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# Chrysler and J. D. Power: Pioneering Scientific Price Customization in the Automobile Industry

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Pricing is a critical component in the marketing-mix plans of automobile manufacturers. Because they tend to keep their manufacturer's suggested retail prices (MSRPs) and wholesale prices fixed throughout the model year, they customize pricing to reflect supply and demand by using incentives; in the US market, they represent approximately \$45 billion per year. In addition, variations in capacity utilization have immediate and substantial effects on profitability. This, together with legacy costs and inflexible labor contracts, makes the effectiveness and efficiency of price-customization decisions particularly vital for the industry.

Chrysler, a pioneer in using science in its pricing decisions, engaged J. D. Power and Associates (JDPA) to implement an incentive planning model. The approach used is based on a random-effects multinomial nested logit model of product (vehicle model), acquisition (cash, finance, lease), and program-type (e.g., consumer cash rebates, reduced interest-rate financing, cash/reduced interest-rate combinations, lease-support) selection. The model uses sales transaction data that are collected daily from approximately 10,000 dealerships. It uses a hierarchical Bayes modeling structure to capture response heterogeneity at the local market level. This specification allows users to apply the model to pricing decisions at the local, regional, and national market levels.

Based on implementing this model, Chrysler learned that, for any given price level, the pricing structure (e.g., a combination of retail price, interest rates, or rebates) is important. The set of the most efficient pricing structures for each price level constitutes an *efficient frontier*; efficient pricing structures vary across products, price levels, and markets. The system provides three alternative approaches to identify efficient (and effective) pricing programs: (a) what-if-scenario simulations, (b) a batch scenario generator that allows users to identify and examine the profit-share/volume efficient frontier, and (c) an optimizer that, given an objective and a set of constraints, allows users to search for incentive programs rapidly. The Chrysler Corporate Economics Office estimates that Chrysler's annual savings from implementing the model are approximately \$500 million.

*Key words:* choice models; nested logit; random coefficients; promotions; automobiles; hierarchical Bayes.

Pricing is a critical component in the marketing-mix plans of automobile manufacturers. Because these companies tend to keep their manufacturer's suggested retail prices (MSRPs) and wholesale prices

fixed throughout the year, they customize pricing to reflect supply and demand by using incentives, which, in the US market, represent approximately \$45 billion per year. Several conditions make

price-customization decisions critical in this industry:

(1) Variations in capacity utilization have immediate and substantial effects on profitability (*The Economist* 2004). In addition to the high fixed costs of plant and equipment, union contracts place severe restrictions on plant closures or shift reductions. Idle unionized workers must be paid approximately 95 percent of their wages.

(2) Legacy costs (e.g., retirement benefits) constrain management's ability to reduce output.

(3) The growth of non-US auto manufacturers (e.g., Toyota and Honda) has increased industry capacity.

(4) The long new-car design and production cycle (typically more than five years) and a heavily regulated distribution system limit the capability to respond to weakening demand.

(5) The numerous tools available to customize auto pricing (e.g., cash incentives to consumers or dealers, reduced interest-rate financing, and reduced lease rates) and their respective elasticities make the task of identifying effective and efficient pricing programs daunting.

Healthy profits and cash flows depend on bringing to market cars and trucks that consumers want—at prices that return reasonable margins (Pauwels et al. 2004). However, a marketing executive who is facing a softening demand cannot wait five years for a new product line and must develop pricing or promotion programs to keep sales volume and capacity utilization at profitable levels. That executive must determine a mix of incentives for many products and regional markets, and, in addition, must evaluate the conflicting information provided by regional managers, each pushing for a greater share of the promotional budget.

Marketing research organizations, e.g., IRI and Nielsen, have implemented models to assist consumer package goods firms in making price-promotion decisions (Abraham and Lodish 1987, 1993; Wittink et al. 1988; Sinha et al. 2005). Silva-Risso et al. (1999) developed a simulated annealing procedure to extend those models to the optimization of promotion calendars. Researchers have analyzed and discussed these models and their implementations (Bucklin and Gupta 1999, Leeflang and Wittink 2000, Hanssens et al. 2005). In contrast, relatively little work has characterized price and promotion responsiveness

in durable goods markets, particularly automobiles. Colombo and Morrison (1989) use a switching matrix to understand cross-competitive effects in the automobile market; however, their analysis does not include any elements of the marketing mix. Thompson and Noordewier (1992) include 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, derive insights on how characteristics of each promotion program have driven the results, or understand the effects of competition. More recently, Berry et al. (1995, 2004), Sudhir (2001), and Train and Winston (2007) quantify consumer response to automobile pricing, but they limit their analyses to MSRPs and do not address the multiple instruments that are used for price customization. Bruce et al. (2006) examine the logic of offering consumer rebates in a context in which consumers face a constraint in their "ability-to-pay" for a durable product (automobiles) considering the second-hand market as an alternative.

This paper describes a model and decision-support system that the Marketing Science Group of the Power Information Network division of J. D. Power and Associates (JDPA) developed to provide automobile manufacturers with a tool to improve the effectiveness and efficiency of their pricing decisions, and Chrysler's pioneering implementation of this tool. This research led to several findings that, to the best of our knowledge, had not been previously documented:

(1) Automobile consumers, in addition to being heterogeneous in their brand preferences, are also heterogeneous in their preferences for transaction types, e.g., acquisition types (purchasing or leasing), promotion types (e.g., cash discount or reduced interest rates), and financing terms.

(2) Consumers are heterogeneous in their relative sensitivity to various pricing instruments—not only on their overall price sensitivity. Some consumers are more responsive to a cash discount, others to a reduced interest rate. Hence, price discounts of the same magnitude may lead to different effects, based on the instruments used and the idiosyncratic price sensitivities of the target consumers.

