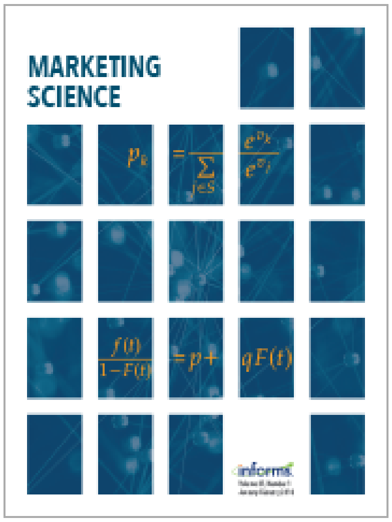

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Practice Prize Winner

A Nested Logit Model of Product and Transaction-Type Choice for Planning Automakers' Pricing and Promotions

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We develop a consumer response model to evaluate and plan pricing and promotions in durable-good markets. We discuss its implementation in the U.S. automotive industry, which "spends" about $45 billion each year in price promotions. The approach is based on a random effects multinomial nested logit model of product (e.g., a vehicle model, such as Hyundai Tucson), and transaction-type choice. Transaction types include combinations of acquisition types (e.g., purchase versus lease) and pricing instruments (cash rebates, reduced APR financing, lease payment discounts). We estimate the model using hierarchical Bayes methods to capture response heterogeneity at the local market level. We find key characteristics unique to durable-good markets. First, consumers are heterogeneous in both their brand and transaction-type preferences. Second, consumers differ in their overall price sensitivity as well as in their relative sensitivity to alternative pricing instruments (e.g., cash discounts, reduced monthly payments). Third, the most effective pricing programs tend to be those in which automakers offer consumers a menu of options to choose from (e.g., a choice among a cash discount, reduced interest rate financing, or a lease payment discount). We illustrate the model through an empirical application to a sample of data drawn from J.D. Power transaction records in the entry SUV segment and discuss examples of actual implementations.

Key words: choice models; nested logit; random coefficients; pricing; promotions; automobiles; hierarchical Bayes
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1. Introduction

Price promotions play an important role in the marketing mix plan of most companies, but especially so for automakers, which collectively spend about $45 billion per year on sales incentives in the U.S. market alone. Several conditions make price promotion decisions particularly vital for the U.S. automobile industry:

(i) Variations in capacity utilization have immediate and substantial effect on car companies' profitability (*The Economist*, September 4, 2004). In addition to the high level of fixed costs of plant and equipment, union contracts put severe restrictions on the closure of plants or reductions of shifts. If production needs to be reduced, idle unionized workers are paid about 95% of their wages.

(ii) Legacy costs (e.g., pensions and other retirement benefits) further constrain management's ability to reduce output for U.S. car manufacturers.

(iii) The incessant growth of "foreign" car manufacturers (e.g., Toyota, Honda, European luxury brands) has been bringing more capacity to the industry.

(iv) The long cycle to design and get into production a new car (typically more than 5 years) and a heavily regulated distribution system limit the available levers to respond to a weakening in demand.

(v) The numerous tools available to customize car pricing (e.g., cash incentives to consumers or dealers, promotional financing with multiple terms, promotional lease rates, lease residual enhancements, etc., and their combinations), with their respective different elasticities, make the task of identifying effective and efficient promotion programs daunting.

To be sure, in the long run, healthy profits and cash flows will depend on bringing to market cars and trucks that consumers would like to buy at prices that return reasonable margins (cf. Pauwels et al. 2004).[1] This is well known by car companies. However, a marketing executive facing a softening in demand cannot wait five years for a new product line to solve the problem. The executive needs to find a pricing or promotion program that will keep sales volume and capacity utilization at profitable levels. The task is daunting. From headquarters, the executive has to decide on the mix of incentives to be used (e.g., consumer rebates, dealer incentives, APR subvention, lease programs) for a wide variety of products (vehicle models) and regional markets. This task is further complicated by the need to evaluate and react to the conflicting information provided by different district managers, each pushing for a greater slice of the promotional budget.

An interesting observation is that well-executed pricing and promotion programs could expand the industry. In fact, industry statistics seem to show that more effective pricing programs in the last five years have helped to keep the industry at a level of 17 million annual unit sales, which a few years ago was considered to be about 2 million units above the sustainable rate of 15 million units. Furthermore, better effectiveness and more thorough planning seems to have helped the industry operate at relatively high and constant levels of capacity utilization.

Following the seminal work of Guadagni and Little (1983), marketing scientists, using widely available scanner data, have developed methods to quantify the impact of price promotions on consumer purchase behavior in frequently purchased consumer packaged goods categories. For example, researchers extended the modeling scope beyond brand choice to include additional behaviors such as category purchase incidence and purchase quantity (e.g., Gupta 1988, Chintagunta 1993, Guadagni and Little 1998) and consumption (Ailawadi and Neslin 1998). These models have been extended to provide decision support tools for promotional planning. Tellis and Zufryden (1995) develop such a tool for a retailer based on a consumer response model that is estimated on scanner panel data.

Researchers have also developed alternative ways of capturing segment-level consumer heterogeneity (e.g., Kamakura and Russell 1989, Bucklin et al. 1998), which Silva-Risso et al. (1999) incorporate into a model to assist manufacturers in planning their promotion calendars. Rossi et al. (1996) suggest that hierarchial Bayes models be used to harness customer purchase histories to design promotional plans targeted to *individual* households, which is implemented in an Internet context by Ansari and Mela (2003).

Marketing research organizations, such as IRI and Nielsen, have implemented models to assist the price promotion decisions of consumer package goods firms (e.g., Abraham and Lodish 1987, 1993; Wittink et al. 1988; Sinha et al. 2005). Researchers have analyzed and discussed these advances in modeling methodology and implementation (e.g., Bucklin and Gupta 1999, Leeflang and Wittink 2000, Hanssens et al. 2005).

In contrast, there has been relatively little work to characterize the price and promotion responsiveness in durable goods markets and particularly in the automobile market. Colombo and Morrison (1989) use a switching matrix to understand cross-competitive effects in the automobile market, but their analysis does not include any elements of the marketing mix. Thompson and Noordewier (1992) included dummy variables in a time-series model to estimate the effects of incentive programs. Unfortunately, their specification does not allow decision makers to plan future promotions or derive insights about how characteristics of each promotion program have driven the results or what the effects of competition might be. More recently, Berry et al. (1995, 2004), Sudhir (2001), Train and Winston (2007), quantify consumer response to price in the automobile market, but their price analyses are limited to MSRP and do not address the multiple instruments that are used for price customization. Bruce et al. (2006) examine the logic of offering consumer rebates by automakers in a context in which consumers face a constraint in their "ability-to-pay" for a durable product (automobiles) with an alternative second-hand market.

This paper builds on the extant literature and offers insights onto the underlying drivers of consumer heterogeneity in preferences for promotion types that are used for price customization for a durable product, such as a car. Differences with respect to frequently purchased products in data, consumer's decisions, and the long interpurchase interval necessitate the use of a specific model structure. First, different from packaged goods, consumers are presented a menu of alternative price promotions to choose from (e.g., cash discounts, reduced interest rate financing, or lease payment discounts). Second, and related to the previous point, consumers also choose how to structure the acquisition (e.g., purchase or lease, and how long to finance). Third, a new car acquisition might involve the trade-in of a used car, which results in additional complexity for pricing. Fourth, except for the information about the product traded in, the transaction data available for modeling do not contain any information about the consumer's previous purchase history. Fifth, with a few exceptions, retailers sell only

[1] Interestingly, in 2001 General Motors built an extensive group tasked with optimizing pricing and incentives and concurrently hired Robert Lutz to revamp its product line (Welch 2001).

one brand, hence product and price comparisons need to be performed across stores. Sixth, automakers are constrained to offer the same pricing and promotional conditions to all their dealers in a local market (i.e., they cannot alternate sales promotions among retailers in a local market).

This research led to several findings that, to the best of our knowledge, have not been documented before. First, we find that in durable-good markets consumers, in addition to be heterogeneous in their brand preferences, they are heterogeneous in their preferences for transaction types. Under transaction types, we include acquisition types (such as purchasing or leasing), promotion types (e.g., cash discount or reduced interest rates), and financing terms.

Second, related to the previous point, consumers are heterogeneous in their relative sensitivity to the different pricing instruments, not just on their overall price sensitivity. This means that beyond their overall pricing sensitivity, some consumers will be more responsive to a cash discount, others to a reduced interest rate, etc. Hence, price discounts of the same magnitude might lead to different effects, according to what instruments are used and the idiosyncratic price sensitivities of the target consumers.

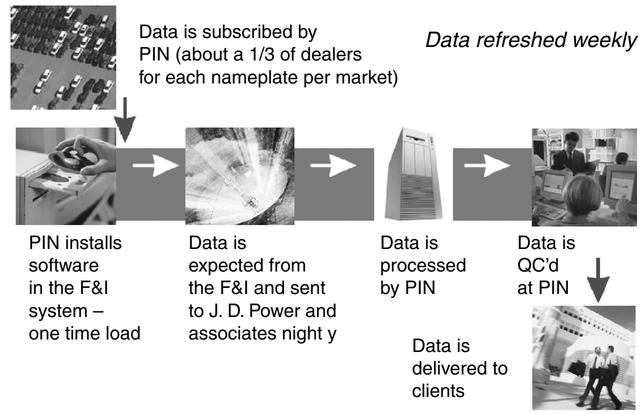
Third, when a manufacturer is constrained to offer a blanket pricing program to a market (as is the case in the automotive industry), then the most effective programs tend to be those that offer a menu of options (e.g., a choice among a cash discount, a reduced interest rate financing, or a lease payment discount) for consumers to choose from. The best combination of pricing instruments and their respective levels depends on the consumers' transaction type preferences and price sensitivities in the target market. Hence, a profit-maximizing manufacturer needs to find the "optimal" structure for its pricing program, not just an overall "optimal" price level.

In the remainder of the paper we proceed as follows. Section 2 provides background information on the Power Information Network (PIN), a division of J.D. Power that collects the data used in our model. Section 3 discusses the modeling objectives and specification. Section 4 discusses an empirical illustration of the model. In §5 we present the results of the estimation and discuss the use of the model to improve current incentive programs. Section 6 provides information about the simulation capabilities that were built to facilitate the planning and evaluation of pricing decisions. In §7 we present an actual example of using the model to improve incentive programs. Section 8 discusses model limitations and topics for future research, and §9 concludes the paper.

2. The Power Information Network

J.D. Power and Associates (now a McGraw-Hill company) founded the Power Information Network (PIN) division in 1993 with the objective of collecting car sales transaction data from a large sample of dealerships representative of the U.S. market. The initial focus was on California (the largest U.S. automobile market). A field operation was deployed to enroll dealers in the PIN system. Using specialized software, each night (after closing operations) participating dealers transmit the daily transactions from their finance and insurance (F&I) system to a J.D. Power and Associates (JDPA) server (Figure 1). In turn, dealers receive access to a web-based reporting portal, which allows them to benchmark their performance with their local market.

Figure 1 Sketch of PIN Data Collection and Delivery System



By the end of 1996, PIN had reached 1,000 dealer franchise points enrolled in California (about 30% of the population). National expansion started in 1997. Markets were targeted in order of their size, and the objective was to recruit about one-third of the dealers of each nameplate in each market (with some adjustments for overrepresentation of the smaller brands). Currently, the PIN sample includes 26 U.S. markets accounting for 70% of total U.S. sales, having about 30% of the total number of dealers of each nameplate in each market (see Figure 2).

