# Capturing the effects of coupon promotions in scanner panel choice models

*Jorge M. Silva-Risso and Randolph E. Bucklin*

**The authors**

**Jorge M. Silva-Risso** is an Assistant Professor of Marketing at the A. Gary Anderson Graduate School of Management, University of California, Riverside, California, USA.
**Randolph E. Bucklin** is a Professor of Marketing at the UCLA Anderson School of Management, Los Angeles, California, USA.

**Keywords**

Coupons, Brand awareness, Data handling

**Abstract**

The authors develop a logit modeling approach, designed for application to UPC scanner panel data, to assess the effects of coupon promotions on consumer brand choice. The effects of coupon promotions are captured via two measures: the prevailing level of availability and the prevailing face value of coupons for each brand. Both of these measures are derived from coupon redemptions of a separate sample of households. The approach captures both the advertising effect and the price discount incentive of a coupon. It also avoids drawbacks of previous choice models which have incorporated coupon effects by subtracting the value of a redeemed coupon from the price of the brand purchased. The authors illustrate their modeling approach on data for two product categories: catsup (light coupon usage) and liquid laundry detergent (heavy coupon usage). Findings are reported for coupon users and non-users as well as across latent segments.

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The effectiveness of coupons as a promotional vehicle has remained a controversial topic for at least two decades. For example, practitioners who regularly analyze coupon promotions have characterized spending on coupons as a poor investment of marketing dollars (Bucklin and Gupta, 1999). In the mid-1990s, some consumer products companies attempted to eliminate coupons, lower the face value of coupons, and shorten the time to expiration (Narisetti, 1996; Schiller, 1996). These actions proved both unpopular and, arguably, lowered profitability (Nevo and Wolfram, 2002). More recently the volume of coupons distributed has again been rising (Fetto, 2001). Furthermore, coupons have become quite ubiquitous in online shopping (Oliver and Shor, 2003). In light of the major role coupons play in the packaged goods marketing mix and the billions of dollars involved in spending, there is an ongoing need for improvements in the models available for assessing the effect of coupons on sales, share, and profitability.

One concern expressed by managers is that coupons are redeemed predominantly by loyal consumers who would have purchased the brand in any event. The conditional logit brand choice model, applied to scanner panel data (Guadagni and Little, 1983), provides a natural – and parsimonious – modeling approach to assess whether or not coupons induce brand switching. Surprisingly, there has been little explicit attention given to the problem of how best to incorporate the effects of coupon promotions into this model. Indeed, most published findings using the logit model have either omitted the effects of couponing activity or include couponing activity as part of the price variable. When the price variable is modified, which we will refer to as the NETPRICE method, the value of any coupons redeemed by a panelist is subtracted from the price of the brand chosen at that purchase occasion. Though used in a number of published studies on brand choice, the NETPRICE approach has an endogeneity problem and restricts shelf price and coupons to share the same response coefficient[1].

Another issue in capturing the effects of coupons is their potential advertising effect. Leone and Srinivasan (1996) proposed an integrated model of coupon redemption, brand sales, and coupon profitability designed to incorporate this effect. Using scanner panel data, their approach divides households into a coupon prone (CP) segment and a coupon indifferent (CI) segment, specifically incorporating the potential for an advertising effect to operate on the CI segment. While the procedure uses panel data to divide

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store-level sales into the CP and CI groups, the market response models are actually fitted to aggregate-level scanner data. As the authors acknowledge in their paper (pp. 283, 288), there is no reliable way to isolate the effect of coupons on brand switching. Thus, a disaggregate-level approach is needed to address the extent to which coupons induce switching versus simply being redeemed by loyal users.

Erdem *et al.* (1999) proposed a model to impute coupon availability using a joint estimation of choice model parameters and a coupon availability function. The procedure avoids the endogeneity that comes from using a price variable that is defined to be net of coupons redeemed. On the other hand, a limitation of the approach is that the imputed coupon availability of unchosen brands does not vary over time nor can the model capture the potential advertising effect of coupons on non-users (p. 182). Model estimation also requires sophisticated simulation techniques not generally accessible to practitioners.

The purpose of this paper is to develop and empirically test a new approach to capture the effects of coupon promotions in logit brand choice models using redemption information. Our approach includes the effects of coupon promotions in the logit model as separate predictor variables that are not confounded with price. Our goals are to overcome the difficulties with the NETPRICE approach while providing a simple, readily estimable modeling alternative (e.g. one that could be used in the growing class of so-called "marketing mix" models which are designed to assess the relative productivity of different marketing activities in consumer products).

We model the effects of coupon activity as a function of the prevailing level of coupon availability and the prevailing coupon face value. We seek to capture the effect of distribution size as well as the discount incentive offered. We compute these measures from the redemption activity reported for a separate set of households purchasing in the same market area. The modeling approach we develop is best suited for situations in which drop information and expiration dates are either unavailable (the case with most scanner panel data sets) or unable to represent the coupon availability and incentive amounts prevailing in a market area at a given time (e.g. due to multiple delivery modes such as direct mail, the Internet, and FSI's).

To be sure, this measure of coupon availability has several limitations. Consumers may have coupons which they may have clipped several weeks earlier. Consumers may also have multiple coupons available. In order to capture these and other phenomena more precisely, we would need to have a variable capturing the stock of coupons at the household level. However, the data limitations previously discussed make such an approach infeasible. We believe that our proposed approach provides a practical and robust solution to the data limitation problem[2].

