



A method to infer coupon availability from coupon redemption in the supermarket scanner panel data

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Abstract

Measuring the impact of coupon availability on consumers' purchase decisions often poses a problem in forecasting market shares of brands in a retail environment. Because, data on actual coupon availability do not exist or can only be obtained by costly field experiments. The widely used supermarket scanner panel data sets offer information on coupons redeemed by the household for only the specific brand that is bought. However, using the redemption variable introduces bias in brand choice or purchase incidence models because redeeming a coupon implies buying the brand or making the purchase. This study presents a way to infer availability from coupon redemption data and to predict market shares for each brand in a supermarket product category. © 1999 Elsevier Science Ltd. All rights reserved.

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1. Introduction

With the advent of scanner panel data sets, marketing researchers have made considerable advances in estimating household level brand choice and purchase incidence models. But, while scanner panels contain detailed information on price promotions for all brands in the store environment, they remain silent on the extent of coupon availability at the household level.¹ In the scanner panel data we only know the coupon redemption for the bought brand. However, when coupon *redemption* is used as a substitute for coupon *availability* in a brand choice model, the coupon coefficient will be over estimated. The *bias* occurs because redeeming a coupon for a specific brand automatically implies buying the brand. Similarly, in a purchase incidence model using a coupon implies that a purchase has occurred. Hence, when brand choice and purchase incidence are attempted to be

explained by the coupon redemption variable, the impact of coupon is overstated.

In 1995, 350 billion coupons were distributed. Procter and Gamble, a major manufacturer of packaged goods, spends about \$25 million annually in coupon distribution. Especially, in categories such as the disposable diaper, where couponed purchases comprise more than 50% of the sales, coupon distribution and competitive couponing strategies are extremely important.

If net price (= price – coupon value) is used in a brand choice model as an explanatory variable, the effect of coupon per se on brand choice cannot be estimated (see, for example, Kamakura and Russell, 1989). Furthermore, in this case the price variable includes the coupon redemption decision and loses its exogeneity property.

Although it is beyond the scope of this paper a comprehensive survey of the coupon literature can be found in Blattberg and Neslin (1990, Ch. 10). The advantages of coupons over direct shelf-price cuts are several: (i) A coupon is a visible reminder of a price reduction whereas a minor change in shelf price may go unnoticed by many consumers. Gönül and Srinivasan (1993) find that coupons are more effective than price cuts in inducing brand switches. (ii) A coupon is an exclusive offer to those consumers who collect coupons and hence enable price

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¹ Availability refers to a specific household's having at least one coupon for a specific brand, that is ready to use (clipped, saved), and prior to expiration.

discrimination (Narasimhan, 1984). (iii) Coupons do not interfere with the image of a product whereas a lower price may signal a lower product quality. (iv) Coupons enable the manufacturer to directly influence the retail price without having to negotiate with the store manager.

Although a growing body of literature exists on coupons, an accurate measure of coupon availability does not exist largely due to lack of data at the household level. One exception is Klein (1981) who obtains availability data from supermarket experiments. Although Klein's data is at the household level and valuable, it is costly to run a field experiment. Furthermore, a field experiment does not help the scanner panel researcher unless the panel members are made subjects of the experiments at the time the scanner data are collected. Neslin (1990) uses coupon data from advertisements in the local newspapers, however, Neslin's data is not at the household level. Shaffer and Zhang (1995) examine competitive couponing strategies in a theoretical framework. Chiang (1995) models coupon use at the category level in the household's utility maximization problem, however, does not address the brand choice problem.

Our study differs from prior works because we (a) conduct an empirical study, (b) use household-level data, (c) infer brand-specific coupon availability probabilities, and (d) model brand choice in addition to coupon redemption. We treat brand-specific coupon availability as an unobserved variable and estimate the probability distribution function of brand-specific coupon availability.

2. Proposed method

Coupon redemption is the joint outcome of exposure (availability) and willingness to redeem it on a given purchase occasion. On a given purchase occasion a coupon for a specific brand is either available to the household or not. In spite of availability, some households may not redeem any coupons, due to lack of time or lack of interest.

Blattberg and Neslin (1990) state that brand choice and coupon redemption decisions can be modeled as simultaneous decisions (Ch. 10).² We adopt the reasoning and assume that a household makes two simultaneous decisions on a given purchase occasion: which brand to purchase and whether or not to redeem a coupon with the purchase. If there exist three brands in a product category then there are eight possible environments for binary coupon availability situations. For example, in an environment where no coupons are available, the choice set consists of three alternatives only: {(Brand A without a coupon), (Brand B without a coupon), (Brand C without a coupon)}. Similarly, in the environment where only Brand A's coupons are available the choice set consists of four alternatives: {(Brand A with or without a coupon), (Brand B without a coupon), (Brand C without a coupon)}. If coupons for all three brands are available to the household on purchase occasion i , then the household chooses among six alternatives.

