.Inc = 1$: When there is no cost change, the odds of a price change are 0.9822 $(= \exp(-0.0179))$. When $Cost.Inc = 1$, the odds that the salesperson changes the price decreases by 17%

Table 7 Customer Sales Moderators

	Customer sales characteristics	
	Stage 1	Stage 2
α	−0.4934	0.2590
	(0.0163)	(0.0204)
Cost.Inc	2.2320	0.7950
	(0.0196)	(0.0045)
Cost.Dec	0.4988	−0.7784
	(0.0108)	(0.0052)
Cost.Inc^2	−0.0068	0.0003
	(0.0001)	(0.0000)
Cost.Dec^2	−0.0019	−0.0013
	(0.0001)	(0.0000)
RPC.Inc	−0.0455	0.1781
	(0.0056)	(0.0047)
RPC.Dec	0.6033	−1.0390
	(0.0334)	(0.0144)
Frac	−0.1873	0.0460
	(0.0330)	(0.0368)
CO	0.5789	−0.0374
	(0.0132)	(0.0149)
T	−0.0050	−0.0002
	(0.0003)	(0.0004)
N.Cust	0.0027	0.0002
	(0.0007)	(0.0009)
N.Item	−0.0008	0.0000
	(0.0000)	(0.0001)
N.New.RPC	−0.0123	−0.0113
	(0.0007)	(0.0009)
RPC.Inc ∗ *Frac*	**0.0170**	0.1502
	(**0.0147**)	(0.0091)
RPC.Inc ∗ *CO*	−0.0121	−0.1063
	(0.0067)	(0.0043)
RPC.Inc ∗ *T*	**0.0002**	0.0012
	(**0.0002**)	(0.0001)
RPC.Dec ∗ *Frac*	−0.3705	0.0317
	(0.0681)	(0.0142)
RPC.Dec ∗ *CO*	−**0.0373**	0.2407
	(**0.0369**)	(0.0140)
RPC.Dec ∗ *T*	−0.0025	0.0008
	(0.0006)	(0.0004)
BIC	237,729	371,676
Pseudo and adj. R^2	0.39	0.81
Std. dev. random effects	0.7	0.48

Table 8 Salesperson Environment Moderators

	Salesperson environment	
	Stage 1	Stage 2
α	−0.5007	0.3109
	(0.0176)	(0.0210)
Cost.Inc	2.2370	0.8137
	(0.0196)	(0.0045)
Cost.Dec	0.4977	−0.7805
	(0.0108)	(0.0053)
Cost.Inc^2	−0.0068	0.0002
	(0.0001)	(0.0000)
Cost.Dec^2	−0.0019	−0.0013
	(0.0001)	(0.0000)
RPC.Inc	−0.0343	0.1505
	(0.0078)	(0.0054)
RPC.Dec	0.4910	−1.0210
	(0.0478)	(0.0056)
Frac	−0.1797	0.3197
	(0.0267)	(0.0330)
CO	0.5627	−0.2041
	(0.0104)	(0.0128)
T	−0.0050	0.0015
	(0.0002)	(0.0003)
N.Cust	0.0052	−0.0046
	(0.0009)	(0.0010)
N.Item	−0.0010	0.0003
	(0.0001)	(0.0001)
N.New.RPC	−0.0106	−0.0121
	(0.0008)	(0.0011)
RPC.Inc ∗ *N.Cust*	−0.0018	0.0026
	(0.0004)	(0.0003)
RPC.Inc ∗ *N.Item*	0.0002	−0.0002
	(0.0000)	(0.0000)
RPC.Inc ∗ *N.New.RPC*	−0.0022	**0.0001**
	(0.0004)	(**0.0004**)
RPC.Dec ∗ *N.Cust*	−0.0088	0.0042
	(0.0023)	(0.0011)
RPC.Dec ∗ *N.Item*	**0.0001**	0.0004
	(**0.0002**)	(0.0001)
RPC.Dec ∗ *N.New.RPC*	0.0254	0.0046
	(0.0031)	(0.0010)
BIC	237,616	372,525
Pseudo and adj. R^2	0.39	0.81
Std. dev. random effects	0.7	0.48