We also report results for an *a priori* segmentation that divides panelists into coupon prone and coupon indifferent segments. This permits us to assess whether coupons have an advertising effect upon the coupon indifferent segment, compare coupon users and non-users, and provide a disaggregate model which fits the profitability analysis proposed by Leone and Srinivasan (1996). We also extend the *a priori* segmentation by estimating the choice model with latent classes within the coupon prone and coupon indifferent household groups. We present results for liquid laundry detergent and catsup, which are a high coupon use category and a low coupon use category, respectively.

## Modeling approach

The objective of our model is to capture the effects of couponing activity on brand choice. To do this, we study the choice of shoppers whose purchases are recorded in scanner panel data. We represent purchase behavior using a probabilistic choice framework and employ a multinomial logit to model the probability that a panelist makes a brand choice. These choice decisions are modeled conditional on a product category purchase having taken place on a given store visit. Most of this basic modeling approach follows Guadagni and Little (1983).

By conditioning on the occurrence of a category purchase, the model isolates the effect of marketing activity on brand choice. Focusing on choice allows us to capture the behavior that we are primarily interested in: the effect of coupons on consumer switching across brands. Brand switching has a direct relationship to incremental sales and, hence, to profitability analysis. We note that our approach does not capture purchase timing effects (acceleration). Nor do we account for consumption effects (another potential source of incremental volume). However, consumption effects do not seem material for the categories we chose (catsup, detergent) for the empirical application (Ailawadi and Neslin, 1998).

To begin the mathematical specification of the model, we write the purchase probability for alternative $i$ at time $t$, given a category purchase and store visit, as

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$$P_t^h(i|\text{cat}) = \frac{\exp\left(U_{it}^h\right)}{\sum_k \exp\left(U_{kt}^h\right)} \quad (1)$$

where $P_t^h(i|\text{cat})$ is the probability panelist $h$ selects alternative $i$, given a store visit and category purchase at time $t$ and $U_{it}^h$ is the deterministic component of utility. We specify the utility, $U_{it}^h$, as

$$\begin{aligned} U_{it}^h = {} & \alpha_i + \beta_1 \text{BLOY}_i^h + \beta_2 \text{LBP}_{it}^h + \beta_3 \text{SLOY}_i^h \\ & + \beta_4 \text{LSP}_{it}^h + \beta_5 \text{PRICE}_{it} + \beta_6 \text{FEAT}_{it} \\ & + \beta_7 \text{DISP}_{it} + \beta_8 \text{COUPAV}_{it} \\ & + \beta_9 \text{COUPFV}_{it} \quad (2) \end{aligned}$$

where $\text{BLOY}_i^h$ is the loyalty of household $h$ to brand of brand-size $i$; $\text{LBP}_{it}^h$ is 1 if $i$ was last brand purchased, 0 otherwise; $\text{SLOY}_i^h$ is the loyalty of household $h$ to size of brand-size $i$; $\text{LSP}_{it}^h$ is 1 if $i$ was last size purchased, 0 otherwise; $\text{PRICE}_{it}$ is the actual shelf price; $\text{FEAT}_{it}$ is 1 if brand-size $i$ appeared in a feature ad at time $t$, 0 otherwise; $\text{DISP}_{it}$ is 1 if brand-size $i$ was specially displayed at time $t$, 0 otherwise. $\text{COUPAV}_{it}$ is the index of coupon availability for brand $i$, time $t$; $\text{COUPFV}_{it}$ is the average coupon face value for brand $i$, time $t$; $\{\alpha_i\}$ is the brand and size constants to be estimated, and $\{\beta_1, \beta_2, \ldots \beta_9\}$ is the parameters to be estimated.

The measures for loyalty (BLOY and SLOY) and last purchase (LBP and LSP) account for cross-sectional and longitudinal heterogeneity in brand and size preference, respectively. The BLOY and SLOY variables are determined from household purchases made in an initialization period and, unlike LBP and LSP, do not vary during the estimation period in the data. This formulation has appeared extensively in the marketing literature and also has been shown to have excellence in-sample and predictive fits when compared with other approaches to handling preference heterogeneity and purchase event feedback (Ailawadi *et al.*, 1999). Price is the actual price on the shelf (in cents per ounce) and feature and display are 0/1 indicator variables. The brand-size constants $\{\alpha_i\}$ follow the formulation given in Fader and Hardie (1996) in which each constant term pertains to a specific brand or a specific size. We now discuss incorporating coupon activity and our two proposed measures, COUPAV and COUPFV.

## Coupon variables in the logit model

The NETPRICE approach, in which the price term becomes net of the value of a redeemed coupon, has been used by Bronnenberg and Wathieu (1996), Chintagunta *et al.* (1991), Kamakura and Russell (1989), Krishnamurthi and Raj (1988), and Papatla and Krishnamurthi (1996)[3]. It has the advantage of incorporating coupons in a simple and straightforward manner and is supported by the economic rationale that shoppers compare the prices of the available brand alternatives net of the value of any coupons redeemed. On the other hand, using contemporaneous redemption information for the same household creates a serious endogeneity problem. This occurs because the coupon affects only the price of the chosen brand. Not only are inferences about coupon effects likely to be incorrect in this procedure, but inferences about shelf prices also will be biased because coupons and shelf prices are assumed to share the same coefficient. The endogeneity problem also means that the model cannot be used for scenario evaluation, simulation or forecasting because it depends upon the revealed redemption information to produce estimates of brand choice probabilities. Lastly, the NETPRICE method cannot incorporate the advertising effect a coupon may have on coupon non-users or the incremental effect that advertising may have on coupon users over and above the economic incentive.