The following table enumerates the choice environments more succinctly (E_i , $i = 1, \dots, 8$):

Environment	Coupon Availability			Coupon environments		Alternatives			
	a_A	a_B	a_C	(A, 1)	(A, 0)	(B, 1)	(B, 0)	(C, 1)	(C, 0)
1	1	1	1	✓	✓	✓	✓	✓	✓
2	0	1	1		✓	✓	✓	✓	✓
3	1	0	1	✓	✓		✓	✓	✓
4	1	1	0	✓	✓	✓	✓		✓
5	0	0	1		✓		✓	✓	✓
6	0	1	0		✓	✓	✓		✓
7	1	0	0	✓	✓		✓		✓
8	0	0	0		✓		✓		✓

ties. In our empirical work, we control for households' willingness to redeem coupons using historical data. Our model provides answers to such questions as: What happens to market shares if a manufacturer decides to eliminate its coupons (as P and G announced in 1994)? Does the brand stand to lose or gain against competing brands that may not follow suit?

In the remainder of the paper Section 2 presents the proposed methodology; Section 3 presents the data; Section 4 presents the tests of the model, the results, and discussion; and Section 5 concludes with a summary and future research directions.

where $a_j = 1$ if coupons are available for brand j and $a_j = 0$ otherwise.

² Although a nested logit may be considered to model conditional brand and coupon use decisions, the lack of data on availability makes the nested logit model inestimable in our context. For example, suppose no coupons were available to the household at a given time. Then the household engages in an unconditional brand choice exercise. On the other hand, suppose only one brand's coupon is available at a given time. Then the household considers a conditional decision for that brand, and unconditional decision for the remaining two brands. Since the scanner panel data does not include availability information the nested logit model cannot be used in this case.

The alternatives can be represented as pairs (y_i, z_i) , where $y_i = A, B, C$ denotes the household's brand choice decision on purchase occasion i (e.g. $y_i = A$ if the household chooses Brand A on purchase occasion i) and z_i denotes the household's coupon redemption decision on purchase occasion i ($z_i = 1$ if the household redeems a coupon on purchase occasion i and 0 otherwise). We let U_{ijk} denote the utilities of each of the six alternatives for $j = A, B, C$ and $k = 0, 1$. We assume that

$$\bar{U}_{ijk}(y_i = j, z_i = k) = \bar{U}_{ijk} + \varepsilon_{ijk}, \quad (1)$$

where $\bar{U}_{ijk}$ is the deterministic component and ε_{ijk} is the random component that is independent and identically distributed as Type I extreme value (McFadden, 1974). The logit choice probability has a *different denominator* depending on the environment. Different denominators (according to environments) drive the estimates of the availability probabilities. For example, in $E_i = 1$, where coupons for all three brands are available, the choice probabilities are

$$P(y_i = j, z_i = k | E_i = 1) = \frac{\exp(\bar{U}_{ijk})}{\sum_{j=A}^C \sum_{m=0}^1 \exp(\bar{U}_{ilm})}, \quad (2)$$

since the household can choose among six alternatives. On the other hand, for $E_i = 7$:

$$P(y_i = j, z_i = k | E_i = 7) = \frac{\exp(\bar{U}_{ijk})}{\exp(\bar{U}_{iA1}) + \exp(\bar{U}_{iA0}) + \exp(\bar{U}_{iB0}) + \exp(\bar{U}_{iC0})} \quad (3)$$

for (j, k) in $\{(A, 1), (A, 0), (B, 0), (C, 0)\}$.