(3) When a manufacturer must offer a blanket pricing program to a market, the most effective programs tend to be those that offer the consumer a

menu of options (e.g., a choice among a cash discount, reduced interest-rate financing, or a lease-payment discount). The best pricing-instrument combination and their respective levels depend on the consumers' transaction-type preferences and price sensitivities in the target market. Hence, to maximize profit, a manufacturer must find the "optimal" structure for its pricing program—not only an overall "optimal" price level.

## The Power Information Network

JDPA (now a McGraw-Hill company) created the Power Information Network (PIN) division in 1993; its objective was to collect automobile sales-transaction data from a large sample of dealerships representative of the US market. After closing operations each night, participating dealers used specialized software to transmit their daily transactions from their Finance and Insurance (F&I) systems to a JDPA server (Figure 1). In turn, dealers receive access to a web-based reporting portal that allows them to benchmark their performance within their local market.

The initial installations were in California, the largest US automobile market; by the end of 1996,

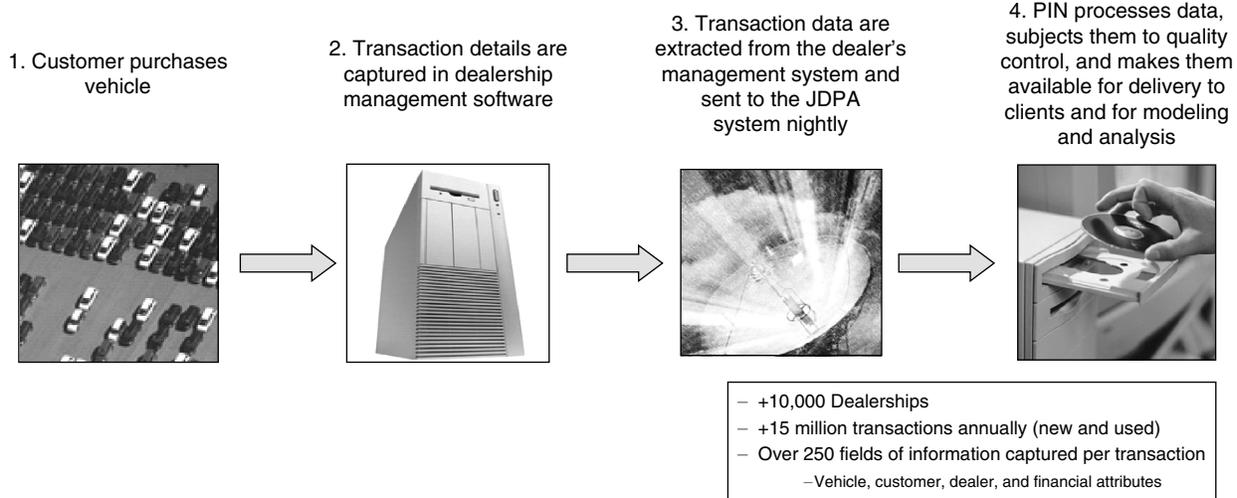
1,000 dealer franchises in California (approximately 30 percent) were PIN participants. National expansion started in 1997, with markets targeted in the order of their size. The objective was to recruit about one third of the dealers of each nameplate in each market (with some adjustments for overrepresentation of the smaller brands). Currently, the PIN sample includes 26 US markets; these US markets represent 70 percent of US retail automotive transactions and include about 30 percent of the dealers of each nameplate in each market.

PIN captures details of each transaction (new and used cars) that the F&I systems of reporting dealers close each day. Figure 2 shows a sample of data elements.

PIN collects details of promotional programs not captured in sales transactions (e.g., dealer cash). It enters them into a database that maintains the history of the multiple promotional programs that, at any given point in time, are available to consumers and dealers in each market for all vehicle models in the United States. PIN has recently added advertising data from third-party providers to the database. It has recently expanded into Canada and has added

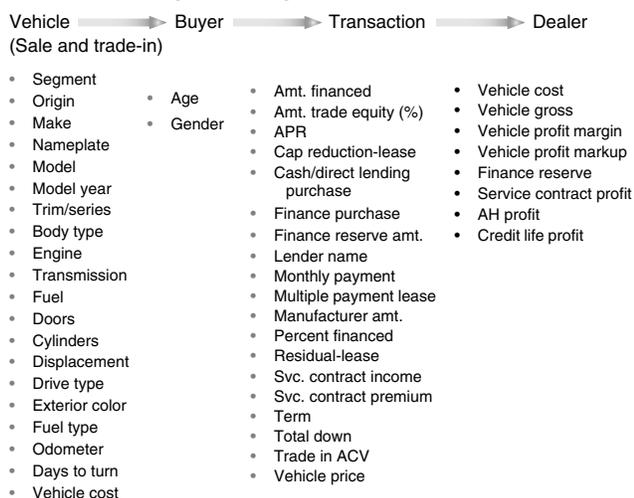
### PIN data collection, processing, and delivery system

The data are transmitted and processed using the following steps:



**Figure 1: Sales transaction data are automatically sent from the dealer management systems of subscribed dealers—about 1/3 for each nameplate (e.g., Chevrolet, Honda, or Lexus) per market. PIN processes data, subjects it to quality control, and delivers it to dealer and automaker clients.**

PIN captures over 250 data elements on each vehicle transaction, including the following:



**Figure 2: PIN captures over 250 data elements on each vehicle transaction and provides information about the vehicle model (product) purchased, the trade-in vehicle (if applicable), the buyer (e.g., age and gender), the transaction (e.g., pricing and financing), and dealer economics.**

Source. J. D. Power and Associates.

dealers in Calgary, Edmonton, Montreal, Toronto, and Vancouver.