($= \exp(-0.1808) = 0.8346$) compared with a situation when there is no change in cost. Similarly, when $Cost.Dec = 1$, the odds that the salesperson changes the price decrease by 3% ($= \exp(-0.0327) = 0.9679$). Therefore, the odds of changing the price are higher when the salesperson faces $RPC.Inc > 0$ and does not face a simultaneous cost change ($Cost.Inc = Cost.Dec = 0$). Conversely, we find that the magnitude of the cost change does not affect the odds of a price change when a salesperson faces a recommended price decrease, that is, $RPC.Dec > 0$. Both interaction terms $RPC.Dec * Cost.Inc$ and $RPC.Dec * Cost.Dec$ are statistically insignificant.

In Stage 2, the coefficient of *RPC.Inc* is positive ($RPC.Inc = 0.123$), implying that even when there is no cost change, each additional \$1 recommended price increase translates into a \$0.123 additional increase in price. The economic impact of the *RPC.Inc* is only modestly moderated by underlying changes in cost; when $Cost.Inc = 1$, the net effect of a \$1 recommended increase in price is almost \$0.13 (\$0.123 + \$0.0069); when $Cost.Dec = 1$, the net effect of a \$1 recommended price increase reduces to \$0.12 (\$0.123 − \$0.003).

We find that *RPC.Inc* exerts an upward lift on prices, even when costs are decreasing. This result is in line with marketing research on external reference prices in consumer markets (B2C). External reference prices arise from prices on products in the same category, prices in competing stores, or the presence of advertised sales or promotions (Yadav and Seiders 1998, Adaval and Monroe 2002) and serve as standards or benchmarks against which the price of a product is judged (Mazumdar et al. 2005). We can argue that the (generally) higher *RPC* serves as an external reference price, nudging salespeople to increase the price.

We find the interaction terms $RPC.Inc * Cost.Dec^2$ and $RPC.Inc * Cost.Inc^2$ to be statistically significant, but their regression coefficients are very small (0.0000 and 0.0001, respectively), implying an insignificant economic impact in all but the extreme cost change settings. Hence, we find that (i) a positive *RPC.Inc* has the highest odds of a price change when costs are unchanged, but (ii) given the decision to change the price, the effect of the *RPC.Inc* is *largest* in Stage 2 when the pricing context includes a larger cost increase.

Table 7 reports our findings on the customer-specific interactions. From the viewpoint of a customer's order and history, contrary to Hypothesis 3, the association of *RPC.Inc* with the decision to change the price is not significantly moderated by *Frac* or *T* in Stage 1. However, we find evidence that it is negatively moderated by *CO*; a salesperson pricing a commodity product ($CO = 1$) is less likely to follow the recommendations of a price increase ($RPC.Inc * CO = -0.0121$). When faced with $RPC.Inc = \$1$, the odds of a salesperson changing the price of a noncommodity product are 0.9555, which reduces to 0.944 when pricing a commodity product (a decrease of 2%).

Conversely, we find that the association of the recommended price change in Stage 2 with ΔP is moderated by all three attributes of the customer sales environment. When we consider the length of the transaction history *T* (i.e., number of times the salesperson and customer have interacted on *any* product over the past 18 months), we find that *T* increases the marginal effect of *RPC.Inc* on ΔP. Consider a recommended price increase of \$1; if $T = 3$ (the minimum value), then a salesperson passes along \$0.18 ($= 0.1781 + 0.0012 * 3$) of the \$1 recommended change; if $T = 26$ (the average value), then a salesperson passes along \$0.21 ($= 0.1781 + 0.0012 * 26$); if $T = 428$ (the maximum value), then a salesperson passes along \$0.69 ($= 0.1781 + 0.0012 * 428$) of the recommended \$1 increase in price.