Note that $P(y_i = j, z_i = k | E_i = 7) = 0$ for (j, k) in $\{(B, 1), (C, 1)\}$ since those two alternatives are *not available* in the seventh environment. More generally, we let $S(n)$ be the set of alternatives available in environment n . Then

$$P(y_i = j, z_i = k | E_i = n) = \begin{cases} \exp(\bar{U}_{ijk}) / \sum_{(l, m) \in S(n)} \exp(\bar{U}_{ilm}) & \text{if } (j, k) \in S(n), \\ 0 & \text{if } (j, k) \notin S(n). \end{cases} \quad (4)$$

We need to work with the unconditional probability that the household chooses alternative (j, k) since we do not observe the choice environment faced by a household. We express the unconditional probability as a weighted average of the conditional choice probabilities given by Eq. (4) with the n th weight corresponding to the probability that the household faces choice environment n . More explicitly,

$$P(y_i = j, z_i = k) = \sum_{n=1}^8 P(y_i = j, z_i = k | E_i = n) P(E_i = n). \quad (5)$$

We define $p_n \equiv P(E_i = n)$ where the probabilities p_n , $n = 1, \dots, 8$ are each nonnegative and sum to one.³

$$\begin{aligned} P(E_i = 1) &= P(a_{iA} = 1, a_{iB} = 1, a_{iC} = 1) = p_1, \\ P(E_i = 2) &= P(a_{iA} = 0, a_{iB} = 1, a_{iC} = 1) = p_2, \\ P(E_i = 3) &= P(a_{iA} = 1, a_{iB} = 0, a_{iC} = 1) = p_3, \\ P(E_i = 4) &= P(a_{iA} = 1, a_{iB} = 1, a_{iC} = 1) = p_4, \\ P(E_i = 5) &= P(a_{iA} = 0, a_{iB} = 0, a_{iC} = 1) = p_5, \\ P(E_i = 6) &= P(a_{iA} = 0, a_{iB} = 1, a_{iC} = 0) = p_6, \\ P(E_i = 7) &= P(a_{iA} = 1, a_{iB} = 0, a_{iC} = 0) = p_7, \\ P(E_i = 8) &= P(a_{iA} = 0, a_{iB} = 0, a_{iC} = 0) = p_8. \end{aligned} \quad (6)$$

We estimate these environment probabilities jointly with the rest of the model parameters. The brand-specific availability probabilities can then be obtained by summing the probabilities of environments where that coupon is available. (For example, the probability of availability of a coupon for Brand A is the sum of the first, third, fourth, and seventh environment probabilities.) We label this specification the *General Coupon Availability Model*.⁴

In a nested version of the General Model, the coupons are assumed to be distributed independently of each other. Then the environment probabilities can be expressed as the product of the probabilities of the independent events, $P(a_{ij} = 1) \equiv q_j$. Hence,

$$\begin{aligned} P(E_i = 1) &= P(a_{iA} = 1, a_{iB} = 1, a_{iC} = 1) = q_A q_B q_C, \\ P(E_i = 2) &= P(a_{iA} = 0, a_{iB} = 1, a_{iC} = 1) = (1 - q_A) q_B q_C, \\ P(E_i = 3) &= P(a_{iA} = 1, a_{iB} = 0, a_{iC} = 1) = q_A (1 - q_B) q_C, \\ P(E_i = 4) &= P(a_{iA} = 1, a_{iB} = 1, a_{iC} = 0) = q_A q_B (1 - q_C), \\ P(E_i = 5) &= P(a_{iA} = 0, a_{iB} = 0, a_{iC} = 1) \\ &= (1 - q_A) (1 - q_B) q_C, \\ P(E_i = 6) &= P(a_{iA} = 0, a_{iB} = 1, a_{iC} = 0) \\ &= (1 - q_A) q_B (1 - q_C), \\ P(E_i = 7) &= P(a_{iA} = 1, a_{iB} = 0, a_{iC} = 0) \\ &= q_A (1 - q_B) (1 - q_C), \\ P(E_i = 8) &= P(a_{iA} = 0, a_{iB} = 0, a_{iC} = 0) \\ &= (1 - q_A) (1 - q_B) (1 - q_C). \end{aligned} \quad (7)$$

³ The purchase occasion subscript on the environment (E_i) does not imply that the probability of an environment changes on each purchase occasion.

⁴ The number of environments increases as the number of brands increase. If the number of brands is high, e.g. 10, then the number of environments is 1024 and the model may run out of degrees of freedom when estimating the 1023 (=1024 - 1) environment probabilities. However, if that is the case, the model can be simplified and the number of parameters can be reduced by assuming coupon distributions are independent across brands, or at least partially correlated as described in the *Independent* model next.

We term the nested specification the *Independent Coupon Availability Model*. For example, if the number of brands is 10 there are only 10 parameters to estimate. If independence assumption is too restrictive (such would be the case when two or more brands are jointly owned by a company), then only those brands can be assumed dependent, and the assumption can be tested by a Lagrange multiplier test against the General Model.