PIN captures about 250 details of each transaction (new and used cars) closed by reporting dealers' F&I systems every day. A sample of data elements is presented in Figure 3. Transaction data are augmented with demographics derived from updates of the U.S. Census, through geocoding and linking PIN transactions to census data at the block group level (see more details and tests in Scott Morton et al. 2001, 2003). Details of pricing and promotional programs not captured in sales transactions (e.g., dealer cash, which is money given by the manufacturer to the dealer to incentivize sales) are collected and entered into a database that keeps the history of the multiple promotional programs that are available to consumers and dealers in each market and at any given point in time for all vehicle models in the United States. More

Figure 2 Markets Reporting Sales Transactions to PIN

Source. J.D. Power and Associates.

recently, PIN has added advertising data from third-party providers to the database.

From the recent expansion into Canada, the PIN database has added dealers in Calgary, Edmonton, Montreal, Toronto, and Vancouver. Enrollment efforts in all markets continue.

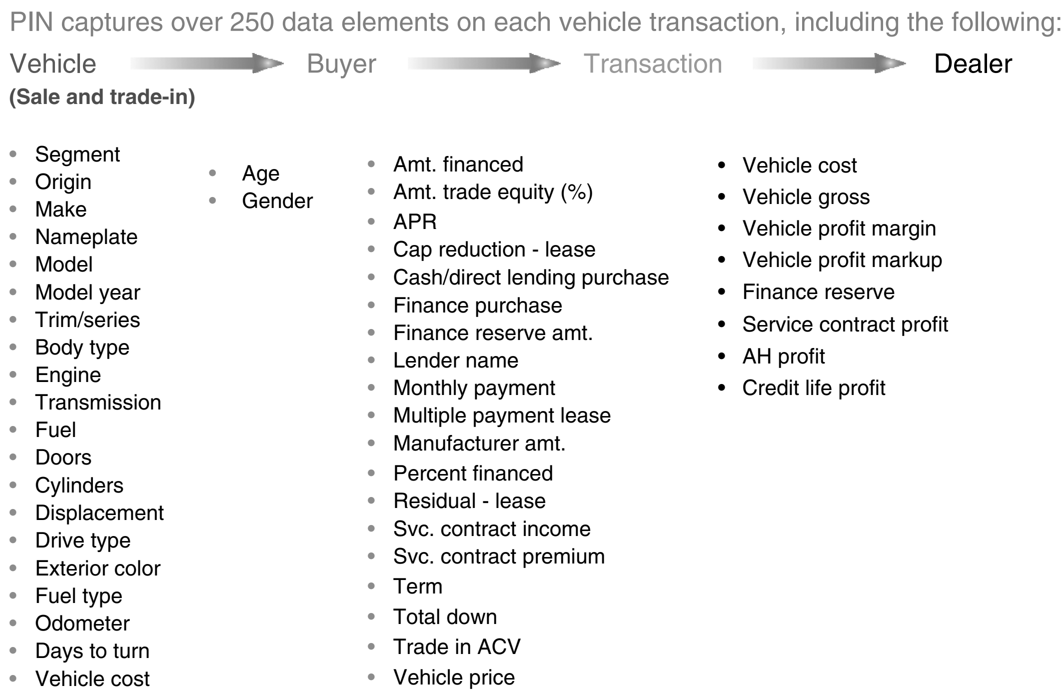
3. Modeling Objective and Specification

Because of increases in worldwide capacity in the automobile industry, by 1999–2000 several car manufacturers (particularly the big three U.S. "domestics") were concerned with sustaining capacity utilization at a profitable level. Indeed, it is believed that concerns about industry-wide overcapacity were an underlying reason that led to the merger of Daimler Benz and Chrysler (Smith 2006). As mentioned before, a drop in capacity utilization could have a dramatic negative effect on automakers' profits.

The long cycle (five years or more) to design, get into production, and launch new products makes it infeasible, in the short term, for automakers to respond to a drop in demand with the introduction of new or redesigned products. In fact, for a horizon of two to three years (time necessary for a redesign), automakers are constrained by the products they have available and need to rely on pricing and promotions to close gaps between supply and demand and keep capacity utilization at profitable levels. Due to the high costs involved in price promotions (about \$45 billion per year industry wide), it is crucial for automakers to be as efficient as possible in those decisions. Note that an increase of 5% in price promotions efficiency would represent more than \$2 billion of savings industry wide in the United States.

Modeling work started in 1998. The ultimate objective was to develop a decision support system that would help automobile manufacturers increase the effectiveness and efficiency of their pricing and other marketing activities. The modeling approach leveraged on the extant literature on response models, but took into account the differences in the data and the product category. The PIN database captures all the transactions recorded at each participating dealer and does not rely on panels that might significantly differ from the overall population (Bucklin and Gupta 1999). However, in contrast to scanner panel data, the long interpurchase times in the automobile industry result in having only one observation per buyer in the

Figure 3 Sample of PIN Automobile Sales Transaction Elements



Source. J.D. Power and Associates.

sample. Instead of having a history of purchases and shopping trips, the only information available about previous consumer purchases is the vehicle the consumer traded in (and that only in the cases when there is a trade-in, about 40%). Thus, for transactions with a trade-in, we capture observed heterogeneity through variables similar to the "last brand" variable used in several CPG scanner panel data models (e.g., Bucklin and Lattin 1991). It should be noted, though, that in the several years since their last car purchase, car buyers are likely to have changed their preferences and needs.

The acquisition of a car involves multiple consumer decisions: the choice of a product (vehicle model, such as Honda Accord), whether to purchase or lease (cf. Dasgupta et al. 2007), and the term of the financing contract (e.g., 36, 48, 60, 72 months). Furthermore, automakers offer a menu of promotional programs (sales incentives) from which the consumer may choose, e.g., customer cash rebates (cash discounts paid by the manufacturer), promotional interest rates (with a schedule for different terms), or lease "support." Some of those programs can be combined (e.g., in some cases automakers offer reduced interest rates in addition to a cash rebate). Consumer response models need to include these decisions and measure the effects of the multiple marketing offerings available to consumers.

Modeling the transaction-type consumer decision is important for several reasons. First, some promotional programs are structured to increase or decrease the penetration of specific types of transactions. For example, a manufacturer might want to increase (or decrease) the proportion of leases. In some cases, the objective is to shorten the financing period and promotional programs target shorter-term contracts (e.g., a substantially lower interest rate for 36 or 48 months compared with 60 months or longer). Second, because promotional programs might affect the penetration of the different types of transactions, a good prediction of those changes is necessary for *cost*[2] and profit estimation.

New-car retailing is different from other product categories in that it is based on a heavily regulated franchise system. Franchised car retailers (dealers) sell just one nameplate (e.g., Buick, Chrysler, Lexus).[3] Furthermore, within the same local market (e.g., DMA), car manufacturers must offer exactly the same pricing and promotional conditions to all their dealers. Additionally, all new car sales or leases have to be processed by a franchised dealer. Automakers are not allowed to sell direct to consumers, discounters, or wholesalers. Hence, we need to take into account that

[2] We consider that referring to price promotions as a "cost" is a misnomer. In fact, price promotions are a tool to customize pricing and increase revenues through price discrimination along consumers' different degrees of price sensitivity (cf. Varian 1980). We use the term "cost" in this article to be consistent with the usage and accounting practices in the automobile industry.

[3] There are a few cases in which dual dealerships are allowed, e.g., for low-share makes or nameplates of the same automaker (e.g., Chrysler and Jeep).

Table 1 Chronology of Model Development Process

Implemented	Modeling objective	Unobserved heterogeneity	References
2000–2001	Multinomial logit model of new car choice	Latent class	Bucklin and Silva-Risso: "Distribution intensity, choice and price: Insights from transaction data for new car sales," 1998 Marketing Science Conference
Ad-hoc projects	Targeted promotions (multinomial logit of new car choice)	Hierarchical Bayes	Siddarth and Silva-Risso: "Developing promotional programs in the automotive industry: A disaggregate hierarchical Bayes model," 2000 Marketing Science Conference
Ad-hoc projects	Finite mixture of multinomial logit models	Latent class	Silva-Risso et al.: "Modeling dynamic interactions between the new and used vehicle markets," 2001 Marketing Science Conference
2002	Nested logit of new car and acquisition-type choice	Random coefficients	Silva-Risso and Ionova: "Modeling promotions effects on consumers' choice of brand and acquisition type for automobiles," 2002 Marketing Science Conference
			Dasgupta et al.: "Lease or buy: An empirical analysis of the choice of payment options in the acquisition of new automobiles," 2002 Marketing Science Conference
			Dasgupta et al. 2007. "Lease or buy? A structural model of a consumer's vehicle and contract choice decisions," Journal of Marketing Research, **44**(August) 490–502.
2003	Regional programs	Hierarchical Bayes	Chang et al.: "Developing regional promotional programs in the automotive industry based on transaction data: A hierarchical Bayes model with regional and zipcode-level response heterogeneity," 2003 Marketing Science Conference and working paper
2003	Program optimization	Hierarchical Bayes	Khavaev et al.: "Optimizing promotion programs in the automotive industry, 2003 Marketing Science Conference
2004–2006	Nested logit of new car and acquisition-type choice with optimization and batch scenario generator (multiple enhancements)	Hierarchical Bayes	This paper

local markets are the finest geographical unit for price customization and that all retail sales should be channeled through franchised dealers.

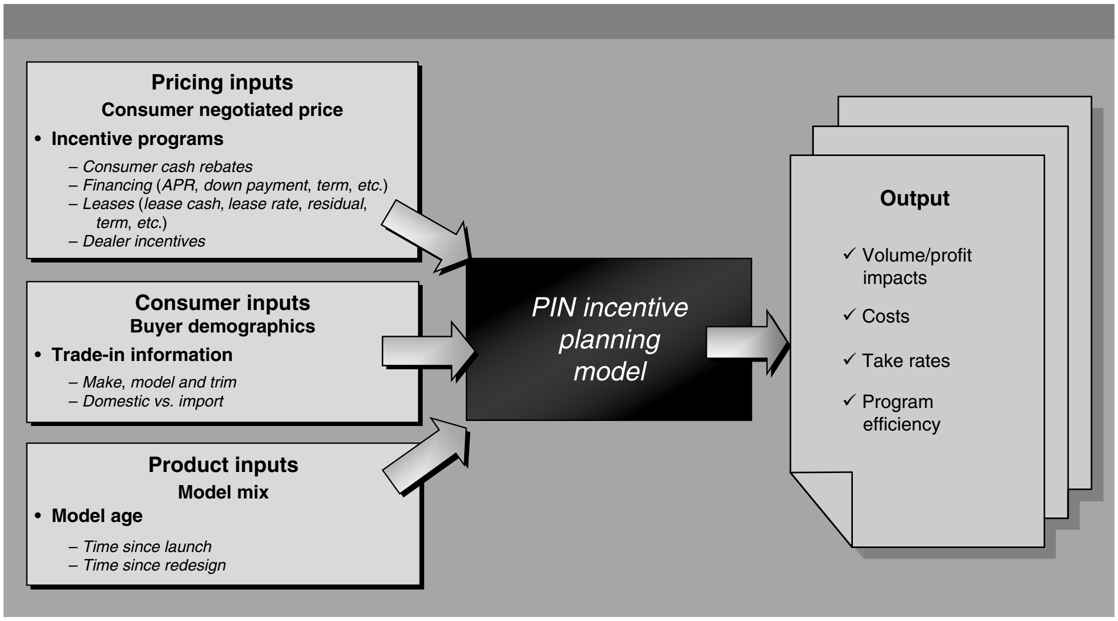
The model development process progressed over multiple years. A chronology is presented in Table 1. In this paper, we describe the specification of the model currently implemented in multiple manufacturers (see sketch in Figure 4). The approach is based on a random-effects multinomial nested logit model of product (vehicle model, such as Hyundai Tucson), acquisition (cash, finance with multiple terms, lease), and program-type choice (e.g., customer cash rebate, promotional APR, cash/promotional APR combination); see the model structure in Figure 5). Geographic location plays an important role in segmenting consumer preferences in the automobile industry. Consumers in California, for example, are more likely than those living in the midwest to purchase Japanese brands. Buyers in rural areas are more likely than those in urban areas to purchase pickup trucks. Furthermore, as mentioned before, the influence of other factors such as state-specific franchise laws, constrain manufacturers to offer same pricing and promotional conditions to all retailers (dealerships) in the same local market (operationalized as Nielsen-designated marketing areas or DMAs). Assessing the price and promotion response of a geographical area is, therefore, an analytically convenient and managerially useful basis on which to develop a promotional planning system.