Mela *et al.* (1997) modeled coupon promotions from redemption data without using the NETPRICE method. In their approach, a brand coupon was deemed to be available to shoppers if the level of redemptions in that week was one standard deviation above the mean level of redemption activity for the brand. Unfortunately, the study did not report findings for the proposed coupon measure because it was combined with feature and price discount to create a variable representing promotion.

Like Mela *et al.* (1997), our proposed measures for coupons are based on redemption data. In our approach, however, coupon availability is a continuous variable (vs a 0,1 discrete variable) and face value is incorporated. Also the Mela *et al.* (1997) approach uses redemptions for the same households used for model estimation. Instead, we use redemption information from a hold-out sample of households so as to avoid introducing endogenous information. Since larger share brands are expected to have higher redemption rates (Blattberg and Neslin, 1990), we normalize (i.e. mean center and standardize) the redemption index for each brand across weeks. This procedure produces a measure of relative coupon availability for each brand in each week. We label this variable $\text{COUPAV}_{it}$ in equation (2). We then incorporate the prevailing face value in the model with the variable $\text{COUPFV}_{it}$. It is defined as the average face value of coupons redeemed for the brand in week $t$, also computed from the hold-out set of panelists.

Because redemption rates increase with coupon face values (Blattberg and Neslin, 1990),

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high-value coupons will have more redemption activity than low-value coupons, *ceteris paribus*. Thus, an availability index based on redemption activity can be pushed upwards when face values are high and downwards when face values are low. For example, the (0, 1) coupon variable proposed by Mela *et al.* (1997) does not control for this effect. Because our approach also incorporates $\text{COUPFV}_{it}$ in the model, we control for the potential inflation or deflation of redemption rates that can be due to higher or lower coupon face values. Thus, our two proposed measures are designed to capture the total impact of prevailing coupon availability and face value on consumers' brand choices. As in Mela *et al.* (1997), we base the coupon measures on the actual redemption activity prevailing in the market (though we use a separate set of panelists). Thus, we continue to utilize observed measures for coupons versus an econometric imputation approach (Erdem *et al.*, 1999).

The modeling approach we develop is best suited for situations in which drop information and expiration dates are either unavailable (the case with most scanner panel data sets) or unable to represent the coupon availability and incentive amounts prevailing in a market area at a given time (e.g. due to multiple delivery modes). Due to the large (and growing) number of delivery vehicles (Harmon and Hill, 2003, p. 167) now used for coupon promotions (e.g. direct mail, check-out, in-store dispensers, Internet and Web sites, and traditional FSI's), it is increasingly difficult to assemble a complete picture of coupon availability and face value without recourse to the information contained in redemption data. For these reasons, we believe that it is important to develop modeling approaches that can be implemented on redemption data alone.

## Empirical application

### Data

We apply our modeling approach to scanner panel data for catsup and liquid laundry detergent. Coupon usage is light to moderate in the catsup category (about 40 percent of households redeem coupons at one time or another) while it is heavy in the detergent category (about 90 percent of households redeem coupons). Both data sets are drawn from panelists shopping in Sioux Falls, SD, from 1986-1988 and were provided by ACNielsen for academic research.

In catsup, we consider the top five selling brands (sold in four sizes) and the data set comprises 823 panelists who made 4,573 purchases over a 52-week estimation period. The brands and their market shares are Heinz (71 percent), Hunt's (15 percent), Del Monte (8 percent), and two private labels (4 and 1 percent). Redemption information is based on a hold-out sample of 2,366 households who made 9,273 category purchases. In laundry detergent, we consider the top seven selling brands (five are offered in four sizes, two are offered in three sizes) and the estimation data set comprises 392 households who made 3,064 category purchases. The brands and their market shares are Tide (25 percent), Wisk (25 percent), Era (15 percent), Surf (15 percent), Cheer (8 percent), Solo (7 percent), and Bold-3 (4 percent). Redemption data are taken from a hold-out set of 1,456 households who made 5,709 purchases.

### Estimation approach and segmentation

We fit the model on the estimation-sample households both with and without the coupon availability and coupon face value measures. This permits us to empirically investigate the problems of the NETPRICE approach that we detailed earlier. We then compare the results from our proposed model against those from applying the NETPRICE approach (where the value of any redeemed coupons is subtracted from the shelf price). In each of these cases, we estimate the parameters of the brand choice model (equation (2)) by maximizing the likelihood of the observed brand choices.

Our next step is to estimate our proposed model based on the *a priori* segmentation scheme introduced by Leone and Srinivasan (1996). We divide the estimation sample into coupon users and non-users and fit the choice model separately for each group. Note that in equation (2), there is potential cross-sectional heterogeneity in the response parameters of the utility function. Even though the households have been segmented according to coupon usage, additional heterogeneity in response may remain within each *a priori* segment. To accommodate this response parameter heterogeneity, we also estimate the model with latent segments (Kamakura and Russell, 1989) for both the coupon users and non-users.