Our models nest a third model where coupons for all three brands are available with probability one. Then,

$$P(E_i = n) = \begin{cases} 1 & \text{if } n = 1, \\ 0 & \text{if } n = 2, \dots, 8, \end{cases} \quad (8)$$

where there is only one choice environment. We term this nested version where all three coupons are always available the *Ordinary Choice Model*. For all three models, a general expression can be given for the log-likelihood function:

$$L = \sum_{i=1}^M \sum_{j=A}^C \sum_{k=0}^1 D_{ijk} \log \left(\sum_{n=1}^8 P(y_i = j, z_i = k | E_i = n) P(E_i = n) \right), \quad (9)$$

where M is the total number of observations, $D_{ijk} = 1$ if the household chooses alternative (j, k) on purchase occasion i and $D_{ijk} = 0$ otherwise. We estimate our models with different starting points and obtain convergence to the reported optimum in all cases.

Note that the General and Independent Models do not suffer from the independence from irrelevant alternatives (IIA) limitation at the aggregate level. Because, the unobserved coupon environments capture potential correlation across alternatives. The choice alternatives that share common environments are linked through the environment probabilities. We have attempted to estimate the multivariate probit model to capture correlation across alternatives more generally. However, we experienced convergence problems in implementing the method of simulated moments even for the simple Ordinary Choice Model, potentially due to our modest sample size. Our specification does not pose problems in estimation due to the closed-form expressions of the logit probabilities, and does not have the IIA problem at the aggregate level.

3. Data and empirical specification

3.1. Data

Our sample is from the A.C. Nielsen scanner panel data on households that purchased disposable diapers during a 52-week period. The diaper wars are fought mainly by manufacturers' coupons: one-half of diaper purchases are made with manufacturer coupons in the

data. Other promotional tools such as store coupons, displays, and feature are practically nonexistent in this category (less than 0.1% in the data). Three national brands account for more than 90% of the total sales in the market. We divide the sample into three parts. The first 13 weeks comprise the initialization sample, for a total of 805 purchases; the middle 26 weeks comprise the estimation sample, for a total of 1414 purchases; the last 13 weeks comprise the holdout sample, for a total of 651 purchases. We use the initialization sample to construct measures of past brand loyalty and coupon proneness for each household. The sample consists of 162 households. The three national brands they buy comprise more than 90% of the market. The observed frequencies in the data are as follows: Brand A is purchased with a coupon 12.4% of the time, Brand A without a coupon 11.2%, Brand B with a coupon 13.6%, Brand B without a coupon 5.4%, Brand C with a coupon 32.2%, and Brand C without a coupon 27.0% of the time.

The average shelf prices per diaper for the brands are, 14.5 cents, 14.3 cents, and 14.3 cents. *PRICE* is the size-adjusted unit price per diaper. We define *LOY_j* as past brand loyalty that we compute from the initialization sample (Bucklin and Lattin, 1991). Omitting the household subscript, $LOY_j \equiv (1/J + N_j)/(1 + N)$, where J is the number of brands ($J = 3$), N_j is the number of purchases of brand j by the household in the initialization sample and N is the total of number of purchases by the household in the initialization sample. Note that $0 < LOY_j < 1$ for all j and that $\sum_{j=A}^C LOY_j = 1$. To capture the effect of recent brand choice we use *BRECENT_{ij}* = 1 if the most recently purchased brand is brand j , 0 otherwise. We construct similar measures to capture coupon proneness. Omitting the household subscript from the right-hand side, we obtain $CINIT_i \equiv (1/2 + N_c)/(1 + N)$, where N_c is the number of purchases in the initialization sample that the household makes with a coupon. The variable *CINIT_i* lies between 0 and 1, indicating degree of coupon proneness. In addition, we use *CRECENT_i* = 1, if the most recent purchase is made with a coupon, and 0 otherwise. The demographic variables are annual household income, scaled to a fraction of 50 000 (*INCOME*), a dummy variable for ownership of residence (*OWN*), dummies for whether male and female heads of households work full-time or not (*MEMP*, *FEMP*), dummies for college degree (*MEDU*, *FEDU*), and the number of members in the household (*NUMMEM*).

3.2. Empirical specification

We model the deterministic part of the utility function as follows:

$$\bar{U}_{ijk} = \alpha_{jk} + \gamma_{1k} PRICE_{ij} + \gamma_{2j} LOY_{ij} + \gamma_{3j} BRECENT_{ij} + \gamma_{4k} CINIT_i + \gamma_{5k} CRECENT_i + DEMOG_i \beta_k, \quad (10)$$

where price is allowed to have a different impact for couponed and noncouponed alternatives; past and recent brand loyalty are captured by LOY_{ij} and $BRECENT_{ij}$; past and recent deal proneness are captured by $CINIT_i$ and $CRECENT_i$; and $DEMOG_i$ includes demographic variables. We arbitrarily set α_{C0} to zero, since not all six intercepts are identified in the discrete choice framework.