Our approach to overcoming the lack of purchase histories at the *individual* level is to estimate choice model parameters at a DMA level using a hierarchical Bayes structure. We specify a panel structure (Rossi and Allenby 2003) in which the units of analysis are local markets (DMAs).[4] Car manufacturers typically set promotional programs at the national or regional level and customize those programs for specific local markets (e.g., New York). Region definitions are specific to each manufacturer. However, because regions are a set of local markets, DMA-level coefficients allow us to estimate program effects at the desired level of analysis: local market (DMA), region, and national for all automakers.[5]

[4] Note that this specification does not assume that consumers in a local market are homogenous. First, we capture observed heterogeneity through information of the car traded in and demographics. Second, we capture within-DMA unobserved heterogeneity through the posterior distribution of the DMA response parameters (analogous to estimating DMA-level random coefficients).

[5] Weights are used to project the PIN data sample to the volumes and shares of each DMA, then to project the respective DMAs to the corresponding region shares and volume, and to project regions to the U.S. market, using a procedure similar to the one described by Maddala (1993) for choice-based samples.

Figure 4 **Incentive Planning System Sketch**



Most implementations of the model have been at the national level, in which we structure the prior distribution of the DMA-level parameters to be distributed around an overall national mean. However, in some cases, automakers are interested in focusing in just one or a few regions. In that case, the DMA-level parameters are structured to be distributed around that specific region mean.

The first step in building the choice model is to identify and define proper competitive sets, i.e., sets of products that tend to be included together in consumers' consideration sets. From survey data (e.g., the J.D. Power vehicle shopping study or VSS) we compute conditional probabilities of co-consideration, e.g., P(consider product B | product A is considered). We specify the distance between brands A and B as a function of the inverse of the sum of two conditional probabilities, i.e., $1/[P(B \mid A) + P(A \mid B)]$. With those distances as an input, we use cluster analysis to classify the 250+ vehicle models in the U.S. market into competitive sets. For custom model implementations, competitive sets are determined by using the client's vehicle models as focal products (i.e., cross shopping data are analyzed around those products).[6] Competitive sets typically include about 15 products.

The basic building block of our modeling approach is a nested logit[7] model of automobile and transaction-type choice behavior in which the utility of a particular vehicle is a function of the marketing mix and other transaction-specific variables (Figure 5). In this model, the first stage of the hierarchical Bayes structure, is a nested logit choice model in which the probability that consumer h in DMA m chooses automobile i and transaction-type τ at time t is given by[8]

$$P^h_{tm}(i,\tau) = P^h_{tm}(\tau \mid i) \cdot P^h_{tm}(i), \tag{1}$$

where the probability of choosing transaction type τ, conditional on automobile i at time t, is given by

$$P^h_{tm}(\tau \mid i) = \frac{\exp(U^h_{tm,\,i\tau})}{\sum_{\tau'} \exp(U^h_{tm,\,i\tau'})}, \tag{2}$$

with the utility of transaction type τ given by

$$U^h_{tm,\,i\tau} = \alpha_{m,\,i\tau} + \boldsymbol{\beta}_{m,\,\tau} \mathbf{X}^h_{tm,\,i\tau}, \tag{3}$$

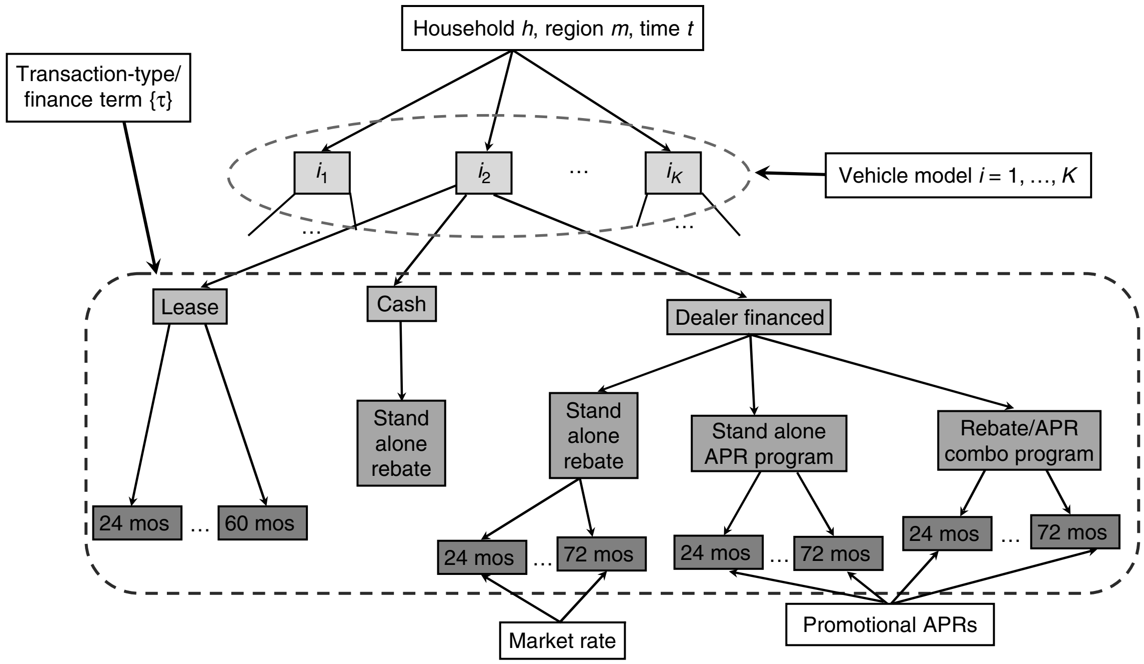
where $\alpha_{m,\,i\tau}$ are transaction-type specific intercepts to be estimated, $\mathbf{X}^h_{tm,\,i\tau}$ is a vector of consumer-specific and marketing variables, and $\boldsymbol{\beta}_{m,\,\tau}$ is a vector of parameters to be estimated.

[6] Typically, a hierarchical clustering algorithm is used, except for custom model applications in which representative products from the client automaker are used as seeds in a k-means clustering algorithm.

[7] Recent examples of the use of nested logit and related models are Ainslie et al. (2005), Cui and Curry (2005), Nair et al. (2005), Sriram et al. (2006), and Yang et al. (2006).

[8] Note that as illustrated in Figure 5, we tested a four-level nested logit (product, acqusition type, program type, term) and a three-level nested logit (product, acquisition/program type, term). However, in the empirical analysis, dissimilarity coefficients (i.e., inclusive value parameters) for financing terms and transaction types resulted not significantly different from 1, and the model reduced to the two-level nested logit illustrated here. Dasgupta et al. (2007) found a similar result. However, in other applications, e.g., at the national level with a larger number of local markets, we have found three- and (in a few cases) four-level structures.

Figure 5 Nested Logit Model Structure



In turn, the probability of choosing automobile i is given by

$$P^h_{tm}(i) = \frac{\exp(V^h_{tm,\,i})}{\sum_k \exp(V^h_{tm,\,k})}, \tag{4}$$

with the utility of automobile i for consumer h, local market (DMA) m at time t given by

$$V^h_{tm,\,i} = \delta_{m,\,i} + \gamma_m \mathbf{Y}^h_{tm,\,i} + \nu_m \ln\left(\sum_{\tau'} \exp(U^h_{tm,\,i\tau'})\right)^9, \tag{5}$$

where $\delta_{m,\,i}$ are product-specific intercepts to be estimated, $\mathbf{Y}^h_{tm,\,i}$ is a vector of consumer-specific and marketing variables, γ_m is a vector of parameters to be estimated, and ν_m is the nested logit dissimilarity coefficient[10] to be estimated.

In the second stage of the hierarchical structure we specify a multivariate normal prior over DMA parameters $\alpha_{m,\,i\tau}$, $\delta_{m,\,i}$, $\beta_{m,\,\tau}$, $\gamma_{m,\,i}$, ν_m:

$$\alpha_{m,\,i\tau}, \delta_{m,\,i}, \beta_{m,\,\tau}, \gamma_m, \nu_m \sim MVN(\mu_n, \Sigma_n), \tag{6}$$

Finally, in the third stage the national mean is assumed to come from a distribution defined by the hyper priors as follows:[11]

$$\boldsymbol{\mu}_n \sim MVN(\boldsymbol{\eta}, \mathbf{C}), \tag{7}$$

$$\Sigma_n^{-1} \sim Wishart((\rho\mathbf{R})^{-1}, \rho). \tag{8}$$

4. Empirical Illustration

We illustrate the modeling approach with an empirical application to entry SUVs (see Table 3) in the western region[12] (Arizona, California, Hawaii, Idaho, Nevada, Oregon, Washington). The PIN database has data from 22 DMAs in the western region (see Table 2). We used 2005 data (January to December) for model estimation. Note that this empirical application does not correspond to any actual client implementation. Confidentiality prevents us from publishing details of actually implemented models. However, this illustration is realistic in that it follows the current model methodology used in the implemented models.

[9] For simplicity we omitted the error terms. The multinomial nested logit assumes generalized extreme-value distribution for the error structure (McFadden 1978; Maddala 1993, p. 70), i.e., that the error terms in each nest are correlated (Train 2003, p. 83).

[10] The dissimilarity parameter is the coefficient of the inclusive value: $\ln(\sum_{\tau'} \exp(U^h_{tm,\,i\tau'}))$. The inclusive value represents the overall attractiveness of the corresponding lower nest, expressed as the natural log of the denominator of the corresponding multinomial logit in Equation (2). McFadden (1978) showed that the dissimilarity coefficient is approximately equal to 1 minus the pairwise correlation between the error terms of the alternatives in that node, which in this case are the transaction-type utilities in Equation (3). Hence, the value of the dissimilarity coefficient should be in the $[0, 1]$ range. Values outside the $[0, 1]$ range are indicative of model misspecification. A value of $\nu_m = 1$ indicates complete independence, and the nested logit reduces to the standard multinomial logit (Train 2003).

[11] Given this hierarchical set-up, the posterior distributions for all unknown parameters can be obtained using either Gibbs or Metropolis-Hastings steps. ρ, $\boldsymbol{\eta}$, $\mathbf{R}$, and $\mathbf{C}$ are set to be the number of parameters plus one, $\mathbf{0}$ (null matrix), $\mathbf{I}$ (identity matrix), and $\mathbf{I} * 1{,}000$, respectively, which represents a fairly diffuse prior yet proper posterior distribution.

[12] This "western" region is for illustrative purpose only and does not correspond to any actual specific automaker region definition.

Table 2 Number of Observations by DMA

DMA	Transaction count
San Francisco-Oak-San Jose	4,083
Portland, OR	3,221
Fresno-Visalia	290
Tucson(Nogales)	1,724
Santabarbra-Sanmar-Sanluob	331
Palm Springs	199
Yuma-El Centro	18
Phoenix	5,103
Sacramnto-Stkton-Modesto	4,051
Chico-Redding	70
Los Angeles	12,614
San Diego	2,563
Bakersfield	570
Bend, OR	34
Seattle-Tacoma	3,503
Monterey-Salinas	226
Honolulu	559
Las Vegas	2,863
Spokane	171
Boise	157
Reno	217
Medford-Klamath Falls	178
Total Observations	42,745

Data Description

The main data source is new car sales transactions collected by the Power Information Network, a division of J.D. Power and Associates. PIN collects sales transaction data from a sample of dealerships in the major metropolitan areas in the United States. These are retail transactions, i.e., sales or leases to final consumers, excluding fleet sales.[13] Each observation in the PIN database contains the transaction date, the manufacturer, model year, make, model, trim and other vehicle information, the transaction price, consumer rebates, the interest rate, term, amount financed (when the vehicle is financed or leased), etc.