In the latent segment logit model, equation (1) is modified to

$$P_t^h(i|\text{cat}) = \sum_s \pi_s P_{st}^h(i|\text{cat}) \qquad (3)$$

where $\pi_s$ equals the size of segment $s$ ($0 < \pi_s < 1$) and $P_{st}^h(i|\text{cat})$ is the brand choice probability given that household $h$ is a member of segment $s$. In this model, the response parameters, $\beta$, in equation (2) become segment-specific. In contrast to the *a priori* segmentation, a model selection criterion is needed to determine the appropriate number of

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latent segments to retain. We assess the predictive validity of all models using the BIC (Rust *et al.*, 1995; Schwarz, 1978).

## Results

Tables I and II show the parameter estimates, model fits, and BIC values, for the base (or null) model, the full model using shelf price, and the same two models using the NETPRICE approach for catsup and liquid detergent, respectively[4]. For the shelf price full model in catsup (Table I), the coupon availability parameter is correctly signed and significant ($\beta_8 = 0.122$, $t = 4.57$) and the model fit improves significantly ($\chi^2 = 21.2$, $p < 0.01$) when compared to the base or null model. The coupon value parameter, though positively signed, is insignificant. In the detergent category (Table II), the parameters for both coupon availability ($\beta_8 = 0.211$, $t = 9.46$) and coupon value ($\beta_9 = 0.916$, $t = 3.94$) are positively signed and significant in the shelf price full model. Model fit improves quite substantially in moving from the base model to the full model (a difference of about 70 log likelihood points, $\chi^2 = 140$, $p < 0.01$). Not surprisingly, the impact of the coupon variables on choice is much stronger in the category with heavy activity (detergent) than in the category with lighter activity (catsup).

Tables I and II also present the same models but with the price variable modified according to the NETPRICE approach (i.e. the price variable is reduced by the amount of any redeemed coupons). In both categories, the results for the base model show that the magnitude of the estimated price coefficient is approximately 30 percent greater in

**Table I** Catsup: models with coupon users and non-users

| | Shelf price | | Net price | |
|---|---|---|---|---|
| | **Base model** | **Full model** | **Base model** | **Full model** |
| **Brand loyalty** | 2.520 (24.181)* | 2.525 (24.074) | 2.539 (23.757) | 2.543 (23.671) |
| **Last brand purchased** | 0.592 (12.066) | 0.594 (11.999) | 0.582 (11.657) | 0.585 (11.647) |
| **Size loyalty** | 2.347 (19.502) | 2.345 (19.477) | 2.357 (19.322) | 2.355 (19.332) |
| **Last size purchased** | 0.761 (13.441) | 0.760 (13.387) | 0.742 (12.925) | 0.742 (12.887) |
| **Price** | −0.929 (−15.4872) | −0.935 (−15.4766) | −1.172 (−24.5772) | −1.172 (−24.4033) |
| **Feature** | 1.383 (23.759) | 1.350 (23.036) | 1.344 (23.371) | 1.316 (22.625) |
| **Display** | 0.595 (6.581) | 0.570 (6.282) | 0.601 (6.480) | 0.580 (6.228) |
| **Coupon availability** | | 0.122 (4.569) | | 0.111 (4.040) |
| **Coupon value** | | 0.139 (0.444) | | 0.170 (0.536) |
| **Log likelihood** | −4855.73 | −4845.14 | −4633.87 | −4625.57 |
| **BIC** | −4914.73 | −4912.56 | −4692.86 | −4692.99 |
| **No. of households** | 823 | 823 | 823 | 823 |
| **No. of purchases** | 4,573 | 4,573 | 4,573 | 4,573 |
| **No. of parameters** | 14 | 16 | 14 | 16 |

**Note:** **t*-values in parentheses

**Table II** Detergent: models with coupon users and non-users

| | Shelf price | | Net price | |
|---|---|---|---|---|
| | **Base model** | **Full model** | **Base model** | **Full model** |
| **Brand loyalty** | 3.080 (32.556)* | 3.168 (32.814) | 3.096 (32.564) | 3.181 (32.826) |
| **Last brand purchased** | 0.907 (19.165) | 0.900 (18.785) | 0.903 (18.971) | 0.895 (18.588) |
| **Size loyalty** | 1.935 (19.355) | 1.917 (19.818) | 1.957 (19.441) | 1.940 (19.444) |
| **Last size purchased** | 0.696 (15.815) | 0.700 (16.011) | 0.684 (15.433) | 0.688 (15.660) |
| **Price** | −0.587 (−17.1289) | −0.554 (−16.1199) | −0.771 (−22.2401) | −0.739 (−21.3223) |
| **Feature** | 1.462 (18.532) | 1.285 (15.773) | 1.373 (17.429) | 1.196 (14.657) |
| **Display** | 1.305 (16.982) | 1.212 (15.681) | 1.249 (16.251) | 1.157 (14.930) |
| **Coupon availability** | | 0.211 (9.457) | | 0.205 (9.097) |
| **Coupon value** | | 0.916 (3.936) | | 0.885 (3.778) |
| **Log likelihood** | −6169.14 | −6098.80 | −6060.41 | −5995.87 |
| **BIC** | −6233.36 | −6171.04 | −6124.63 | −6068.12 |
| **No. of households** | 392 | 392 | 392 | 392 |
| **No. of purchases** | 3,064 | 3,064 | 3,064 | 3,064 |
| **No. of parameters** | 16 | 18 | 16 | 18 |

**Note:** **t*-values in parentheses

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the NETPRICE models than in the shelf price models. All other parameters remain essentially unchanged. Thus, including coupon activity as part of the price variable significantly alters (biases upwards) the estimated magnitude of the price coefficient. This occurs even when the coupon variables are incorporated.