Based on prior research with the data we do not expect the demographic variables to significantly influence the brand choice part of the decision. Thus, we enter the demographic variables only in couponed alternatives (that is, where $k = 1$). We achieve this by setting the parameters of the corresponding variables to zero in noncouponed alternatives ($\beta_0 = 0$). The formulation allows us to explore whether demographics play a role in coupon redemption tendencies. For example, if we find that male household head's education has a negative and significant coefficient, then we will be able to conclude that male household heads with relatively higher education are less likely to redeem coupons.

Similar to demographics, we enter the coupon-proneness variables only in couponed alternatives ($\gamma_{40} = 0$, $\gamma_{50} = 0$). Such a formulation allows us to estimate if past and recent coupon-proneness significantly influence current coupon redemption. Coupon redemption is costly for some consumers but is favored as a smart-shopping opportunity by other consumers (Shimp and Kavas, 1984). We let the consumer heterogeneity in past and recent deal-proneness contribute to the explanation of coupon redemption as a choice.

4. Results and discussion

We find that the General Coupon Availability Model fits the best and achieves the highest log-likelihood value in the estimation sample (Table 1). The likelihood ratio tests reject the two nested models: We reject the Ordinary Choice Model in favor of the Independent Coupon Availability Model ($\chi^2_{(3)} = 8.2$, $p < 0.05$), and by implication, in favor of the General Model. The Independent Model imposes the restriction of independence across brands' coupon distribution decisions. We reject the Independent Coupon Availability Model in favor of the General Availability Model ($\chi^2_{(4)} = 23.4$, $p < 0.01$).⁵ The Consistent Akaike Information Criterion (CAIC, Bozdogan, 1987) also indicates that the General Model fits the best. See the bottom of Table 1.

Table 1
Parameter estimates and standard errors^a

Coupon availability probabilities ^b	Ordinary model	Independent model	General model
Environment 1 ($a_A = 1$, $a_B = 1$, $a_C = 1$)	1	0.34*** (0.12)	0.31*** (0.13)
Environment 2 ($a_A = 0$, $a_B = 1$, $a_C = 1$)	0	0.08** (0.04)	0.28*** (0.08)
Environment 3 ($a_A = 1$, $a_B = 0$, $a_C = 1$)	0	0.18*** (0.07)	0.15 (0.10)
Environment 4 ($a_A = 1$, $a_B = 1$, $a_C = 0$)	0	0.19*** (0.08)	0.02 (0.05)
Environment 5 ($a_A = 0$, $a_B = 0$, $a_C = 1$)	0	0.04 (0.03)	0.00 (0.00)
Environment 6 ($a_A = 0$, $a_B = 1$, $a_C = 0$)	0	0.04 (0.03)	0.00 (0.00)
Environment 7 ($a_A = 1$, $a_B = 0$, $a_C = 0$)	0	0.10** (0.05)	0.00 (0.00)
Environment 8 ($a_A = 0$, $a_B = 0$, $a_C = 0$)	0	0.02 (0.02)	0.231*** (0.03)
Coefficients	Ordinary model	Independent model	General model
α_{A1} (intercept)	-1.96** (0.84)	1.60* (0.95)	-1.11 (1.45)
α_{A0} (intercept)	-0.45 (0.27)	-0.48 (0.31)	-0.74** (0.34)
α_{B1} (intercept)	-1.37* (0.83)	-1.04 (0.95)	-0.82 (1.45)
α_{B0} (intercept)	-0.40 (0.26)	-0.42 (0.30)	-0.58 (0.35)
α_{C1} (intercept)	-1.55* (0.80)	-1.42 (0.90)	-1.01 (1.42)
γ_{11} (Price with coupon)	-0.20*** (0.05)	-0.21*** (0.06)	-0.27*** (0.07)
γ_{10} (Price without coupon)	-0.19*** (0.06)	-0.19*** (0.06)	-0.13*** (0.07)
γ_{2A} (LOY_A)	2.31*** (0.35)	2.58*** (0.40)	2.83*** (0.45)
γ_{2B} (LOY_B)	1.59*** (0.40)	1.97*** (0.49)	2.01*** (0.53)
γ_{2C} (LOY_C)	1.42*** (0.31)	1.52*** (0.35)	1.35*** (0.36)
γ_{3A} ($BRECENT_A$)	0.81*** (0.18)	0.89*** (0.21)	1.01*** (0.23)
γ_{3B} ($BRECENT_B$)	0.51*** (0.18)	0.63*** (0.22)	0.64*** (0.23)
γ_{3C} ($BRECENT_C$)	1.29*** (0.16)	1.42*** (0.19)	1.28*** (0.20)
γ_{41} ($CINIT$)	2.85*** (0.26)	3.19*** (0.35)	5.75*** (0.85)
γ_{51} ($CRECENT$)	0.64*** (0.13)	0.76*** (0.16)	1.29*** (0.32)
β_1 ($INCOME$)	-0.03 (0.30)	0.00 (0.22)	0.19 (0.53)