We complemented sales transactions with a database containing full details of promotional programs (incentives) offered by automakers compiled by J.D. Power. For example, this database contains details of the term structure of promotional APRs (e.g., 1.9% for 24 months, 2.9% for 36 months, 3.9% for 48 months, and 4.9% for 60 months), several types of dealer and customer cash programs (e.g., loyalty, captive, conquest),[14] etc. Demographic data are also augmented with updated census data by linking PIN transactions with census data at the block group level (see Scott Morton et al. 2001 for more details).

Table 3 Entry SUVs Included in Model

Vehicle model	Share
Chevrolet Equinox	0.099
Ford Escape	0.125
Honda CR-V	0.114
Honda Element	0.043
Hyundai Santa Fe	0.051
Hyundai Tucson	0.046
Jeep Liberty	0.126
Jeep Wrangler	0.060
Kia Sorento	0.036
Kia Sportage	0.022
Mazda Tribute	0.028
Mercury Mariner	0.026
Nissan Xterra	0.055
Saturn VUE	0.070
Subaru Forester	0.041
Suzuki Grand Vitara	0.007
Toyota RAV4	0.053

Transaction Types

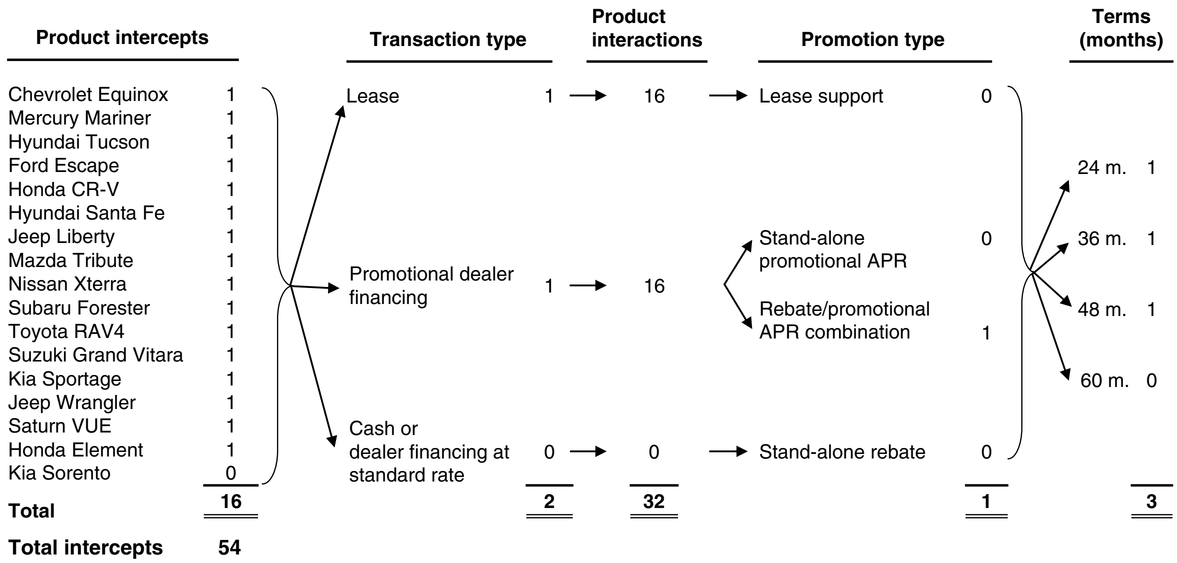
Car transactions are, typically, classified in three categories: (a) cash, which are those transactions in which the consumer purchased the vehicle, but did not arrange financing through the dealer; (b) finance, if the consumer buys a car and finances it through the dealer; and (c) lease, if the consumer contracts a lease instead of purchasing the car. For price promotion planning and budgeting we need to estimate the proportion of consumers who take each type of promotion. Hence, these three basic transaction types need to be expanded to also reflect the specific type of promotion the consumer opted for (Figure 5).

Three basic types of price promotions (incentives) offered by manufacturers to consumers are customer cash rebates, reduced interest rate finance programs, and lease promotions. Those programs are commonly offered as alternatives that cannot be combined. For example, an automaker might offer consumers the option of taking $2,000 in customer cash rebate or promotional financing with rates of 0.9%, 1.9%, 2.9%, and 3.9% for 24, 36, 48, and 60 months, or a reduction of $30 in monthly lease payments. It should be noted that the consumer can choose to take the customer cash (rebate) and finance the transaction through the dealer at market rates. That consumer executes a finance transaction (at the market rate), but instead of taking a financing incentive takes customer cash. Another consumer who decides to take the 1.9% APR and finance at 36 months results in a finance transaction as well, but in this case the consumer opted for the promotional APR (finance) program.

[13] A major source of fleet sales is vehicles sold to rental car companies, which are often affiliated with or owned by a car manufacturer. Hence, fleet sales are frequently "managed" by automakers to partially offset supply-demand gaps. Using total sales, which include fleet sales, as is done by Berry et al. (1995, 2004), Sudhir (2001) would bias response parameter estimates.

[14] Loyalty cash is a rebate available to owners of the same nameplate (e.g., Jeep); captive cash is a rebate available to consumers who finance or lease through the financial "captive" arm (e.g., DaimlerChrysler Financial Services); conquest cash is a rebate available to consumers who own (or trade in) a specific competitor nameplate or vehicle model (e.g., Dodge Ram might offer a rebate to consumers who trade in a Ford F-150).

Table 4 **Empirical Illustration—Intercept Structure**



Additionally, automakers also offer combinations of customer cash and promotional APRs, and they might do so while offering stand-alone (not combinable) rebates and promotional APRs.[15] For instance, a promotional program could include the option of taking a \$2,000 rebate, or a stand-alone APR program of 0.9% (36 months), 1.9% (60 months); or a combination of \$1,000 rebate, and a 3.9% (36 months), 4.9% (60 months); or a monthly lease payment discount of \$25. To accommodate these offerings, we need to expand each financing term into three alternatives: stand-alone customer cash and financing at market rate, stand-alone promotional APR (no rebate), or a combination of both (see Figure 5). There are other types of programs, such as loyalty cash and captive cash (to promote business for the automaker's financing arm),[16] but all of them can be addressed with this expanded set of transaction types.

Intercepts

Product- and transaction-type intercepts should be defined carefully to recover product shares and shares of the different types of transactions and promotions. Note that transaction-type shares vary from brand to brand. The resulting set of intercepts that accommodates all these needs is composed of (see Table 4):

1. Brand (product) intercepts: number of products—1; in this case 16 intercepts.
2. Transaction-type-specific intercepts for promotional dealer financing and lease: 2 intercepts. We chose to set to 0 the cash transaction type together with transactions in which the consumer takes the stand-alone rebate and still finances through the dealer at market rate. We define these as *stand-alone rebate transactions*.[17]
3. A brand specific (all brands but one) for promotional finance transactions (to recover shares of promotional financing by brand): 16 intercepts.
4. A brand specific (all brands but one) for lease transactions (to recover lease penetration by brand): 16 intercepts.[18]
5. A common (across brands and terms) intercept denoting a combination of rebate and promotional financing.
6. Term-specific (common across brands) intercepts for all terms but one. If the terms available are 24, 36, 48, 60 months, then we need to have 3 intercepts (e.g., 24, 36, 48 months) and set to 0 the intercept for 60 months: 3 intercepts.

This structure results in a total of 54 intercepts to estimate (see Table 4).

Model Variables

A description of the variables used to calibrate the model follows:

$LMODEL^h_{mi} = 1$ if consumer h trades in the same vehicle model i (e.g., Liberty), 0 otherwise.

[15] In this case, the cash rebate amount of the combined promotion is usually lower than the stand-alone rebate, and the promotional APRs are, term by term, higher than the respective stand-alone promotional APRs.

[16] Captive cash is money offered by the automaker's captive financing arm (e.g., Chrysler Financial, GMAC, Ford Credit) to consumers who finance or lease through the "captive." In this case, all dealer transactions financed through the captive, whether at a promotional APR or at market rate, count toward the objective of increasing the captive penetration of the financing market.

[17] Another intercept could be added, if desired, to classify separately rebate cash and finance (market rate) transactions.

[18] Leases could also be classified into multiple terms. In this data set the dominant majority of the lease transactions were at 36 months.

$LMAKE^h_{mi} = 1$ if consumer h trades in the same make as i (e.g., Jeep), 0 otherwise.

$LOGPRICE_{mt,i}$ = natural log of consumer price for vehicle model i in week t in DMA m, adjusted for product configuration variations, trade-in valuation, supply effects, trade promotions (see Appendix A)

$LOGREBATE_{mt,i\tau}$ = natural log of consumer rebate (customer cash) offered by manufacturer of vehicle model i in week t, in DMA m, and transaction type τ (there could be different amounts of customer cash offered, e.g., stand-alone and combination with APR)

$LOGMPMTFIN60_{mt,i\tau}$ = natural log of synthetic monthly payment for vehicle model i in week t, in DMA m, and transaction type τ for 60 months financing loans (there could be different monthly payments for different transaction types, e.g., market rate, stand-alone APR program, rebate/APR combination program). See Appendix B for details in the computation of synthetic monthly payments for loan financing.

$LOGMPMTFIN48_{mt,i\tau}$ = similar to the previous case for 48 months

$LOGMPMTFIN36_{mt,i\tau}$ = similarly for 36 months

$LOGMPMTFIN24_{mt,i\tau}$ = similarly for 24 months

$DLRCASHFLAG_{mt,i\tau} = 1$ if dealer cash (manufacturer to dealer promotion) is available in DMA m, at week t, for brand i, and transaction τ.

This variable captures the effect in dealer selling effort when there is a manufacturer reward per unit of sale. The additional effect of dealer cash is captured through a price reduction (see Appendix A)

$LOGMPMTLEASE_{mt,i}$ = natural log of synthetic lease monthly payment for vehicle model i in week t, in DMA m, for a 36 month lease[19] See Appendix C for details in the computation of synthetic monthly payments for lease transactions.

$INCLUSIVEVALUE^h_{mt,i}$ = The nested logit inclusive value for vehicle model i in week t, in DMA m, for consumer h, i.e., $\ln(\sum_{\tau'} \exp(U^h_{tm,i\tau'}))$

Demographic variables (e.g., consumer age, gender, household income) are introduced as interactions with the products. For a detailed structure of the random utility specification for each branch of the nested logit with the corresponding parameters, see Appendix D.

5. Estimation Results

Plots of parameter estimates are presented in Figure 6. The plots show that the model behaved well in that the mean of the posterior distribution of the parameters have the expected sign, and very rarely there is a sign change within a 95% interval. The plots also reveal substantial differences in response parameters across local markets.

[19] In this empirical application most lease transactions were contracted at 36 months. In other segments that might not be the case, and the model includes the relevant terms.

Simulations

For illustration purposes, we used the model to improve the promotional offerings as of the beginning of May 2006. Ideally, we should seek an increase in profits (defined as the product of volume times the corresponding contribution margin). However, because manufacturing variable costs and margins are not publicly available, we focused on searching for pricing programs that would deliver a similar volume at a lower cost per unit, more volume at a similar cost, or both a higher volume at a lower cost. In this case, cost represents the price discount offered by the automaker through a specific menu of incentives.[20]

Kia Sorrento is the vehicle model in this set that is spending the highest amount in price promotions, about $3,600. Sorrento was offering consumers a choice among $3,000 in customer cash, or a promotional APR of 3.9% through 60 months, or a lease program with $1,500 in lease cash and a lease rate of 1.08%. Additionally, Sorrento offered $700 in dealer incentives, $500 in loyalty cash, and $1,000 in captive cash (promotional money applied when a consumer finances through the financing captive arm).