We also examined the predicted choice probabilities for the items actually chosen in the catsup category. For purchase occasions in which a coupon was redeemed, the shelf price model without coupon variables has a mean predicted probability for the item actually chosen of 0.30. On the other hand, the net price model, also without coupon variables, has a corresponding mean predicted probability of 0.59. Comparing this to purchase occasions in which no coupon was redeemed, we find that the shelf price model predicts 0.39 while the net price model also predicts 0.39. In sum, our results support the concerns raised about the NETPRICE approach and indicate the need for alternative ways of incorporating coupon activity into the logit.

### Segment results

Following Leone and Srinivasan (1996), those households recording one or more redemptions were placed into a coupon prone group while households recording no redemptions were placed into a coupon indifferent group. This segmentation permits us to evaluate differences in market response across the two groups and to specifically assess whether coupons have an advertising effect on the non-user group. Also, if coupons are to be effective as a price discrimination device (Narasimhan, 1984), the coupon prone group should be more sensitive to changes in price (i.e. have higher absolute price elasticities) than the coupon indifferent group. Finally, knowing the membership of each group permits an analysis of differences in demographic and purchase-pattern characteristics.

In addition to this *a priori* segmentation scheme, we use latent class analysis to accommodate potential response-parameter heterogeneity within each group[5]. Thus, our procedure combines *a priori* segmentation with *post hoc* segmentation. To do this, we estimate the choice models for both the coupon-prone and coupon-indifferent households with latent segments. For catsup, a one-segment solution is selected for the coupon user group while the two-segment model is selected for the non-user group. Following the Bayesian Information Criterion (Rust *et al.*, 1995; Schwarz, 1978) for detergent, a three-segment model is selected for the user group and a one-segment model for the non-user group[6].

Table III reports the parameter estimates and *t*-values for the various segments in both catsup and laundry detergent. In the catsup coupon-user segment, the coefficient for coupon availability is correctly signed and significant while neither latent segment of coupon non-users shows a significant effect for this variable. Coupon value is not significant in any of the catsup segments[7].
In detergent, coupon availability is positively signed and significant in each of the latent segments of coupon users. It is correctly signed and significant at the.10 level ($\beta_8 = 0.186$, $t = 1.79$) in the non-user segment, providing some evidence of an advertising effect of coupons among the non-user panelists. The (marginal) significance of the effect in detergent and its non-significance in catsup may be related to the extent of couponing activity in the category (Srinivasan *et al.*, 1995) – i.e. large numbers of coupons need to be dropped and redeemed for an advertising effect to be meaningful. As expected, coupon value is not significant for non-users but is significant for user segments 1 and 2 and marginally so for user segment 3.

### Posterior analysis of the segments

To explore the potential cross-sectional differences among the various segments, we conducted an informal posterior analysis of the various groups. In Table IV, we report segment-level means for elasticities, loyalty indices, measures of deal proneness, and demographics for the *a priori* segmentation of users and non-users for both categories. This permits us to illustrate potential differences among panelists that come directly from whether or not they redeem the coupons[8]. In Table V, we report the same measures for each of the latent segments. Since assignment to latent segments (e.g. segment 1 or 2 of the non-coupon users in catsup) is probabilistic, the segment-level means we report are weighted by the posterior probability of a given panelist belonging to a given segment.

Turning first to Table IV, we begin with elasticities. All of the elasticities are arc elasticities computed from simulating the effect of a change in the marketing variable on the choices made by the panelists during the estimation period. Price elasticities are computed as the percentage change in choice shares given a one percent change in price. Coupon availability elasticities are computed as the percentage change in choice shares given a change in availability from the lowest level to the highest level in the estimation period. Coupon value elasticities are computed as the percentage change in choice shares given a one percent change in coupon value (this computation is made only in those cases where the variable coefficient was correctly signed).

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**Table III** Parameter estimates for segment models