We find that a larger portion of the *RPC.Inc* is passed along for larger values of *Frac* ($RPC * Frac = 0.1502$), suggesting that it becomes more important to pass along price increases as *Frac* increases, as doing so will generate significant additional revenue. For example, when $RPC.Inc = 1$, if $Frac \to 0$ (the minimum value), the salesperson passes along \$0.178. If $Frac = 0.13$ (the average value), then he passes along $\$0.178 + 0.1502 * 0.13 = \$0.1975$. Finally, if $Frac = 1$ (the maximum value), he passes along $\$0.178 + 0.1502 * 1 = \$0.3282$ of a \$1 *RPC.Inc*. In summary, we do not find support for Hypothesis 3.

Finally, we find that the nature of the product, that is, whether or not the customer is demanding a commodity, has an effect on the influence of *RPC.Inc*. We find that a larger portion of the *RPC.Inc* is passed along for noncommodity items (\$0.1781 for each \$1 recommended price increase for noncommodities) versus commodities ($\$0.1781 - 0.1063 = \$0.07$ passed along for each \$1 recommended price increase).

A final question is whether the impact of price recommendations is the same across all the salespeople. To investigate the moderating effects of salespeople-specific factors on the influence of the *RPC.Inc*, we include interaction terms for *RPC.Inc* with variables representing attributes of the salesperson's business environment (*N.Cust*, *N.Item*, and *N.New.RPC*) as well as the interaction of *RPC.Inc* with the salesperson random effects. The regression results are presented in Table 8.

We find that the association of *RPC.Inc* in Stage 1 is negatively moderated by *N.Cust* (with a regression coefficient of $RPC.Inc * N.Cust = -0.0018$) and *N.New.RPC* ($RPC.Inc * N.New.RPC = -0.0022$), but its marginal effect is increasing (is positively moderated) in *N.Item* ($RPC.Inc * N.Item = 0.0002$), providing partial support for Hypothesis 4. For example, consider the moderating effect of *N.Item* on *RPC.Inc* in Stage 1; if the salesperson handles (or prices) only one product across all of the customers, $N.Item = 1$ (the minimum value), the odds are 1-to-1 that a salesperson changes the price. If the salesperson has 268 items (the average number of items managed by a salesperson), then the odds that he changes the price increase by 4% to 1.0417. Finally, if he has 716 items (the maximum number a salesperson handles), the odds that he changes the price increase by more than 11% to 1.1153.

Next consider the moderating effect of *N.Cust* on *RPC.Inc*. If the salesperson only handles one customer, $N.Cust = 1$ (the minimum value), the odds that he changes the price are 0.9981 when facing a \$1 recommended price increase. When the salesperson is managing 22 customer accounts (the average number for *N.Cust*), the odds that he changes the price decrease by 4% to 0.9604. Finally, when

$N.Cust = 55$ (the maximum number), the odds that he changes the price when faced with $RPC.Inc = 1$ drop by almost 10% to 0.9039. A similar negative moderating effect can be found with $N.New.RPC$: When $N.New.RPC = 1$ (the minimum value), the odds of a price change are almost 1-to-1 in the face of a recommended price increase of \$1. When the salesperson faces $N.New.RPC = 6$ (the average value), the odds of a price change decrease slightly to 0.9866, but when the salesperson faces $N.New.RPC = 101$ (the maximum value), the odds of a price change drop by almost 20% to 0.7971.

We again find partial support for Hypothesis 4 in Stage 2; we find that the marginal effect of $RPC.Inc$ is negatively moderated by $N.Item$ ($RPC.Inc * N.Item = -0.0002$), is increasing in $N.Cust$ ($RPC.Inc * N.Cust = 0.0026$), but is not moderated by $N.New.RPC$ in Stage 2. Given a recommended price increase of \$1, if $N.Item = 1$ (the minimum value), the salesperson passes along \$0.1505. If the salesperson has 268 items (the average number of items managed by a salesperson), then he passes along \$0.0969 (=\$0.1505 − 0.0002 ∗ 268) of a \$1 recommended price increase. Finally, if he has 716 items (the maximum number in our data set), he passes along only \$0.0073 (=\$0.1505 − 0.0002 ∗ 716). Given a recommended price increase of \$1, a salesperson passes along \$0.1531 of a \$1 recommended price increase when $N.Cust = 1$. If the salesperson has 22 customers (the average number of customers held by a salesperson), he passes along \$0.1945 of a \$1 recommended price increase. Finally, if he has 55 customers (the maximum number in our data set), he passes along \$0.2935 of a \$1 recommended price increase. In summary, these associations imply that the odds a salesperson follows the $RPC.Inc$ and changes the price are largest when the salesperson (i) handles a small number of customers, (ii) is presented with few new price recommendations, and (iii) prices or sells a large number of products across the entire customer base.