The cost of the finance promotions is computed by discounting the cash flows (i.e., monthly payments) at the market rate (at the time of the transaction) and subtracting that net present value from the amount financed (see Equation (B1)). A similar procedure is followed to compute the cost of lease promotions. The average cost per unit (in this case $3,600) is the result of the weighted average of the cost of all transaction types (see Figure 5).

We built a market simulator based on the sample of consumers used for calibration. We updated the environment (i.e., the pricing and incentive programs for all products and markets) to reflect market conditions in May 2006. Then we created a set of scenarios, in which Kia Sorrento would change the incentive offerings.[21] Drawing from the posterior distributions of the response parameters we obtained distributions for the expected share and program cost (price discount) for Kia Sorrento. We used the means of the resulting distributions (share and cost) to evaluate

[20] Because the cost (effective average price discount) of an incentive program depends on the proportion of consumers who will choose each component of the program (e.g., cash rebates, reduced interest rate, lease), the effective cost is not known a priori. We need to estimate the impact on sales (or share) and the cost for each program using the model.

[21] These scenarios were created by modifying the levels of the components of the incentives offered by Kia Sorrento and searching for *better* programs in a trial-and-error mode. In the next section we describe more advanced simulation capabilities that allow users to automate this task. For simplicity, we kept the pricing and incentives offered by competitors fixed at the May 2006 levels. However, competitive programs could be modified simultaneously with the target product (in this case, Kia Sorrento).

Figure 6 Sample of Model Estimates

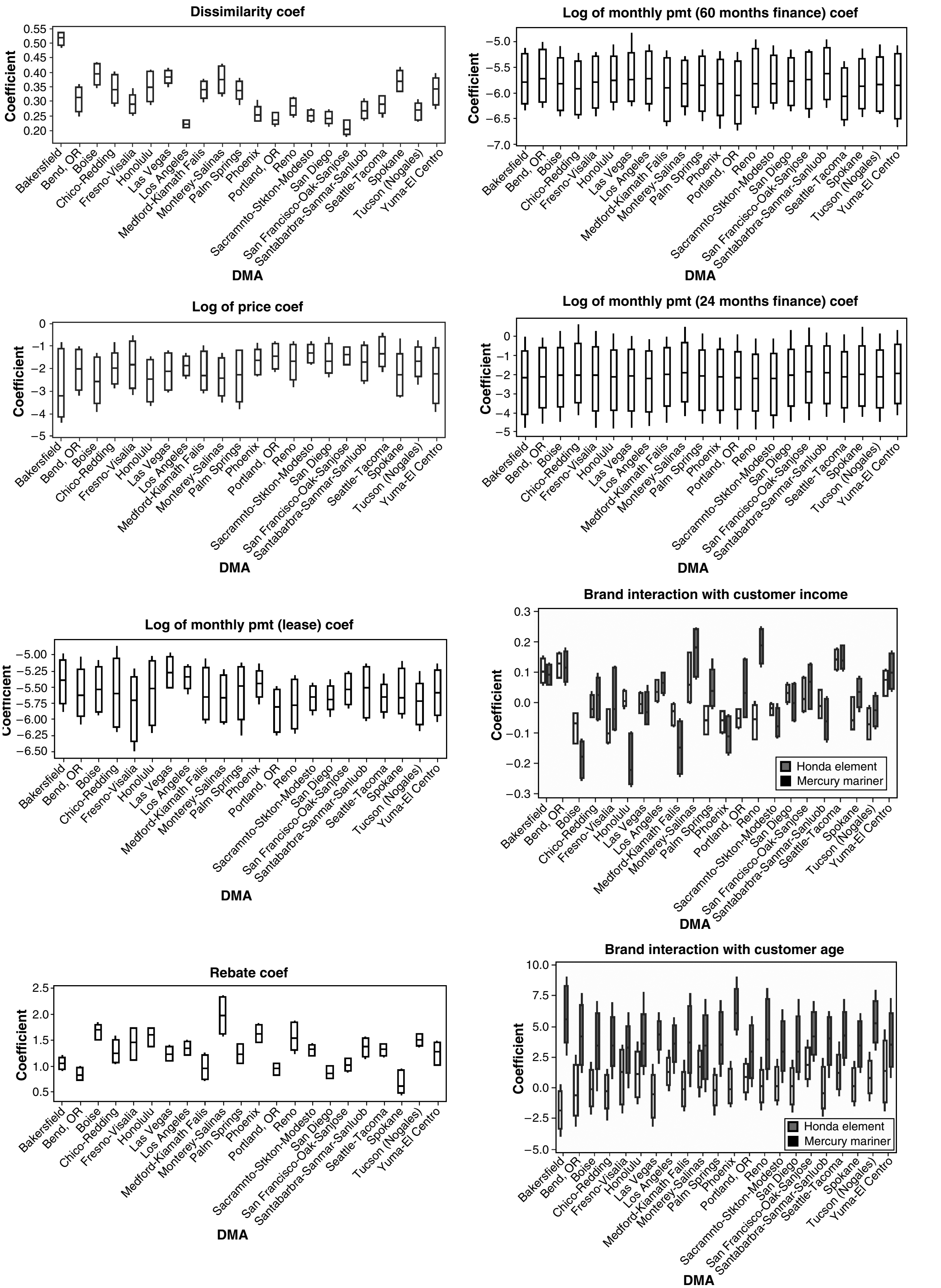
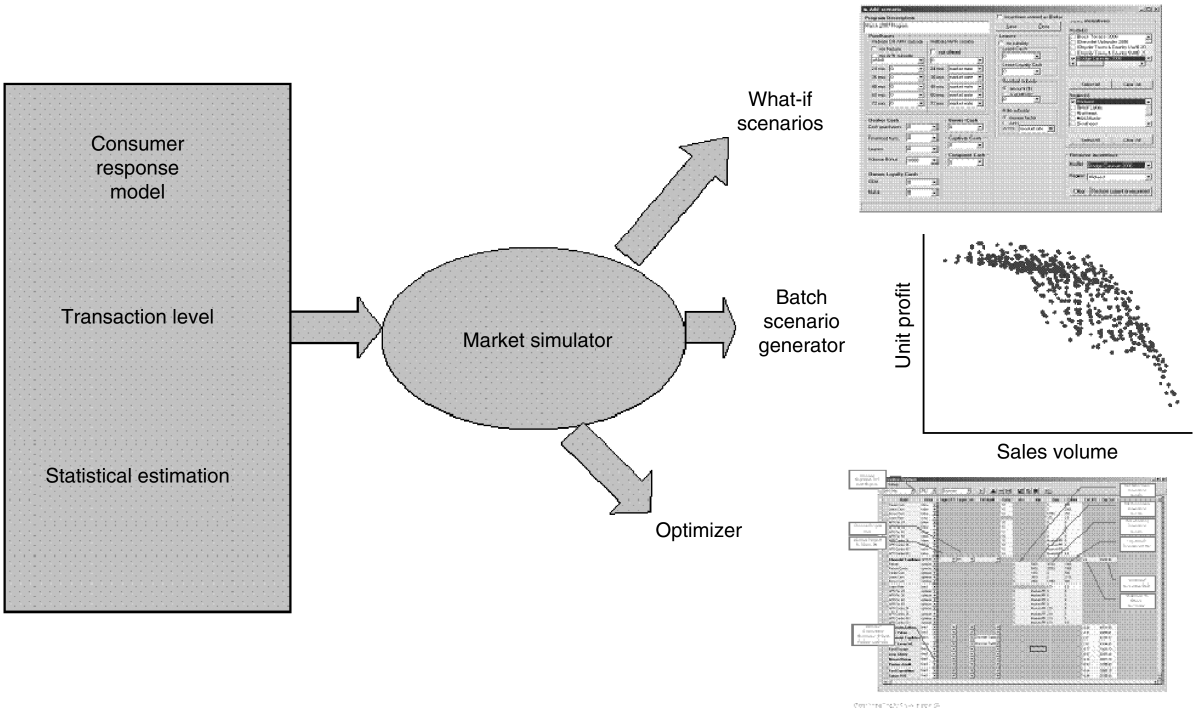


Figure 7 Model Simulation Capabilities



programs. For example, increasing customer cash to \$3,500, while lowering the APRs to 0.9% (36 months), 1.9% (48 months), 2.9% (60 months); adding a combination of \$2,500 customer cash and a 1.9% (36 months), 2.9% (60 months) APR program, lowering lease cash to \$1,250; and discontinuing \$700 in dealer cash, would result in an increase of sales of 2.9% with a reduction in unit cost of \$278. We also found programs that would increase sales by 6% for the same cost, or that would keep sales at the same volume with savings greater than \$300 per unit.

6. Implemented Simulation Capabilities

On the basis of the consumer response models (described in §4), we also developed additional capabilities to improve the efficiency and ease of use of the system (see Figure 7 for a sketch of the system).

Market Simulator with What-If Scenario Capabilities

This capability consists of an interface that allows users to generate several scenarios for their and competitive products along the lines explained in the previous section. Through this interface, decision makers analyze how to respond to a competitor, how to improve current programs, how to plan the pricing and promotion schedule that would achieve the next quarter's goals efficiently, etc. Typically, at the beginning of each month analysts produce and document market outcome predictions on the basis of the marketing offerings of the target product and its key competitors. These predictions are compared with actual market outcomes at the end of the month. This exercise is similar to the one we illustrated in the previous section for Kia Sorrento.

Batch Scenario Generator

The batch scenario generator automates the generation of scenarios and the respective simulations. The user enters ranges and increments for each incentive type (e.g., customer cash from \$0 to \$3,000 increasing by \$250; stand-alone 36 month APR from 1.9% to 4.9% increasing by 0.5%). Additionally, the user can specify assumptions about competition (e.g., no reaction, fully or partially matching increases of the target product, etc.). Furthermore, the user can specify several rules for the scenario generation, e.g., APR for longer terms should not be lower than APRs for shorter terms, etc.

With those inputs, the system generates an input table with all the scenarios to be analyzed and sends them sequentially to the market simulator engine. For speed and decision timing, the user could specify that the scenarios would be simulated "plugging in" posterior means of the response parameters instead of drawing from the posterior distribution. Rossi et al. (1996) and Rossi and Allenby (2003) point that the "plug-in" approach could result in "overconfident" strategies. However, the time needed to simulate a massive number of scenarios drawing from the parameters posterior distributions might exceed the time allotted to make a timely decision. The potential problems induced by the use of point estimates are alleviated by a second-step analysis of a few candidate strategies. For each of those promising incentive programs, the decision maker analyzes a set of neighbor programs using the full decision-theoretic approach. In most cases, this two-step approach has shown to lead to effective decisions.

The system automatically produces a table with results along the dimensions chosen by the user. The primary outputs from the system are *lift* and *cost*. Those outputs are ported to user-specific templates that make the conversions to other dimensions, e.g., *profit* and *net price*.[22] Finally, the system plots the scenarios along the chosen dimensions to identify the efficient frontier. As mentioned before, there are multiple alternatives to structure an incentive program that could result in a similar *cost* (or price discount or net price), but those different structures might result in a wide range of incremental volume (or profits). The efficient frontier analysis helps identify the most promising programs along the chosen dimensions (e.g., the most profitable program for a given net price, the least costly program for a market share objective, etc.).

Incentive Optimizer

The third simulation capability is an optimization module (Ionova et al. 2003). We chose to use the Nelder-Mead method for the optimization problem. It has the advantage over gradient-based methods of not requiring derivatives, which in this case should be numerical and when optimizing over a large number of dimensions (e.g., more than 50) become computationally expensive. Another alternative, sampling-based methods, such as genetic algorithms and simulated annealing, are significantly slower, especially in this case in which we have a shallow global optimum with a lot of ripples and flat directions.