| | Catsup | | | Detergent | | | |
|---|---|---|---|---|---|---|---|
| | | Non coupon users | | | Coupon users | | |
| | Coupon users | Segment 1 | Segment 2 | Segment 1 | Segment 2 | Segment 3 | Non coupon users |
| **Brand loyalty** | 2.578 (15.199)* | 5.009 (8.217) | 1.073 (4.762) | 5.630 (20.070) | 1.191 (3.681) | 2.952 (14.235) | 2.886 (8.990) |
| **Last brand purchased** | 0.511 (7.232) | 0.102 (0.500) | 0.656 (6.507) | 0.357 (3.224) | 0.192 (1.708) | 1.248 (11.528) | 1.782 (9.885) |
| **Size loyalty** | 1.826 (9.169) | 3.752 (10.736) | 0.578 (1.485) | 4.174 (12.979) | 1.677 (6.565) | 0.464 (2.200) | 1.989 (7.253) |
| **Last size purchased** | 0.554 (6.593) | 0.853 (5.077) | 0.521 (2.752) | 0.322 (3.127) | 0.704 (6.349) | 0.614 (6.991) | 0.468 (3.105) |
| **Price** | −1.107 (−12.4915) | −0.796 (−4.0100) | −0.829 (−4.7722) | −0.733 (−9.1339) | −0.795 (−7.5348) | −0.316 (−4.2874) | −0.370 (−3.0728) |
| **Feature** | 1.389 (17.131) | 1.489 (6.787) | 1.323 (8.574) | 0.802 (3.710) | 0.826 (3.901) | 1.948 (10.947) | 1.646 (4.994) |
| **Display** | 0.484 (3.724) | 0.947 (3.130) | 0.462 (2.028) | 1.360 (7.503) | 1.030 (5.492) | 1.401 (9.133) | 1.382 (4.934) |
| **Coupon availability** | 0.209 (5.560) | 0.042 (0.382) | 0.013 (0.215) | 0.176 (3.846) | 0.248 (5.438) | 0.249 (5.461) | 0.186 (1.790) |
| **Coupon value** | −0.505 (−1.1407) | 1.160 (1.244) | 0.710 (1.067) | 1.287 (2.142) | 1.151 (2.201) | 0.888 (1.889) | −0.711 (−0.7342) |
| **Segment size** | n/a | 0.097 (0.406) | n/a | −0.242 (−1.2538) | −0.349 (−1.6357) | n/a | n/a |
| | | 0.524 | 0.476 | 0.315 | 0.283 | 0.402 | |
| **Log likelihood** | −2286.09 | −2438.69 | | −5390.53 | | | −447.42 |
| **BIC** | −2348.00 | −2566.24 | | −5612.83 | | | −497.43 |
| **No. of households** | 327 | 496 | | 350 | | | 42 |
| **No. of purchases** | 2,297 | 2,276 | | 2,805 | | | 2,59 |
| **No. of parameters** | 16 | 33 | | 56 | | | 18 |

**Note:** * *t*-values in parentheses

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**Table IV** Characteristics of coupon users and non-users

| | Catsup | | Detergent | |
|---|---|---|---|---|
| | Coupon users | Non coupon users | Coupon users | Non coupon users |
| **Elasticities** | | | | |
| Price | − 1.243 | − 0.978 | − 1.816 | − 0.893 |
| Coupon availability | 33.434 | 4.363 | 98.617 | 55.198 |
| Coupon value | 0.000 | 0.055 | 0.396 | 0.000 |
| **Loyalty indices** | | | | |
| Brand | 0.743 | 0.767 | 0.551 | 0.740 |
| Size | 0.816 | 0.840 | 0.597 | 0.581 |
| Store | 0.437 | 0.493 | 0.465 | 0.584 |
| **Deal proneness** | | | | |
| Coupon propensity | 32.983 | 0.000 | 63.627 | 0.000 |
| Feature propensity | 35.020 | 26.957 | 17.897 | 10.463 |
| Display propensity | 12.175 | 10.814 | 20.619 | 16.710 |
| Percent savings from coupons | 11.867 | 0.000 | 15.045 | 0.000 |
| **Demographics** | | | | |
| Usage (annual oz.) | 242.398 | 153.169 | 628.846 | 525.714 |
| Family size | 3.489 | 3.210 | 3.091 | 3.238 |
| Percent single/multiple family house | 94.495 | 90.323 | 93.714 | 85.714 |
| Percent vollege education | 56.575 | 45.968 | 57.714 | 54.762 |
| Percent income >30K | 42.813 | 39.516 | 44.857 | 42.857 |
| Percent dual employment | 43.425 | 45.968 | 40.571 | 57.143 |
| No. of households | 327 | 496 | 350 | 42 |

**Table V** Segment characteristics

| | Catsup | | | Detergent | | | |
|---|---|---|---|---|---|---|---|
| | | Non coupon users | | Coupon users | | | |
| | Coupon users | Segment 1 | Segment 2 | Segment 1 | Segment 2 | Segment 3 | Non coupon users |
| **Elasticities** | | | | | | | |
| Price | − 1.243 | − 0.652 | − 1.337 | − 2.038 | − 2.747 | − 0.904 | − 0.893 |
| Coupon availability | 33.434 | 3.845 | 0.065 | 75.477 | 140.657 | 107.987 | 55.198 |
| Coupon value | 0.000 | 0.051 | 0.065 | 0.413 | 0.462 | 0.294 | 0.000 |
| **Loyalty indices** | | | | | | | |
| Brand | 0.743 | 0.824 | 0.704 | 0.617 | 0.431 | 0.583 | 0.740 |
| Size | 0.816 | 0.836 | 0.845 | 0.615 | 0.633 | 0.559 | 0.581 |
| Store | 0.437 | 0.515 | 0.469 | 0.476 | 0.451 | 0.467 | 0.584 |
| **Deal proneness** | | | | | | | |
| Coupon propensity | 32.983 | 0.000 | 0.000 | 59.991 | 72.600 | 60.151 | 0.000 |
| Feature propensity | 35.020 | 24.749 | 29.391 | 12.423 | 18.330 | 21.888 | 10.463 |
| Display propensity | 12.715 | 10.145 | 11.551 | 16.060 | 21.381 | 23.659 | 16.710 |
| Percent savings from coupons | 11.867 | 0.000 | 0.000 | 13.753 | 21.148 | 11.754 | 0.000 |
| **Demographics** | | | | | | | |
| Usage (annual oz.) | 242.398 | 153.340 | 152.981 | 708.636 | 515.840 | 645.957 | 525.714 |
| Family size | 3.489 | 3.180 | 3.242 | 3.157 | 3.081 | 3.048 | 3.238 |
| Percent single/multiple family house | 94.495 | 90.728 | 89.875 | 93.338 | 93.115 | 94.432 | 85.714 |
| Percent college education | 56.575 | 52.789 | 53.708 | 57.464 | 55.847 | 59.204 | 54.762 |
| Percent income >30K | 42.813 | 39.578 | 39.448 | 47.853 | 43.646 | 43.360 | 42.857 |
| Percent dual employment | 43.425 | 45.842 | 46.107 | 47.556 | 34.353 | 39.477 | 57.143 |
| No. of households | 327 | 260 | 236 | 110 | 99 | 141 | 42 |