## Modeling Objective and Specification

By 1999–2000, due to capacity increases in the worldwide automobile industry, several car manufacturers (particularly General Motors, Ford, and Chrysler—the “Big 3”) had concerns about sustaining capacity utilization at a profitable level. Indeed, some believe that concern about industry-wide excess capacity was an underlying reason that led to the merger of Daimler Benz and Chrysler (Smith 2006).

The five-year cycle required to design, produce, and launch a new product, and the two to three years required for a redesign, constrain automakers to available products in responding to a decrease in demand. They must rely on pricing and promotions to close gaps between supply and demand and keep capacity utilization at profitable levels. Because of the approximately \$45 billion cost of price promotions annually, US automakers must make very efficient pricing decisions. A five-percent increase in price-promotion efficiency would represent more than \$2 billion in savings.

In 1998, we began modeling work to develop a decision-support system that would help automobile manufacturers increase the effectiveness and efficiency of their pricing and other marketing activities. A chronology of the model development progress is presented in Table 1. The modeling approach leveraged the extant literature on response models, taking into account the differences in the data and the product categories. Most consumer response model literature has focused on frequently purchased products, such as consumer packaged goods. As the following paragraphs explain, the acquisition of a vehicle requires that a consumer make several decisions. These must be reflected in the model structure.

These consumer decisions include product, purchase or lease (Dasgupta et al. 2007) decisions, and the terms of the financing contract. In addition, because automakers offer a menu of promotional programs from which the consumer may choose (e.g., customer cash rebates, promotional interest rates, or lease “support”) and may allow some of the programs to be combined, consumer response models must include these decisions and measure the effects of the multiple available marketing offerings.

Modeling these consumer decisions is important for several reasons. First, some promotional programs are structured to increase or decrease the penetration of specific transaction types (e.g., the proportion of leases). If a promotion’s objective is to shorten the financing period, it will target shorter-term contracts (e.g., the program will provide a substantially lower interest rate for 36 months than for 60 months). Second, because promotional programs may affect the penetration of the different types of transactions, an accurate prediction of these penetration changes is necessary for cost and profit estimation. We believe that referring to price promotions as a “cost” is a misnomer. Price promotions are a *tool* to customize pricing and increase revenues through price discrimination at different levels of consumer price sensitivity (Varian 1980). However, in this paper, our use of “cost” is consistent with the usage and accounting practices in the automobile industry.

New-car retailing differs from other industries in that it is based on a heavily regulated franchise system. Franchised car retailers (dealers) sell vehicles of one automaker *only* although, in a few cases,

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Implemented	Modeling objective	Unobserved heterogeneity	References
2000–2001	Multinomial logit model of new-car choice	Latent class	Bucklin and Silva-Risso (1998)
Ad-hoc projects	Targeted promotions (multinomial logit of new-car choice)	Hierarchical Bayes	Siddarth and Silva-Risso (2000)
Ad-hoc projects	Finite mixture of multinomial logit models	Latent class	Silva-Risso et al. (2001)
2002	Nested logit of new-car and acquisition-type choice	Random coefficients	Silva-Risso and Ionova (2002) Dasgupta et al. (2002) Dasgupta et al. (2007)
2003	Regional programs	Hierarchical Bayes	Chang et al. (2003)
2003	Program optimization	Hierarchical Bayes	Khavaev et al. (2003)
2004	Nested logit of new-car and acquisition-type choice with optimization and batch scenario generator (multiple enhancements)	Hierarchical Bayes	Silva-Risso and Ionova (2008)

**Table 1: The chronology of the model-development process shows that the process spanned multiple years.**

dual dealerships are allowed, e.g., for low-share vehicles—and, some automakers allow dealers to carry multiple nameplates (e.g., Chrysler and Jeep). In addition, within the same local market (e.g., a Nielsen-designated marketing area or DMA), car manufacturers must offer exactly the same pricing and promotional conditions to all their dealers. Additionally, all new car sales or leases must be processed by a franchised dealer. State laws prevent automakers from selling directly to consumers, discounters, or wholesalers. Hence, we consider local markets as the best geographical unit for price customization and channel all retail sales through franchised dealers.

The input parameters that we use in the incentive planning model include marketing variables (e.g., transaction prices, consumer incentives, and dealer incentives), consumer characteristics (e.g., buyer demographics and the consumer trade-in, if any), and product characteristics (e.g., make, model, time since launch, and time since redesign). Once we have calibrated the incentive planning, we build a market simulator that produces predictive outputs (e.g., sales volumes, profits, costs, and program penetration); see Figure 3.

Geographic location plays an important role in segmenting consumer automotive preferences. For example, California consumers are more likely to purchase Japanese brands than those living in the Midwest. Buyers in rural areas are more likely to purchase pickup trucks than those in urban areas. State-specific franchise laws and other factors also constrain manufacturers to offer the same pricing and promotional conditions to all retailers (dealerships) in the

same local market. Assessing the price and promotion response of consumers within a geographical area is, therefore, an analytically convenient and managerially useful basis on which to develop a promotional planning system. Appendix 1 and Silva-Risso and Ionova (2008) show the technical details of our modeling approach.

## Simulation Capabilities for Analysis and Decision Making

On the basis of the consumer response models that we describe in the *Modeling Objective and Specification* section, we developed additional capabilities to improve the system’s efficiency and ease of use (see Figure 4).

### Simulator with What-If Scenario Capabilities

This capability consists of an interface that allows pricing and promotion analysts to generate several scenarios for their products and for competitive products following the structure that Figure A.1 (Appendix 1) summarizes. It allows decision makers to analyze how to respond to a competitor, improve current programs, and plan their pricing and promotion schedule to achieve the next quarter’s goals efficiently. 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. At the end of the month, they compare these predictions with actual market results.