This system allows the user to search for optimal programs given a set of objectives, constraints, and assumptions about competitive reaction. For example, maximizing profit subject to a sales volume constraint, or maximizing sales volume subject to a profit or cost constraint, etc. Competitive reaction could be specified as no reaction, fully or partially matching the increase in incentives offered by the target brand, or a simultaneous optimization problem for all or a set of competitors. In the current specification, the optimization algorithm uses as input the posterior means of the response parameters, i.e., point estimates, instead of the full posterior distribution. For that reason, the solutions are tested through the two-step approach described in the discussion of the batch scenario generator.

[22] Profit margins and manufacturing variable costs at the product level are not available to the public.

7. Implementation Example

Next we present an actual example of the use of the model. Automaker and product name are masked to preserve client confidentiality.

Mid-Size Domestic SUV—Improving Efficiency

In January 2006, a change on incentive programs was recommended to automaker X to move mid-size SUV Y to the efficient frontier.

In Figure 8, we show the efficient frontier for the MY2006 mid-size SUV Y indicating the position of the price promotion program being offered at the beginning of January 2006 and the proposed program (along the cost per unit and unit volume dimensions). The estimated impact was a reduction in incentive cost (i.e., a lower price discount) without a decrease in sales volume. The economic effect was estimated in an efficiency gain of $4.6 million per month (see Table 5).

To understand the logic of the results, first let us take a look at the comparative structure of the promotional program at the beginning of January 2006 and the proposed program in Table 5. The two programs are similar, except that the proposed program offers a much lower promotional APR for financed purchases instead of the $1,000 in captive cash. Captive cash is an additional cash bonus offered to consumers for financing or leasing through the automaker's financing arm. As such, consumers who take the cash rebate and finance through the captive at the market standard rate, as well as consumers who take the promotional APR or lease program, qualify for the $1,000 captive cash.

The lower financing interest rates in the proposed program result in a greater discount (net present value) of about $2,400. Thus, after accounting for the elimination of the captive cash, APR transactions enjoyed a net enhancement of $1,400, while the promotional money for rebate and lease transactions got reduced by $1,000 (by the elimination of captive cash). In sum, the efficiency gains hinge in reducing promotional money from rebate and lease transaction by $1,400 while enhancing promotional APR transactions by about $1,400. Note that the 84% penetration of captive cash results from the 40% of consumers who lease, the 11% of consumers who take the promotional APR program, and 33%[23] of consumers who take the rebate and finance at the dealer through the automaker's financing arm (captive).

[23] Note that of the 49% of consumers who prefer to take the rebate of $2,500 at the beginning of January 2006, 33% also finance through the captive and qualify for the additional $1,000 captive cash. The remaining 16%, either pay out of their pockets or finance through other financing institutions (e.g., a credit union).

Figure 8 Mid Size Domestic SUV—Incentive Change/Volume Relationship

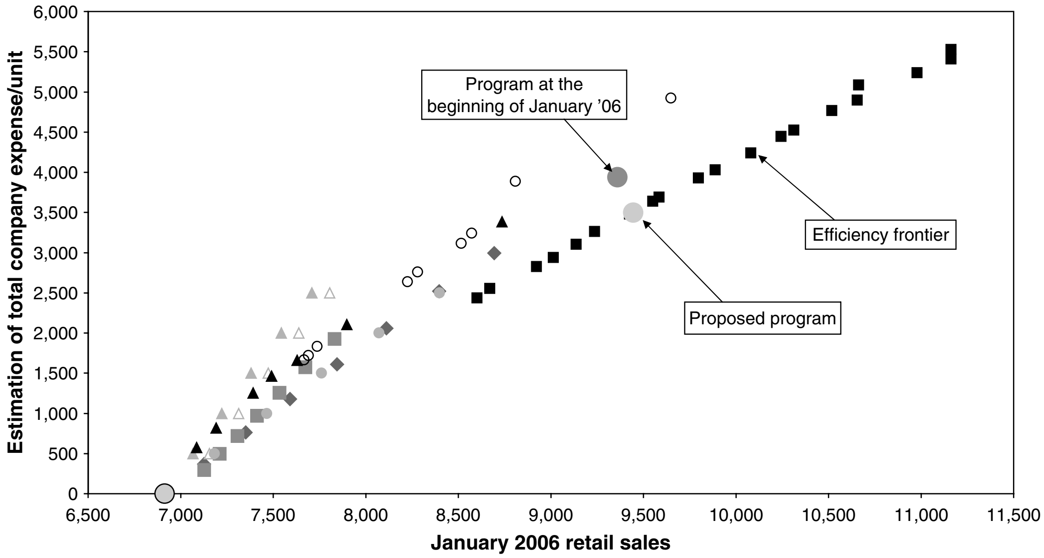


Table 5 Mid Size Domestic SUV—Effects of Proposed Incentive Program (1/06)

Program structure

	Beginning of January '06	Proposed
Customer cash rebate	$2,500	$2,500
APR up to 60 months	4.90%	0.00%
APR 72 months	*Market rate*	2.90%
Lease cash	$2,500	$2,500
Lease APR 36 month	3.74%	3.74%
Lease loyalty cash	$1,000	$1,000
Captive cash	$1,000	$0

Cost structure

	Beginning of January '06		Proposed	
	Penetration (%)	Cost per affected unit ($)	Penetration (%)	Cost per affected unit ($)
Customer cash rebate	49	2,500	38	2,500
Promotional finance rate	**11**	**1,509**	**29**	**3,927**
Captive cash	**84**	**1,000**	**0**	**0**
Lease cash	40	2,500	33	2,500
Promotional lease rate	40	1,499	33	1,499
Lease loyalty cash	11	1,000	9	1,000

	Beginning of January '06	Proposed
Average cost per unit	**$3,937**	**$3,498**
Estimated retail sales (1/06)	**9,360**	**9,445**
Estimated savings per unit		$439
Estimated incremental sales		85
Estimated cost savings		$4,147,452
Estimated margin from incremental units		$459,000
Total efficiency gains (1/06)		**$4,606,452**

In spite of a reduction in the effective price discount of $1,000, due to their relative preferences for transaction types, enough consumers were expected to stay with the rebate[24] and lease programs to make the average cost of the proposed program lower than the program at the beginning of January 2006. These effects are captured by the transaction type intercepts (idiosyncratic preference for a specific transaction type) together with the respective response parameters. The computation of the estimated efficiency gains are presented in the lower panel of Table 5.

8. Discussion and Limitations

In this section, we discuss model potential limitations and topics for future research.

Endogeneity Bias

Working (1927) shows how in a simultaneous system in which demand and supply are function of price, when quantity is regressed on price, we are not estimating either supply or demand (Hayashi 2000). Price is endogenous (i.e., correlated to the error term) in both equations. Within this framework, Villas-Boas and Winer (1999) analyze endogeneity bias in the context of brand choice models. One problem they mention is that prices and purchases are determined simultaneously based on market conditions that are not observable to the researcher (p. 1324). A similar argument is posed by Sudhir (2001), but in the context of a structural analysis of the automobile industry.

However, for reasons explained before, production decisions in the automotive industry are not as flexible as in other industries. Based on an expectation of a demand level at certain price point, automakers build capacity several months before product launch and tend to keep the plants producing at a set level. Hence, over a period of time that could be several months, supply is fixed. If inventories begin piling up, automakers might offer factory-to-dealer promotions (dealer cash) or consumer incentives to increase sales. This specific industry behavior attenuates the potential endogeneity bias. Furthermore, there are observable variables, such as the number of days vehicles stay in dealer lots (or days to turn), that we can use to capture this phenomenon (see Appendix A, Equation 11).

Under the assumption of fixed supply, a variation in inventory levels (which will result in variations of days to turn) captures demand shocks and, hence, would lessen the problem of endogeneity bias.

[24] This result is consistent with the finding of Bruce et al. (2006) about rebates being used to enhance the ability to pay, particularly for consumers who have negative equity in the car they are trading in.

Having said that, we acknowledge that we have only a partial solution to this problem, and future research should explore how to integrate a more formal approach to endogeneity bias into our model.

Purchase Acceleration

Our model focuses on the product and transaction-type consumer decisions, i.e., *what* and *how*. We do not model the effects of pricing and promotion on the timing of consumer purchases, i.e., *when*. In this section we discuss the repercussions of this limitation on the model estimates.

An early conceptualization and analysis of purchase acceleration is Neslin et al. (1985). Later on, the advent of household shopping trip data in CPG scanner panels facilitated the development and diffusion of choice and incidence models. In a 1987 working paper, Guadagni and Little proposed to model the *what* and *when* consumer decisions as a nested logit (see Guadagni and Little 1998), where the brand choice decision was multinomial logit conditional on buying in the category (incidence). The authors modeled the purchase in the category (incidence) decision as a binary logit of *whether* or not to buy in the category given a household shopping trip. The nested logit inclusive value is an indicator of the overall category value for that household at the time of the shopping trip. Guadagni and Little's working paper spurred a rich stream of research that extended their framework in various directions.[25] In an analysis of automobile incentives, Thompson and Noordewier (1992) find evidence of purchase acceleration effects induced by rebates.

The question is how our choice model (what and how) estimates may be affected by not including in the model the purchase incidence decision. Several researchers (e.g., Amemiya 1978, Maddala 1983, Ben-Akiva and Lerman 1985) showed that the sequential estimation of a nested logit results in consistent, though inefficient, estimates. In other words, the parameter estimates in the first step (i.e., the choice model) are not biased by the omission of the incidence model.[26]

Our observation over several years of implementing this model is that the model tends to underpredict market outcomes at the beginning of a promotional

[25] See comments toward the end of Gudadgni and Little (1998).

[26] Sun et al. (2003) found that a stand-alone multinomial logit choice model overstates switching elasticities, which in turn would overstate incremental sales. However, the authors include a LAST-BRAND as a state variable in their model, but, ignore all the previous history. Bucklin and Gupta (1991) and several other articles show that not including the previous purchase history (e.g., with a BRANDLOYALTY variable) results in missing observed brand preference heterogeneity. The omission of a BRANDLOYALTY from their model at least partially explains Sun et al. (2003) results.

program and overpredict toward the end of the program. Hence, if the analysis is done over a period long enough (in most cases about 2 to 3 months), we observe the acceleration and post-promotion dip cancelling each other, resulting in an incremental volume consistent with model estimates.[27]

To be sure, modeling purchase acceleration is important. A better understanding of timing effects would result in better planning in the channel. In particular, it will help to plan for inventory levels and assortment at the dealership in anticipation of the acceleration peak, as well as to avoid overstocking during the post-promotion trough. Extending our model to include purchase acceleration should be a priority of future research.

Dynamic Effects and Policy Changes
If consumers are forward looking, then current consumer decisions will not only depend on current prices and promotions, but also on expected prices and promotions (Keane 1997).[28] Ignoring dynamic effects could lead to several biases in model estimates. For example, Erdem et al. (2003) find that the long-term price elasticites from a dynamic model are more than twice the magnitude of short-run cross-price elasticities. Sun et al. (2003) find that the most important shortcoming of models that do not take into account dynamic effects, such as consumer forward looking, is when they have to make predictions after a policy change (cf. Lucas 1976).

We acknowledge this limitation of our model. Data limitations (no purchase histories, no shopping trips), together with the complexity of a model that needs to capture in very fine detail all the aspects of pricing and price promotions, have precluded (for the time being) the inclusion of dynamic effects. However, we have taken active steps to alleviate this potential shortcoming. First, the implemented models are recalibrated on a quarterly schedule using a moving window of 12 months. Second, there is a process to compare predictions with market outcomes for most of the pricing and promotion programs in the market place. Significant deviations are reported and analyzed. Third, this shortcoming has been communicated to users of the model so that they are aware about potential problems in model estimates when there is a policy change from that firm or its major competitors.