5. Conclusion

In this paper we empirically analyze the pricing decision of salespeople in a B2B market using a large-scale field database to uncover associations between pricing tool recommendations and pricing decisions. Given the expressed importance of recent past prices on the new price quotes process by salespeople, we propose a reduced-form model to explain *changes* in price over time. We propose a two-stage model of the pricing process, whereby the decision to change the price is made in Stage 1, and then the decision by how much to change the price is modeled in Stage 2. We demonstrate that the two-stage model represents our data much better than a benchmark (single) linear regression model. Once a salesperson decides to make a price change, the salesperson then considers a wider spectrum of factors, including cost-, product-, and customer-related factors, when deciding on the final price. Marketing experts (Mazumdar et al. 2005) have long recognized that consumer choices can be manipulated by providing external reference prices, such as advertisements of the form *original price* \$100, *sale price* \$75. Our results suggest that recommended prices serve as external reference prices; the analyses in §4 suggest that the influence of this external reference price is moderated by the cost, customer, and salesperson environment.

The question of *which* and *how many* price recommendations to pass along to a salesperson for a particular customer naturally follows. The results of our paper serve as a starting point for discussion and further investigation. Our results suggest that a recommended price increase has a stronger association with the decision to change the price (Stage 1) if the underlying costs of the product are relatively stable, the salesperson faces few new price recommendations, the salesperson handles a larger number of products, or the salesperson has a relatively small customer base. We further find that a recommended price increase has a positive association with the final price change (Stage 2) if the product represents a larger expenditure category for the customer, the product has experienced a cost increase, the salesperson has interacted frequently with the customer, or the salesperson has a relatively large customer base. We hope that our results serve as a catalyst for new theoretical investigations of price optimization in the presence of multiple products with a constraint on the total number of new prices (price changes) in any time period.

One of the main limitations of our data is that they are observational in nature. In particular, since the data were provided to us by the GPD, we have no control over what information about the salesperson-customer relationship has been recorded and whether other potentially useful predictors were not collected. Thus, while the omission of important predictors could lead to biases, our holdout analysis shows no sign of such biases. It is also important to note that, because of our limited access to the price optimization software and the nature of the pricing process, we are unable to gauge the "goodness" of the price recommendations. That is, we cannot comment on the degree to which the recommended price would increase/decrease salespeople's sales and profit margins. We believe that, while less than ideal, this is not a limiting factor in the interpretation of our results. We find that the recommended price *does* influence the pricing process and our findings have implications regardless of the informational content in the recommended price. If the recommended price is uninformative and rational salespeople would be wise to ignore it completely, our results show that salespeople are nonetheless influenced by it, paralleling the experimental results of Nunes and Boatwright (2004) on the impact of incidental but irrelevant price information in consumer goods markets. If the recommended price is informative and rational salespeople would be wise to follow its recommendation, our results show that they are influenced by it but do not follow it blindly.

Our work is just a first step in further advancing our understanding of B2B pricing and how to increase the effectiveness of price optimization tools in B2B markets. There are a few limitations to our data set and analysis that should be discussed. We analyze the price change decision for the last recorded transaction for each triplet (salesperson, customer, product). Ideally, further investigations in the area of salespeople's pricing decisions would track the interactions of triplets over time, allowing for a deeper investigation of how the pricing process unfolds over time and if the influence of the recommended price is moderated by time. Furthermore, our data include only successful transactions, that is, when the salesperson was able to make a sale following a customer inquiry. From our discussions with salespeople, we learned that less than 5% of customer inquiries did not result in a successful transaction because of the negotiation process by which the final price is determined as well as the fixed costs of switching to a new supplier in the short term. That said, we hope that our paper serves as a building block for future empirical studies of B2B pricing.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/msom.2015.0537.

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