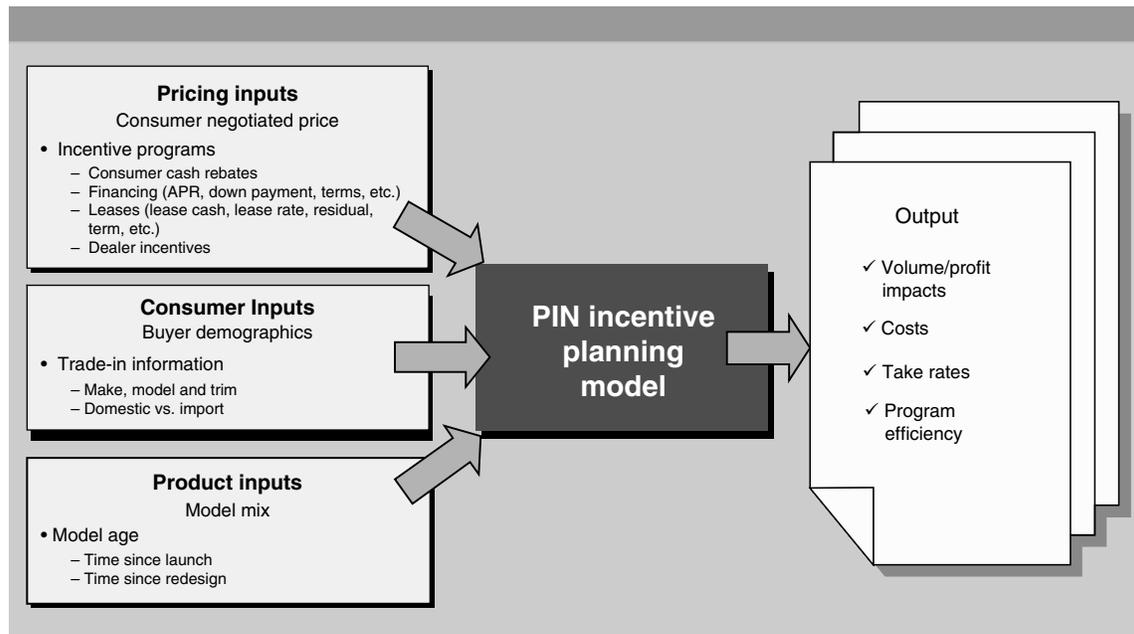


Figure 3: The graphic illustrates the components of the incentive planning system.

### 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 with \$250 increments; stand-alone, 36-month APR from 1.9 percent to 4.9 percent with 0.5 percent increments). Additionally, the user can specify assumptions about competition (e.g., no reaction or full or partial match of the target-product’s increase). 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).

Using those inputs, the system generates an input table including all the scenarios to be analyzed and sends them sequentially to the market simulator engine. For a more rapid response, the user could specify that the scenarios be simulated by “plugging in” posterior means of the response parameters, instead of using the posterior distribution. Rossi et al. (1996) and Rossi and Allenby (2003) point out that the “plug-in” approach could result in “overconfident” strategies. However, the time needed to simulate a massive number of scenarios by using the parameter’s posterior distributions may exceed the

time allotted to make a timely decision. The potential problems that using point estimates might cause are alleviated by a second-step analysis of a few candidate strategies. For each of the promising incentive programs, the decision maker analyzes a set of neighbor programs using the “full decision-theoretic approach” (Rossi et al. 1996). In most cases, this two-step approach has led to effective decisions.

The primary system outputs, which are “lift” (i.e., the increase or decrease in market share or volume) and “cost,” are ported to user-specific templates that make the conversions to other dimensions (e.g., “profit” and “net price”). Finally, the system plots the scenarios along the chosen dimensions to identify the efficient frontier. As we mentioned above, there are multiple alternatives to structure an incentive program that may result in a similar “cost” (i.e., price discount or net price); however, these different structures may result in a wide range of incremental volume (or profits). The efficient frontier analysis helps to identify the most promising programs along the chosen dimensions (e.g., the most profitable program for a given net price or the least costly program for a market-share objective).

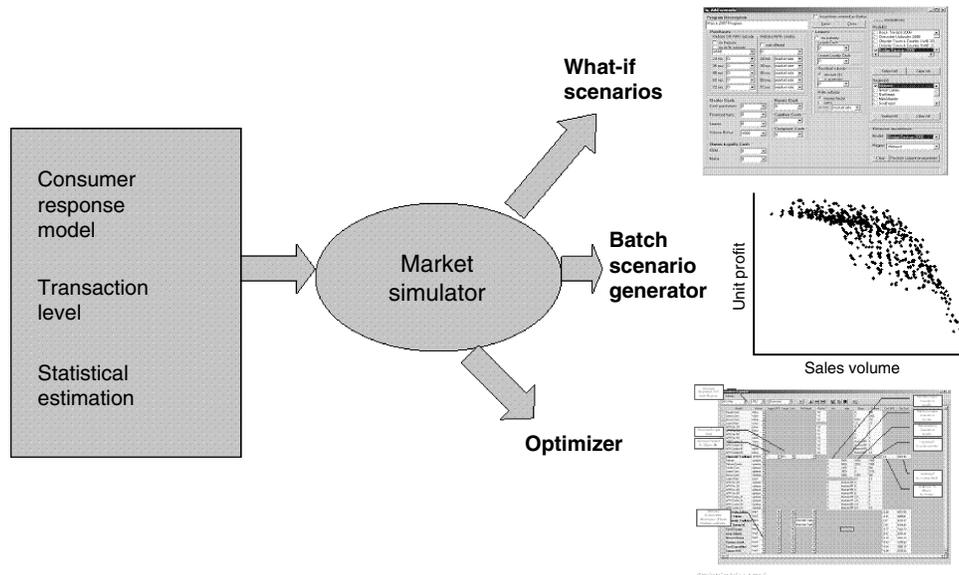


Figure 4: The diagram outlines the model's simulation capability.