[27] Note that approaches such as Abraham and Lodish (1987, 1993) tend to overestimate incremental sales, because they measure differences between actual market outcomes with respect to a baseline. Their approach measures effects only during promotional weeks. Hence, the part of the dip that occurs after the promotional period is not taken into account. In contrast, our approach focuses on measuring effects on choice probabilities only.

[28] A recent example of a dynamic model in the context of the decision to product launch and exit is Hitsch (2006).

Market Expansion
Our model focuses on share effects and does not include market expansion. To be sure, new car sales jumped from an average of 15 million units, from 1995 to 1998, to an average of 17 million units since 2000. Berry et al. (1995, 2004) and Sudhir (2001) include an outside good to account for market expansion/contraction. This is a promissory path to explore for a future extension of our model.

We are aware of this limitation. Our focus has been on the estimation of brand market share and within brand transaction-type shares. These modeling capabilities were not available in the automotive industry a few years ago. In contrast, automakers usually have expert teams on the estimation of industry overall and by industry segment (e.g., minivans, mid-size SUVs, etc.). Those capabilities in terms of macroeconomic models are also available at consulting firms, such as J.D. Power. Our model typically is coupled with a macroeconomic industry and segment forecast to convert share estimates into sales volumes.

We consider this a pragmatic approach, while we extend the model to include market expansion.

Structural Models
As mentioned before, we have included procedures to alleviate the potential endogeneity bias. A theory-based approach would lead to a formulation of a structural model of supply and demand (e.g., Sudhir 2001, Yang et al. 2003). However, the procedures detailed in Appendix A, together with quarterly model calibrations and monthly review of predictions, prevent any significant deviation go undetected.

The additional complexity that would be added by a structural model specification is not trivial, particularly for a model as complex in details as ours. Furthermore, structural models tend to involve assumptions that are difficult to test and constrain elasticities (Chintagunta et al. 2006). This could be problematic if these models are used for pricing. For example, Berry et al. (2004) need to plug in a value for the industry elasticity in order to be able to derive secondary demand and cross elasticities and other parameters (see Table 8, p. 94). Still, we acknowledge this limitation, and future research should focus on this topic.

Spatial Effects
By estimating parameters at the local market level, our model captures geographical heterogeneity. However, we have not modeled spatial effects, such as correlation among neighboring markets or markets that have similarities in other dimensions. Extending the model to capture those spatial effects could make the model more robust and also provide the means to design specific pricing programs for markets for which we do no have data (e.g., Bronnenberg and Sismeiro 2002).

New and Used Market Interactions
In addition to competing with other brands in the new market, new cars compete with used cars of the same and other brands (Silva-Risso et al. 2001, Bruce et al. 2006). This interaction affects prices in both directions. For example, price promotions in the new market tend to depress used car prices. At the same time a large inflow of used market (e.g., through lease returns) result in lower prices in the used market, which in turn drives down new car prices. These interactions are not trivial to model, because the effects are not just within the brand or within the industry segment. For example, luxury brands tend to position pre-owned cars as an alternative to new mass-market cars (e.g., a pre-owned Lexus E-300 might compete with new Toyota Camry and Honda Accord). Reflecting these interactions and supply shocks is a topic for future research.

9. Concluding Remarks
This paper documents the development and implementation of a consumer response model to evaluate and plan pricing and promotions in the automotive market. The PIN Incentive Planning System, as this model is known, is based on a multinomial nested logit model of car and transaction-type choice. The system is currently being used by most major automobile manufacturers. It has been credited to help save hundred of millions of dollars to several automakers.

We found that consumers are heterogeneous in their preferences for products as well transaction types, which might be a characteristic unique to durable-good markets. Interestingly, consumers differ in their overall price sensitivity as well in their relative sensitivities to specific pricing instruments (e.g., cash discounts, reduced interest financing, reduced lease payments). This phenomenon results in some consumers being more responsive to cash discounts, while other consumers are more responsive to low interest financing, and so on. Hence, automakers find it more effective to offer a menu of alternative incentives for consumers to choose from (e.g., a choice among cash discount, reduced interest financing, discounted lease payments, etc.) The specific levels at which each pricing instrument (or incentive) should be offered depends on the specific combination of consumer preferences and relative sensitivities in a given market, as well as product categories, channel effects, etc. The search for efficient pricing programs is not trivial, and this is a core competency that this model has brought to the automotive industry.

We should note some limitations from our work. Our model focuses only on choice effects and does not capture the peaks and troughs driven by consumers accelerating or postponing their decisions (not necessarily affecting choice). Even though, incremental sales are driven by choice effects, it is also relevant to capture the up and down waves driven from consumer time decisions for proper planning in the channel.[29] A priority for future research should be to extend the model to include purchase acceleration.

Other important areas for future research are to extend the model to capture industry expansion effects, as well as integrating supply and demand in a structural model.

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Appendix A. LOGPRICE Variable
The operationalization of the price variable needs to take into account several factors. First, cars are not homogenous products. A vehicle model, e.g., Honda Accord, might offer multiple body types (sedan, coupe), engines (4 and 6 cylinders), interior trims (leather or fabric seats), and a myriad of different accessories. Some of those characteristics can be accounted for (Scott Morton et al. 2001), but many still are not part of the information contained in VINs (vehicle identification numbers). Even if automakers' production data were available with full details for each car, we will miss information on product differences because several accessories are installed at the dealership. Hence, we need to tease out and remove the effect of product variation on prices in order to avoid a confound between product and true price variation.

Second, car prices are negotiated (Busse et al. 2006, Zettelmeyer et al. 2006). For a specific point in time and a specific market, we need to have all market environment variables (e.g., prices, incentives) to properly reflect the underlying market conditions the consumer is facing when making a decision. In CPG scanner panel models for all shopping trips of a household, we know the prices and in-store promotions available at the store the household is shopping. Furthermore, because grocery stores sell multiple brands in a category we have data for the brand the household bought and the competitor brands in that category on the same date of the shopping trip and in the specific store the consumer is shopping. Additionally, prices are not negotiable at grocery stores and stores. In contrast, car prices are negotiable and dealerships sell just one brand (nameplate).

[29] Additionally, making predictions for peaks and troughs explicit and linked to purchase acceleration would help prevent a misleading read of outcomes (e.g., if a purchase acceleration peak is interpreted as a higher incremental volume than true).

Each transaction contains only data about the price the consumer negotiated for the chosen product. Prices for the other products in the competitive set need to be derived from other transactions. Moreover, if we use the actual negotiated price for the purchased car and other transactions for the other alternatives, we will bias the price variable in favor or against the alternative chosen, depending on how skillfully the consumer is in negotiating prices. In sum, we need to use a set of transactions around the time the consumer made the car purchase (and from the same market) to construct a vector of prices (for all alternatives) that reflects the pricing environment that consumer faced when he made the purchase.

Third, supply conditions affect prices (Zettelmeyer et al. 2006). The Power Information Network data does not contain inventory data, but there is a field with information of the number of days the vehicle stayed at the dealer lot before being sold. We use this field (days to turn, or DTT) as a proxy for supply conditions. Vehicles that are in over-supply tend to have high DTT values, while vehicles that are scarce tend to be sold shortly after they arrive at the dealership.

Fourth, transactions with a trade-in are adjusted for over- and under-valuation of the car the consumer is traded in. The PIN database collects both how much the dealer paid to the consumer and the actual cash value at which the car traded in was booked by the dealership. Overallowance (i.e., when the consumer is paid above the actual cash value) is subtracted from the transaction price. Underallowance (i.e., when the consumer is paid below the actual cash value) is added to the transaction price (see Scott Morton et al. 2001, Busse et al. 2006 for more details).

Fifth, trade promotions (typically referred to as dealer cash) are partially passed through to the consumer, resulting in a price reduction (Busse et al. 2006). Furthermore, the pass-through rate of dealer cash is likely to be affected by supply conditions. Dealers are likely to pass through more of the trade promotion when facing over-supply of a product. Conversely, dealers might pass through less of the trade promotion when there is under-supply of a product.

We incorporate these effects through the following regression:

$$\begin{aligned} PRICE_{mti} = {} & \beta_1 \times VEHICLECOST_{mti} + \beta_2 \times DTT_{mti} \\ & + \beta_3 \times DLRCASH_{mti} + \beta_4 \times DLRCASH_{mti} \\ & \times DTT_{mti} + \mu_i + \nu_{mt} + \varepsilon_{mti}, \end{aligned} \tag{A1}$$

where

$PRICE_{mti}$ = transaction price adjusted by trade-in over (under) allowance for a specific transaction of vehicle model i in week t in DMA m;

$VEHICLECOST_{mti}$ = vehicle cost to the dealer for the same specific transaction of vehicle model i in week t in DMA m;

DTT_{mti} = number of days the vehicle sold stayed at the dealer lot for vehicle model i in week t in DMA m;

$DLRCASH_{mti}$ = trade promotion (dealer cash) available to the dealer for vehicle model i in week t in DMA m;

μ_i = vehicle model fixed effects;

ν_{mt} = local market (DMA) by week fixed effects;

ε_{mti} = regression error term, assumed to be i.i.d.

$\beta_1, \beta_2, \beta_3, \beta_4$ = parameters to be estimated.

This regression is estimated at the transaction level. The subscripts m, t, i indicate the corresponding fixed effects. β_1 captures dealer mark up, β_2 captures supply effects, and β_3, β_4 capture the dealer cash pass-through rate as a function of supply levels operationalized by DTT_{mti}.

We estimate (A1) by OLS. Then, for each DMA, week and vehicle model we build the variable as

$$LOGPRICE_{mti} = LOG\left(\begin{array}{l} \hat{\beta}_1 \times \overline{VEHICLECOST}_i + \hat{\beta}_2 \times \overline{DTT}_{mti} \\ + \hat{\beta}_3 \times DLRCASH_{mti} + \hat{\beta}_4 \times DLRCASH_{mti} \\ \times \overline{DTT}_{mti} + \hat{\mu}_i + \hat{\nu}_{mt} \end{array}\right), \tag{A2}$$

where

$\overline{VEHICLECOST}_i$ = median vehicle cost to dealers across all transactions of vehicle i during the calibration period;

$\overline{DTT}_{mti}$ = median number of days that vehicle models i sold in week t, in market m, stayed at dealers;

$\hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3, \hat{\beta}_4, \hat{\mu}_i, \hat{\nu}_{mt}$ = estimated coefficients and fixed effects.

The use of $\overline{VEHICLECOST}_i$ removes the noise induced by product variations on prices. $\overline{DTT}_{mti}$ is used as an instrument to account for supply shocks. We used weeks as the temporal unit of analysis. Finer temporal units, such as days, will result in noisy estimates due to small sample issues. We defined weeks as going from Wednesday to Tuesday because pricing programs tend to end on a Monday or Tuesday (particularly on holiday weekends).

Appendix B. Synthetic Monthly Payment for Financing Loans

The synthetic monthly payment for financing loans is computed as a function of the interest rate available to the consumer in the following way:

$$MPMT = AMTFIN \frac{r/12}{1/(1+r/12)^T - 1}, \tag{B1}$$

where

$AMTFIN$ is the amount financed computed as function of the price level,

r is the annual interest rate,

T is the term of the loan (in months).

The effect of promotional APRs is captured through their impact in monthly payments.

Appendix C. Synthetic Monthly Payment for Lease Transactions

The synthetic monthly payment for lease transactions is computed as a function of the lease rate, depreciation, and residual applicable to the consumer in the following way:

$$\begin{aligned} MPMTLEASE = {} & \frac{CAPCOST + RESIDUAL}{2} \times \frac{r}{12} \\ & + \frac{CAPCOST - RESIDUAL}{T}, \end{aligned} \tag{C1}$$

where

$CAPCOST$ is the capitalized cost computed as function of the price level and the drive-off payment, *RESIDUAL* is the value stated in the lease contract the consumer would have to pay to keep the car at the expiration of the lease,

r is the annual interest rate,

T is the term of the lease (in months).