First, we note the difference in price elasticities across the users and non-users in both categories. Price elasticities are larger (in absolute magnitude) for coupon users than non-users. The catsup means are −1.24 and −0.98 and the detergent means are −1.82 and −0.89, respectively. These results directly corroborate Narasimhan (1984). Second, the elasticities for coupon availability suggest that large changes in share can be induced by changes in coupon activity. For example, a move from the lowest level of availability to the highest level of availability approximately doubles the choice share for a brand among coupon users in detergent while increasing it by 33 percent among coupon users in catsup. Lastly, the calculations for coupon value elasticity

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(significant only for detergent coupon users) shows an inelastic response level of about 0.4. This indicates that choice share can be expanded by 40 percent (among detergent coupon users) if coupon face value is doubled. (We address the profitability implications of this below.)

In Tables IV and V we also present indices for brand loyalty, size loyalty, and store loyalty. In general, coupon users appear to be less brand and store loyal than coupon non-users. There is relatively little difference among the segments in size loyalty. Turning to the deal proneness measures, catsup coupon users make approximately one third of their purchases with a coupon, while detergent coupon users redeem a coupon about 64 percent of the time. The proportion of items bought while on feature is also higher for coupon users and, to a lesser degree, so is the proportion of items bought while on display. Note that these proportions do not reflect response (i.e. the effect of changes in feature or display on choice) which was previously shown to be the same or higher for coupon non-users. Overall, catsup coupon users saved about 12 percent while detergent coupon users saved about 15 percent by redeeming coupons.

With respect to demographics, coupon users in both categories are, on average, heavier users than coupon non-users. One exception to this is the second latent segment of detergent coupon users. Its average usage rate is the lowest of all four detergent segments. Interestingly, this segment is both most price elastic and most responsive to coupon availability and coupon face value. Perhaps the need to buy somewhat less often in the category may enable these panelists to purchase more opportunistically than those in detergent user segments 1 or 3.

Coupon users are, on average, somewhat more likely to live in houses than apartments (Table IV). They are also better educated and have higher incomes (Harmon and Hill, 2003, p. 166). Interestingly, they also may have more time to take advantage of coupons: the percentage of coupon-using panelists with dual head-of-household employment is lower in both categories than the percentage for coupon non-users. This finding is reinforced by the pattern for the latent segments of coupon users in detergent. Again, segment 2, with the highest level of coupon elasticities, has the lowest level of dual employment (34 percent).

### Cross-validation

In order to ensure that our latent segment results are stable and are not capitalizing on chance variation within the estimation sample we conducted a double cross-validation assessment for the segmentation of the coupon users in the detergent category. Using the redemption information from the calibration sample of households for the coupon variables, we also estimated the model on the hold-out sample of households ($n = 334$). The three-segment solution was also selected by the BIC and the pattern of results paralleled the three-segment solution for the coupon users in the calibration sample. To double cross validate, we then used the parameters obtained from the hold-out sample to fit the model to the calibration sample and the parameters from the calibration sample to fit the model to the hold-out sample. In both cases, the three-segment solution provided better fits to the data than the single-segment solution. For the calibration sample using hold-out parameters, the log likelihood values were $-5662.8$ and $-5581.3$ for the single- and three-segment solutions, respectively. For the hold-out sample using calibration parameters, the log likelihood values were $-4936.0$ and $-4855.1$ for the single- and three-segment solutions, respectively.

### Implications for profitability assessment

The findings regarding the market response to changes in coupon availability and coupon face value have implications for the assessment of coupon profitability. In detergent, for example, share can be increased by either increasing coupon availability or by increasing face value or both. In catsup, on the other hand, share appears to respond meaningfully only to changes in availability[9]. The profitability of increasing availability depends upon the gross margin realized from new sales due to brand switching, the fixed costs of additional distribution and the variable costs of redemption. The profitability of higher face values depends upon gross margin from new sales and the variable costs of redemption.

More generally, the model can be used as an input to a decision support system for evaluating coupon profitability (e.g. as the market response component of a system like the one proposed by Leone and Srinivasan, 1996). In order to do this, the coupon availability measure will need to be scaled to the corresponding levels of coupon distribution activity. The net sales attributable to a change in availability can then be linked to the additional marketing spending that was required to produce it. The approach is similar to the notion that a given number of gross rating points (GRPs) can be directly connected to the media spending levels needed to produce them.