### Incentive Optimizer

We chose to use the Nelder–Mead optimization module. Its advantage over gradient-based methods is that it does not require derivatives, which in this case should be numerical; when optimizing over a large number of dimensions (i.e., more than 50), this would be computationally expensive. Sampling-based methods, such as genetic algorithms and simulated annealing, are also alternatives but are significantly slower, particularly because we have a shallow global optimum with many “ripples” and flat directions.

This system allows the user to search for optimal programs, given a set of objectives, constraints, and assumptions about competitive reactions (e.g., maximizing profit subject to a sales-volume constraint or maximizing sales volume subject to a profit or “cost” constraint). We could specify competitive reaction as (1) no reaction, (2) a full or partial match of the target-brand’s increase in incentives, or (3) 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. Therefore, the solutions are tested using the two-step approach that we described in the *Batch Scenario Generator* section.

### Chrysler Implementation

#### Background

When development on the Chrysler model began in 2000, monthly incentive-program spending ranged from \$1,500 to \$2,000 per vehicle; optimizing the dollars spent seemed like a good idea. By the fourth quarter of 2002, incentive spending by General Motors, Ford, and Chrysler averaged over \$3,600 per month per vehicle; a good idea had become a great idea.

Prior to using the model, Chrysler had used the best information then available. It monitored its own sales daily but competitor data were only available monthly. It could identify a decline in Chrysler sales quickly; however, the causes were generally unclear. The Chrysler Corporate Economics team calculated elasticities based on traditional regression analysis; however, because of the data limitations, the estimates were not robust. Depending on the size of available supply and Chrysler wholesale order conditions, its sales operations would create sales incentive programs based on the calculated elasticity, personal history, anecdotal evidence, and input from the field organization and dealers. Dealer and automaker objectives rarely align perfectly; therefore, the incentives offered would rarely be optimal—dealers make

money on the retail transaction; manufacturers make money on the wholesale transaction. There were neither data nor rigorous techniques to evaluate and monitor results to improve future performance.

## Model Validation

Chrysler had the pioneering vision that the magnitude of those pricing decisions would clearly merit introducing science into the process. It contracted with JDPA to build a decision-support system based on state-of-the-art OR analytics and models. However, before full implementation, Chrysler decided that the magnitude of the problem would also justify hiring an independent party to evaluate the solution that JDPA was developing.

Chrysler engaged Booz Allen Hamilton, the management consulting firm, to perform two studies. The Booz Allen Hamilton team tested and validated predictions for Chrysler and competitor pricing programs. Each of the two studies confirmed the high accuracy of the model's predictions for different incentive programs and different products. However, the reports also stated that, in many cases, the data used were significantly outside of historically observed values. Because of the variability in the quality of the pre-model implementation decisions, it predicted that the model's contribution would be substantial but would be over a relatively wide range—\$250 to \$900 million annually.

At the beginning of each month, the team predicted the market results of the actual pricing decisions and of alternative (better) programs the model had suggested (if they had not been implemented); at the end of each month, it analyzed the accuracy of its predictions. It found high accuracy both in cases in which the model recommendations had been implemented and in cases in which they were not. For the latter, the team measured the missed profit opportunity.

## The Role of Chrysler Corporate Economics in Model Implementation

The Chrysler Corporate Economics team was involved in the initial model development in 2000 and 2001. The model validations, discussed above, had created a comfort level in the sales and marketing teams; by the end of 2001, they were using

it as an ad-hoc “what-if” tool. At that time, there was no systematic process for program evaluation or improvement. The Chrysler sales organization consequently requested assistance from Chrysler Corporate Economics to improve the pricing planning process using the model.

As a result, Chrysler Corporate Economics and JDPA, which dedicates a full-time, on-site consultant to this project, now work closely with the sales operations and sales and marketing finance teams to analyze the competitive environment and adjust programs based on their analysis. Based on sales targets and the current interest rates that Chrysler Financial (Chrysler's financing arm) sets, the joint JDPA/Chrysler Corporate Economics team develops recommendations for monthly incentive plans. To meet the timing needs of the sales group, it must provide a full analysis of the prior month's results early in each month. Because computer power is critical to completing the process within this constraint, 14 machines are used to run PIN. This allows a complete analysis of the incentive environment for each nameplate. Summary incentive program results are distributed throughout the sales and marketing organization and up to the CEO. Appendix 2 shows details of Chrysler's measurement of the model's impact.

## Efficiency Gains

Repeating the process that we detailed in the previous section for all products over a 12-month period, we can estimate annual efficiency gains in dollars for the Chrysler Group. Table 2 shows a summary of the results.

The average annual estimate is about \$500 million and resulted in incremental profitability of approximately \$2.5 billion from 2003 to 2007. Chrysler estimates that the model will continue to deliver gains of approximately \$500 million annually in the future.

Pricing is not the only variable that affects profits. Other forces, such as market interest rates, gasoline prices, the fuel economy of the product mix, and the competitive environment, are also relevant. These variables are outside the realm of variables that automakers can affect with their decisions, at least in the short term.