The effect of lease promotions is captured through the effects of lease rates, residual enhancements, or lease cash (CAPCOST reduction) on monthly lease payments.

Appendix D. Empirical Illustration Detailed Structure of Nested Logit Random Utility Equations (3) and (5)

The random utility of each branch of the nested logit will include the applicable variables at the corresponding value. In the upper node (product choice), the alternatives are the set products, and the random utility includes the corresponding product intercept, product-consumer demographic interactions, $LMODEL^h_{mi}$ and $LMAKE^h_{mi}$, the respective inclusive value $\ln(\sum_{\tau'} \exp(U^h_{tm,\,i\tau'}))$, and the corresponding parameters to be estimated. Hence, the detailed expression of Equation (5) results in

$$V^h_{tm,\,i} = \delta_{m,\,i} + \gamma_{LMODEL_m} LMODEL^h_{mi} + \gamma_{LMAKE_m} LMAKE^h_{mi} + \gamma_{DEMOG_m} DEMOG^h_t + \nu_m \ln\left(\sum_{\tau'} \exp(U^h_{tm,\,i\tau'})\right). \tag{D1}$$

In the lower node (transaction-type choice conditional on product choice), the alternatives are the different transaction types. For example, the random utility of a purchase financed by the dealer at 60 months with a stand-alone manufacturer customer rebate will include the corresponding intercepts (see Table 4), $LOGPRICE_{mt,\,i}$, $LOGREBATE_{mt,\,i\tau}$, $LOGMPMTFIN60_{mt,\,i\tau}$ computed at the prevailing standard rate for the consumer's credit score at point in time t in DMA m and the corresponding parameters to be estimated. Instead, the random utility of a purchase financed by the dealer at 48 months with a stand-alone promotional APR includes the corresponding intercepts, $LOGPRICE_{mt,\,i}$, $LOGMPMTFIN48_{mt,\,i\tau}$ computed at the reduced APR for 48 months corresponding to the consumer's credit tier at point in time t in DMA m and the corresponding parameters to be estimated.[30]

The random utility of a purchase financed by the dealer at 36 months with a combination of rebate and promotional APR includes the corresponding intercepts, $LOGPRICE_{mt,\,i}$, $LOGREBATE_{mt,\,i\tau}$ at the corresponding value for the combination program (which is typically lower than the stand-alone rebate), $LOGMPMTFIN36_{mt,i\tau}$ computed at the reduced APR for 36 months for the combination program, which is typically higher than the stand-alone promotional APR corresponding to the consumer's credit tier at point in time t in DMA m and the corresponding parameters to be estimated.

Furthermore, the random utility of a lease transactions includes $LOGPRICE_{mt,\,i}$, $LOGMPMTLEASE_{mt,\,i}$ computed at the lease rate for the consumer's credit tier at point in time t in DMA m and the corresponding parameters to be estimated.[31]

See details in Table D.1.

[30] Note that there is not a term for *LOGREBATE* in this branch.

[31] Note that there is not a term for *LOGREBATE* in this branch.

Table D.1. Empirical Illustration—Detailed Formulation of Equation (3)

Transaction type	Program type	Term (months)	Intercepts: Transaction type	Intercepts: Product interaction	Intercepts: Promotion type	Intercepts: Term	Response parameter 1	Marketing variable 1	Response parameter 2	Marketing variable 2	Response parameter 3	Marketing variable 3	Response parameter 4	Marketing variable 4	
Lease	Lease support	36	α_{LEASE_m}	$+\,\delta_{LEASE,\,i_m}$			$+\,\beta_{LOGPRICE_m}$	$\times\, LOGPRICE_{mt,\,i}$	$+\,\beta_{DLRCASHFLAG_m}$	$\times\, DLRCASHFLAG_{mt,\,i\tau}$	$+\,\beta_{LOGMPMTLEASE_m}$	$\times\, LOGMPMTLEASE_{mt,\,i}$			(1)
Cash	Stand-alone rebate						$\beta_{LOGPRICE_m}$	$\times\, LOGPRICE_{mt,\,i}$	$+\,\beta_{DLRCASHFLAG_m}$	$\times\, DLRCASHFLAG_{mt,\,i\tau}$	$+\,\beta_{LOGREBATE_m}$	$\times\, LOGREBATE_{mt,\,i\tau}$			(2)
Dealer financed purchase	Stand-alone rebate	24				φ_{24_m}	$+\,\beta_{LOGPRICE_m}$	$\times\, LOGPRICE_{mt,\,i}$	$+\,\beta_{DLRCASHFLAG_m}$	$\times\, DLRCASHFLAG_{mt,\,i\tau}$	$+\,\beta_{LOGREBATE_m}$	$\times\, LOGREBATE_{mt,\,i\tau}$	$+\,\beta_{LOGMPMT24_m}$	$\times\, LOGMPMTFIN24_{mt,\,i\tau}$	(3)
		36				φ_{36_m}	$+\,\beta_{LOGPRICE_m}$	$\times\, LOGPRICE_{mt,\,i}$	$+\,\beta_{DLRCASHFLAG_m}$	$\times\, DLRCASHFLAG_{mt,\,i\tau}$	$+\,\beta_{LOGREBATE_m}$	$\times\, LOGREBATE_{mt,\,i\tau}$	$+\,\beta_{LOGMPMT36_m}$	$\times\, LOGMPMTFIN36_{mt,\,i\tau}$	(3)
		48				φ_{48_m}	$+\,\beta_{LOGPRICE_m}$	$\times\, LOGPRICE_{mt,\,i}$	$+\,\beta_{DLRCASHFLAG_m}$	$\times\, DLRCASHFLAG_{mt,\,i\tau}$	$+\,\beta_{LOGREBATE_m}$	$\times\, LOGREBATE_{mt,\,i\tau}$	$+\,\beta_{LOGMPMT48_m}$	$\times\, LOGMPMTFIN48_{mt,\,i\tau}$	(3)
		60					$\beta_{LOGPRICE_m}$	$\times\, LOGPRICE_{mt,\,i}$	$+\,\beta_{DLRCASHFLAG_m}$	$\times\, DLRCASHFLAG_{mt,\,i\tau}$	$+\,\beta_{LOGREBATE_m}$	$\times\, LOGREBATE_{mt,\,i\tau}$	$+\,\beta_{LOGMPMT60_m}$	$\times\, LOGMPMTFIN60_{mt,\,i\tau}$	(3)
	Stand-alone reduced APR	24	$U^h_{tm,\,i_\tau} =$ $\alpha_{PROMO\ APR_m}$	$+\,\alpha_{PROMO\ APR,\,i_m}$		$+\,\varphi_{24_m}$	$+\,\beta_{LOGPRICE_m}$	$\times\, LOGPRICE_{mt,\,i}$	$+\,\beta_{DLRCASHFLAG_m}$	$\times\, DLRCASHFLAG_{mt,\,i\tau}$	$+\,\beta_{LOGMPMT24_m}$	$\times\, LOGMPMTFIN24_{mt,\,i\tau}$			(4)
		36	$\alpha_{PROMO\ APR_m}$	$+\,\alpha_{PROMO\ APR,\,i_m}$		$+\,\varphi_{36_m}$	$+\,\beta_{LOGPRICE_m}$	$\times\, LOGPRICE_{mt,\,i}$	$+\,\beta_{DLRCASHFLAG_m}$	$\times\, DLRCASHFLAG_{mt,\,i\tau}$	$+\,\beta_{LOGMPMT36_m}$	$\times\, LOGMPMTFIN36_{mt,\,i\tau}$			(4)
		48	$\alpha_{PROMO\ APR_m}$	$+\,\alpha_{PROMO\ APR,\,i_m}$		$+\,\varphi_{48_m}$	$+\,\beta_{LOGPRICE_m}$	$\times\, LOGPRICE_{mt,\,i}$	$+\,\beta_{DLRCASHFLAG_m}$	$\times\, DLRCASHFLAG_{mt,\,i\tau}$	$+\,\beta_{LOGMPMT48_m}$	$\times\, LOGMPMTFIN48_{mt,\,i\tau}$			(4)
		60	$\alpha_{PROMO\ APR_m}$	$+\,\alpha_{PROMO\ APR,\,i_m}$			$+\,\beta_{LOGPRICE_m}$	$\times\, LOGPRICE_{mt,\,i}$	$+\,\beta_{DLRCASHFLAG_m}$	$\times\, DLRCASHFLAG_{mt,\,i\tau}$	$+\,\beta_{LOGMPMT60_m}$	$\times\, LOGMPMTFIN60_{mt,\,i\tau}$			(4)
	Rebate/APR combination program	24	$\alpha_{PROMO\ APR_m}$	$+\,\alpha_{PROMO\ APR,\,i_m}$	$+\,\alpha_{REBATE/APR\ COMBO}$	$+\,\varphi_{24_m}$	$+\,\beta_{LOGPRICE_m}$	$\times\, LOGPRICE_{mt,\,i}$	$+\,\beta_{DLRCASHFLAG_m}$	$\times\, DLRCASHFLAG_{mt,\,i\tau}$	$+\,\beta_{LOGREBATE_m}$	$\times\, LOGREBATE_{mt,\,i\tau}$	$+\,\beta_{LOGMPMT24_m}$	$\times\, LOGMPMTFIN24_{mt,\,i\tau}$	(5)
		36	$\alpha_{PROMO\ APR_m}$	$+\,\alpha_{PROMO\ APR,\,i_m}$	$+\,\alpha_{REBATE/APR\ COMBO}$	$+\,\varphi_{36_m}$	$+\,\beta_{LOGPRICE_m}$	$\times\, LOGPRICE_{mt,\,i}$	$+\,\beta_{DLRCASHFLAG_m}$	$\times\, DLRCASHFLAG_{mt,\,i\tau}$	$+\,\beta_{LOGREBATE_m}$	$\times\, LOGREBATE_{mt,\,i\tau}$	$+\,\beta_{LOGMPMT36_m}$	$\times\, LOGMPMTFIN36_{mt,\,i\tau}$	(5)
		48	$\alpha_{PROMO\ APR_m}$	$+\,\alpha_{PROMO\ APR,\,i_m}$	$+\,\alpha_{REBATE/APR\ COMBO}$	$+\,\varphi_{48_m}$	$+\,\beta_{LOGPRICE_m}$	$\times\, LOGPRICE_{mt,\,i}$	$+\,\beta_{DLRCASHFLAG_m}$	$\times\, DLRCASHFLAG_{mt,\,i\tau}$	$+\,\beta_{LOGREBATE_m}$	$\times\, LOGREBATE_{mt,\,i\tau}$	$+\,\beta_{LOGMPMT48_m}$	$\times\, LOGMPMTFIN48_{mt,\,i\tau}$	(5)
		60	$\alpha_{PROMO\ APR_m}$	$+\,\alpha_{PROMO\ APR,\,i_m}$	$+\,\alpha_{REBATE/APR\ COMBO}$		$+\,\beta_{LOGPRICE_m}$	$\times\, LOGPRICE_{mt,\,i}$	$+\,\beta_{DLRCASHFLAG_m}$	$\times\, DLRCASHFLAG_{mt,\,i\tau}$	$+\,\beta_{LOGREBATE_m}$	$\times\, LOGREBATE_{mt,\,i\tau}$	$+\,\beta_{LOGMPMT60_m}$	$\times\, LOGMPMTFIN60_{mt,\,i\tau}$	(5)

Notes. (1) The product category in the empirical illustration does not have a high lease penetration and most lease transactions are contracted at 36 months.
(2) Rebate value at stand-alone manufacturer customer rebate offered
(3) Rebate value at stand-alone manufacturer customer rebate offered. APR at market standard interest rates (nonpromotional).
(4) APR at reduced (promotional) interest rates for stand-alone APR programs.
(5) Rebate and APR at values offered for the rebate and APR combination program. Typically, this rebate is lower and these APRs are higher than those in stand-alone programs.

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