## Conclusion

The purpose of this paper has been to develop and illustrate an approach to capture the effects of

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coupon activity in logit models of brand choice applied to scanner panel data. Methodologically, our approach is designed to take advantage of the information contained in coupon redemption data and to incorporate the effects of both coupon availability as well as coupon face value. Our model is especially suited to situations in which information on coupon distribution is either unavailable or unlikely to accurately reflect the week-to-week availability of brand coupons (e.g. due to the use of multiple delivery vehicles, overlapping drops, etc.). We measure weekly coupon availability based on normalized redemptions and face value as the average value, in each week, of all coupons redeemed for the brand by a hold-out set of households. Our approach therefore avoids the endogeneity problems in previous choice models that handle coupons by subtracting the value of any redeemed coupons from price – what we have termed the NETPRICE approach.

We present an empirical application of our modeling approach on two categories of scanner panel data, catsup and liquid laundry detergent. We show that our proposed measures of coupon activity (prevailing availability and face value) are predictive of brand choice and significantly improve the fit of the models to the data.
A comparison of our model with the NETPRICE approach specifically illustrates the drawbacks of incorporating coupons via the price term in the logit. We find that the magnitude of the price coefficient is biased upwards quite substantially (about 30 percent in our data). Thus, a major limitation of the NETPRICE procedure is that it is likely to systematically overstate consumer response to changes in price.

Our estimation work in catsup and liquid laundry detergent also provides a number of substantive insights into the nature and segmentation of market response to coupons.
In illustrating our modeling approach, we conduct a segment-level estimation, employing both an *a priori* division of the sample as well as a *post hoc* segmentation using latent class analysis. Following Leone and Srinivasan (1996), we estimate the model separately for coupon users and non-users. This produces the following key findings.
First, price elasticities are higher for coupon users than non-users, corroborating Narasimham (1984). Second, we find evidence (at the $p < 0.10$ level) for an advertising effect of coupons on non-users in laundry detergent, though no effect in catsup. We also compute elasticities for the coupon variables which show that changes in coupon activity can lead to large changes in brand shares. Lastly, the results show coupon users to be less brand loyal, more deal prone, and demographically advantaged in having the time to take advantage of coupon promotions. Collectively, these findings suggest that coupons function much as the other short-run promotion vehicles used in packaged goods.

A limitation of our approach is that both the coupon availability and coupon face value variables are likely to be measured with error – though we do not expect this error to be systematic. The consequence of measurement error in these variables – as in most variables in the utility function – will be a bias in the parameter estimates towards zero. Thus, the true impact of coupon promotions on brand choice may be understated by this model. This limitation needs to be balanced against the drawbacks of the other extant approaches to handling coupons in logit choice models for scanner panel data.

The model and some of the substantive findings from its estimation on the two product categories should be of interest to both manufacturers and retailers. Manufacturers can use the model to obtain estimates of new sales that are truly incremental for the brand due to coupon promotions. They can also study the nature of market segmentation in coupon response and how it relates to segmentation in response to other marketing mix activity. The model can also reveal whether coupons are delivering an advertising effect in the market to coupon non-users.
If significant, this effect should be incorporated into the computation of coupon promotion profitability (Leone and Srinivasan, 1996).

While the value of the model is perhaps immediately clearest for manufacturers, it should be of interest to retailers as well. Retailers incur substantial expenses in honoring and processing coupons. In many markets, competitive conditions have also prompted retailers to double the value of manufacturer coupons. Thus, coupons have an important impact on the profitability of grocery retailers. With the advent of so-called "frequent shopper clubs," retailers now have individual-level transaction data for many – if not most – of their customers. As a consequence, many retailers are now in the position to analyze the effects of coupons without relying on data analyses provided by manufacturers.

The ability to independently assess the impact of promotion activity can provide retailers with information and countervailing power that they otherwise would have lacked. For example, coupon response elasticities can be contrasted with price, feature, and display elasticities to suggest allocations of promotional spending that provide "win-win" outcomes for both manufacturer and retailer. For example, an application of the model might reveal that coupons induce little response but end-aisle displays induce large response.

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The implication is that both manufacturer and retailer could be better off if couponing were reduced and those dollars shifted into supporting increased display activity.

## Notes

1 In fact, Leone and Srinivasan (1996), using data on specific coupon drops, found different effects from price cuts and coupons of the same value.
2 We thank an anonymous reviewer for suggesting that we note these limitations.
3 This list is intended to be representative and not exhaustive.
4 Our objective with this comparison is to provide a symmetric contrast of our approach with the NETPRICE approach to highlight the econometric differences. We therefore present in Tables I and II results for the shelf price and NETPRICE models both with and without the coupon measures.
5 Previous research (e.g. Andrews *et al*., 2002; Kamakura and Russell, 1989) has shown that if modelers do not account for unobserved heterogeneity when estimating disaggregate (household-level) econometric models, the estimated response parameters could be biased. In our approach we account for both observed heterogeneity via the *a priori* classification in coupon users and non-users and unobserved heterogeneity via latent class (or a finite mixture).
6 Complete model estimation and fit results are available from the first author upon request.
7 We conjecture that the (unexpected) negative sign for coupon value in the user segment may be due to the correction it can provide for overstated availability if redemptions run higher when face values increase.
8 Our exploratory analysis does not conduct the formal tests of coefficient equivalence which would be required to establish whether or not differences across segments are statistically significant.
9 This result could be due to the limitations of the natural experiment provided by the data. If there is little variation in coupon face value, it will have an insignificant effect on choice in the model.

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## Further reading

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