Year	Achieved efficiency (%)	Efficiency gains (\$ millions)
2003	79	416
2004	86	474
2005	90	498
2006	93	537
2007 YTD annualized	92	532
Average efficiency gain per year		491
Total efficiency gains in five years		2,457

**Table 2: Chrysler has estimated annual efficiency gains in percentages and actual cost savings as a result of implementing the incentive planning model. Baseline efficiency before model implementation = 71%.**

### Generalizing the Model

The development of this model has provided JDPA and Chrysler with a platform that they can extend to other areas using a consistent underlying methodology. Examples include the following:

- Marketing-mix models that also include advertising programs;
- Product-planning applications that decompose vehicles into attributes at the lowest level possible and capture substitution patterns across the industry to improve long-term planning efforts;
- Pricing optimization to assist Chrysler’s finance arm to make better decisions about interest rates to offer to dealers and consumers.

The pioneering work of JDPA and Chrysler has inspired other automakers to implement the system to plan their price promotions; this has led to a more disciplined approach, and to the use of OR in other key areas as well.

### Concluding Remarks

This paper documents the development of the PIN Incentive Planning System and its pioneering implementation at Chrysler. The system is based on a nested logit model of car and transaction-type choice. Most major automobile manufacturers now use it. The Chrysler Chief Economist has estimated that the consistent and systematic use of PIN has resulted in annual savings of \$500 million. Other automakers estimate industry-wide efficiency gains at about \$2 billion annually.

### Appendix 1: Modeling Approach

The basic building block of our modeling approach is a random-effects nested logit (Chang et al. 1999) model of automobile and transaction-type selection behavior in which the utility of a particular vehicle is a function of the marketing mix and other transaction-specific variables (Figure A.1).

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 local market (e.g., Nielsen-designated marketing area or DMA)  $m$  chooses automobile  $i$  and transaction-type  $\tau$  at time  $t$  is given by

$$P_{tm}^h(i, \tau) = P_{tm}^h(\tau | i) \cdot P_{tm}^h(i), \tag{1}$$

where the probability of choosing transaction-type  $\tau$ , conditional on automobile  $i$  at time  $t$ , is given by

$$P_{tm}^h(\tau | i) = \frac{\exp(U_{tm, i\tau}^h)}{\sum_{\tau'} \exp(U_{tm, i\tau'}^h)}, \tag{2}$$

with the utility of transaction-type  $\tau$  given by

$$U_{tm, i\tau}^h = \alpha_{m, i\tau} + \beta_{m, \tau} \mathbf{X}_{tm, i\tau}^h, \tag{3}$$

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

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

$$P_{tm}^h(i) = \frac{\exp(V_{tm, i}^h)}{\sum_k \exp(V_{tm, k}^h)}, \tag{4}$$

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

$$V_{tm, i}^h = \delta_{m, i} + \gamma_m \mathbf{Y}_{tm, i}^h + \nu_m \ln \left( \sum_{\tau'} \exp(U_{tm, i\tau'}^h) \right), \tag{5}$$

where  $\delta_{m, i}$  are product-specific intercepts to be estimated,  $\mathbf{Y}_{tm, i}^h$  is a vector of consumer-specific and marketing variables,  $\gamma_m$  is a vector of parameters to be estimated, and  $\nu_m$  is the nested logit dissimilarity coefficient to be estimated. The dissimilarity parameter is the coefficient of the inclusive value. The inclusive value represents the overall attractiveness of the corresponding lower nest, expressed as the natural

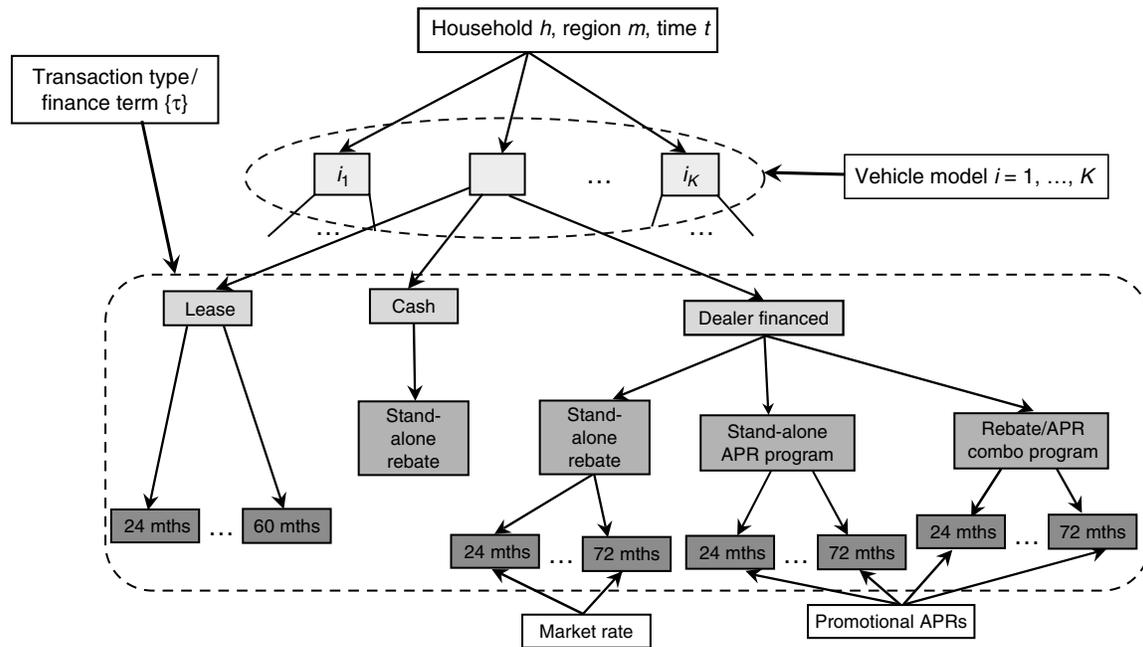


Figure A.1: The modeling approach is based on a random-effects multinomial nested logit model of product, acquisition, and program type.

log of the denominator of the corresponding multinomial logit in Equation (2).

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

$$\alpha_{m,i,\tau}, \delta_{m,i}, \beta_{m,\tau}, \gamma_{m,i}, \nu_m \sim MVN(\boldsymbol{\mu}_n, \boldsymbol{\Sigma}_n). \quad (6)$$

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

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

$$\boldsymbol{\Sigma}_n^{-1} \sim Wishart((\rho\mathbf{R})^{-1}, \rho). \quad (8)$$

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

Silva-Risso and Ionova (2008) show model specification details and an empirical illustration.

## Appendix 2: Measuring Impact

Chrysler needed a framework to measure the model's contribution. The objective was to measure the increase in pricing-decision efficiency relative to the baseline efficiency as measured in a period prior to the model's implementation.

Consider the profit equation

$$\Pi = Q \cdot (m - d) - F, \quad (9)$$

where  $\Pi$  is net profit,  $Q$  is sales volume,  $m$  is gross margin at the regular wholesale price,  $d$  is a price discount (or amount of sales incentives offered), and  $F$  are fixed costs, including costs for plants and labor.

Because wholesale prices change infrequently during the year, the unit gross margin is relatively fixed. Incentive actions or discounts represented by  $d$  change the effective profit margin. Also, note that fixed costs include direct labor costs that are fixed by union contracts. As we mentioned before, in the monthly analysis process, Chrysler maps the efficient frontier in terms of sales volume and unit profits for all Chrysler products. For a given price-discount level, there are multiple ways to structure that pricing

customization (sales incentive) program that result in different sales volumes. The points in the efficiency frontier consist of programs that deliver the highest sales volume for each given price-discount level. Chrysler has performed extensive evaluations over the years and confirmed the high precision of the system's predictions. Those validations provided strong confidence in the efficiency frontier as an instrument to evaluate programs.

Business considerations or changes in the environment may result in the implementation of programs that are outside of the efficiency frontier (Figure A.2). In the figure, point A represents an implemented program. Point B would deliver a higher profit for the same sales volume, while point C would deliver a higher sales volume for the same unit profit. However, the point that maximizes total profit is O. Some factors (e.g., a "truck month" promotion must include all trucks) impose constraints.

We use several steps to measure efficiency. First, we determine local efficiency—the relative efficiency of the implemented program A with respect to the corresponding profit and volume-maximizing programs B and C:

$$\begin{aligned} \text{LOCAL EFFICIENCY} &= \frac{\Pi_A + F}{(\Pi_B + \Pi_C)/2 + F} \\ &= \frac{Q_A \cdot (m - d_A)}{(Q_B \cdot (m - d_B) + Q_C \cdot (m - d_C))/2}. \end{aligned} \quad (10)$$

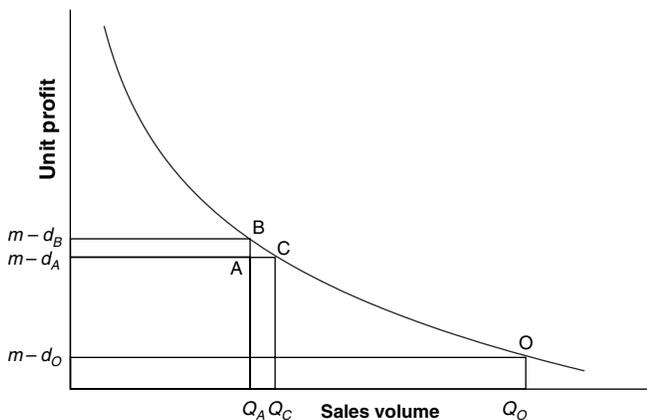


Figure A.2: The graph illustrates a promotional program that is outside of the efficiency frontier.

In the second step, we measure global efficiency—the profit ratio of B and C with respect to O (the global optimal program). Note that, although B and C are the efficient programs for the unit profit/sales volume targeted in program A, they are not necessarily the programs that would deliver the largest total profit as represented by program O:

$$\begin{aligned} \text{GLOBAL EFFICIENCY} &= \frac{(\Pi_B + \Pi_C)/2 + F}{\Pi_O + F} \\ &= \frac{(Q_B \cdot (m - d_B) + Q_C \cdot (m - d_C))/2}{Q_O \cdot (m - d_O)}. \end{aligned} \quad (11)$$

In the third step, by combining local and global efficiency, we compute the overall efficiency achieved by the actual pricing program A:

$$\begin{aligned} \text{ACHIEVED EFFICIENCY} &= \text{LOCAL EFFICIENCY} \times \text{GLOBAL EFFICIENCY} \\ &= \frac{\Pi_A + F}{\Pi_O + F} = \frac{Q_A \cdot (m - d_A)}{Q_O \cdot (m - d_O)}. \end{aligned} \quad (12)$$

In the fourth step, we translate the achieved efficiency into efficiency gains in dollars. Comparing the efficiency achieved by the actual program with the baseline efficiency prior to model implementation for that product line (computed applying Equation (12) to the year before model implementation), we determine the increase in efficiency in percentage points of profit. Multiplying this value by the profit opportunity (i.e., the global maximum profit) corresponding to program O, we obtain the estimate in dollars of the efficiency gain from the actual program A.

Consider a hypothetical car X for which a pricing program resulted in 10,000 units of sales at a gross margin (before price discounts) of \$8,000, less a price discount of \$2,000. Thus, the profits from this program (not considering fixed costs) were \$60 million:

$$\begin{aligned} \text{Program A: } \Pi + F &= 10,000 \cdot (\$8,000 - \$2,000) \\ &= \$60 \text{ million.} \end{aligned} \quad (13)$$

Consider that Program B is the corresponding profit-maximizing program for that sales volume; it offers a price discount of \$1,800, and results in profits (not considering fixed costs) of \$62 million:

$$\begin{aligned} \text{Program B: } \Pi + F &= 10,000 \cdot (\$8,000 - \$1,800) \\ &= \$62 \text{ million.} \end{aligned} \quad (14)$$

Program C is the corresponding volume-maximizing program for that unit profit level; it has a sales volume of 10,300 units and profits of \$61.8 million:

$$\begin{aligned} \text{Program C: } \Pi + F &= 10,300 \cdot (\$8,000 - \$2,000) \\ &= \$61.8 \text{ million.} \end{aligned} \quad (15)$$

The overall optimal program is O, which the optimizer determined; it has a sales volume of 13,000 units, a price discount of \$3,000, and profits of \$65 million:

$$\begin{aligned} \text{Program O: } \Pi + F &= 13,000 \cdot (\$8,000 - \$3,000) \\ &= \$65 \text{ million.} \end{aligned} \quad (16)$$

Then, local and global efficiency are, respectively, 97 percent and 95 percent:

$$\begin{aligned} \text{LOCAL EFFICIENCY} \\ &= \frac{\Pi_A + F}{(\Pi_B + \Pi_C)/2 + F} = \frac{60}{(62 + 61.8)/2} = 0.97, \end{aligned} \quad (17)$$

$$\begin{aligned} \text{GLOBAL EFFICIENCY} \\ &= \frac{(\Pi_B + \Pi_C)/2 + F}{\Pi_O + F} = \frac{(62 + 61.8)/2}{65} = 0.95; \end{aligned} \quad (18)$$

this would represent an overall achieved efficiency of 92 percent from the actual program A with respect to the overall optimal program O:

$$\text{ACHIEVED EFFICIENCY} = 0.97 \times 0.95 = 0.92. \quad (19)$$

To illustrate this example, let us assume the baseline efficiency for that product line is 71 percent. Then, efficiency increase is the difference between the achieved and baseline efficiencies or 21 percentage points of the profit opportunity:

$$\text{INCREASED EFFICIENCY} = 0.92 - 0.71 = 0.21. \quad (20)$$

Multiplying the 21 percentage points of increased efficiency by the profit of the overall optimal program of \$65 million, we compute an efficiency gain of approximately \$13.7 million:

$$\begin{aligned} \$ \text{ EFFICIENCY GAIN FROM MODEL} \\ &= \text{PROFIT OPPORTUNITY} \\ &\quad \times \text{EFFICIENCY GAIN FROM MODEL} \\ &= \$65,000,000 \times (0.92 - 0.71) = \$13,650,000. \end{aligned} \quad (21)$$

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Van E. Jolissaint, Chrysler chief economist, stated: “The incentive planning model has evolved such that the corporation’s senior management uses the model to guide incentive-planning and pricing decisions on a month-to-month basis. Each month, The Chrysler Corporate Economics team estimates the efficient frontier for incentive and pricing planning for all vehicle models of the corporation. Whether we go for volume or profit is a senior management decision—as long as we stay at or close to the efficient frontier. The Corporate Economics team reviews a detailed report with the Incentive Planning team, Sales Operations, and the Sales Planning organizations. We also review a summary of this analysis with the Executive Vice President of Sales and Marketing.

“Since 2003, we have used the model consistently and have seen a progression on the percentage and dollar achievement of efficiency gains. The average annual savings estimate of approximately half a billion dollars has resulted in incremental profits of about 2.5 billion dollars over the 2003–2007 period.

Chrysler estimates that the model will continue to deliver gains of about half a billion dollars annually in the future. However, we should note additional incremental gains in efficiency will become more difficult over time as the organization continues to learn.

“The use of the model by Chrysler and other manufacturers allowed incentives to play a bigger role in the 2001 recession than they had in previous recessions. Historically, when the US has entered a recession, automotive industry sales have fallen 15 percent to 20 percent, depending on the extent of the recession. In the 2001 recession, industry sales fell only 4 to 5 percent. Incentives were instrumental in keeping industry sales volumes up, at a reasonable cost. We developed incentives with a better knowledge of what the effects of those programs would be.

“One of the biggest contributions of the incentive planning model was the close cooperation that developed between the staffs of J. D. Power and Chrysler. The developments we did as a team made the model a very powerful tool—fast enough, timely enough, and easy enough—and a major decision-making tool for senior management at Chrysler.”

On April 30, 2007, at the Franz Edelman Award Competition, J. David Power III, founder of JDPA stated, “For four decades, our firm has focused on the voice of the customer—listening to its messages and helping businesses chart out ways to turn that information into profitable action. During that time, I’ve seen again and again how powerful an operational force customer information can be—driving quality, design, and profits for companies that master its use.

“Today, we are very pleased and honored to be among the five finalists to the prestigious Edelman award. Fifteen years ago, J. D. Power and Associates began to collect transaction data from a large sample of automotive dealerships. We saw that the competitive battleground would shift from manufacturing to retail. We hoped to develop an OR practice that would harness the power of this information and create advanced analytical methods that could help automakers and dealers make better business decisions. I am very pleased to present, along with our business partner DaimlerChrysler, the J. D. Power and Associates PIN Incentive Planning System.

“Working together, J. D. Power and Chrysler used the PIN Incentive Planning System to fundamentally change the way Chrysler approaches pricing and promotions. Chrysler’s successful experience provided a template that most major auto manufacturers are

now following. The Pin Incentive Planning System has transformed major investment decisions traditionally made through a combination of gut feeling, hope, and guesswork, into ones based on solid science.”