⁵ The degrees of freedom for the chi-squared test is the difference in the number of parameters. The restrictions that the null hypothesis imposes on the test can be nonlinear as in our case. For further details, see Judge et al. (1985, Ch. 6).

Table 1 (continued)

Coefficients	Ordinary model	Independent model	General model
β_2 (OWN)	0.15 (0.14)	0.20 (0.16)	0.31 (0.31)
β_3 (MEMP)	0.04 (0.13)	0.05 (0.15)	0.42 (0.28)
β_4 (FEMP)	0.03 (0.14)	0.04 (0.16)	0.41 (0.34)
β_5 (MEDU)	0.22 (0.20)	0.30 (0.25)	0.32 (0.43)
β_6 (FEDU)	− 0.02 (0.19)	− 0.03 (0.22)	− 0.35 (0.41)
β_7 (NUMMEM)	− 0.20 (0.05)	− 0.03 (0.06)	0.06 (0.14)
Log-likelihood	− 1830.8	− 1826.7	− 1815.0
CAIC ^c	3705.6	3703.4	3688.0

^a Standard errors are placed in parentheses. The last intercept is set to zero for identification purposes.

^{*} Denotes significance at the 10% level. ^{**} Denotes significance at the 5% level. ^{***} Denotes significance at the 1% level.

^b Since we report only two digits after the decimal point, some probabilities may appear as zero. The marginal availability probabilities for brands (q_j) are 0.81, 0.65, and 0.64 (for the Independent Model) and 0.48, 0.61, and 0.74 (for the General Model). In the Independent Model the estimated parameters are the three marginal probabilities. The eight environment probabilities reported for the Independent model are derived using Eq. (7); their standard errors are computed using the S.E. formula for nonlinear functions of parameters (Judge et al., 1985).

^c The CAIC (Consistent Akaike Information Criterion) is often employed as a goodness-of-fit measure (Bozdogan, 1987). $CAIC = -2\log L + 2p$ where p is the number of parameters. A lower value indicates a better fit.

We compute the log-likelihood values on the holdout sample using parameter estimates from the estimation sample. The General Model performs slightly better than the Independent Availability Model (−967 versus −968). The Ordinary Model fares worse than either model (−971).

4.1. Coupon availability probabilities

We find that the coupon environment probabilities in the General Availability Model are vastly different from those in the nested models. For instance, the probability of being exposed to a coupon by at least one brand is estimated to be 0.77 in the General Model, but 0.98 in the Independent Model. To put it differently, the probability of no coupons is 0.23 in the General Model, but almost 0.0 in the Independent Model.

We compare our estimates of coupon availability probabilities with coupon drop data obtained from the Nielsen clearing house (NCH). Since the earliest year for which we could obtain NCH data is 1989, whereas our data span mid-1986 to mid-1987, the NCH data only

loosely correspond to the scanner panel data that we use. Moreover, the NCH data are national whereas our data are from only two cities. None the less, we use the coupon drop data to serve as a rough check on our estimates of availability probabilities, since this seems to be a natural way to check the reasonableness of our estimates. Assuming that all coupons are of equal duration and that an equal number of coupons are distributed in each drop, the national average coupon frequencies for Brands A, B, and C are calculated as 0.67, 0.86, and 0.90 from the NCH data. In our best-fitting model, the estimates of the availabilities are 0.48, 0.61, and 0.74. Our estimates match the actual coupon drop figures well in terms of the relative order of availability; that is, we predict that Brand A's coupons are the least available and Brand C's coupons are the most widely available. The Independent Model, for which the estimated probabilities are 0.81, 0.65 and 0.64, does a poor job of matching the relative order.

4.2. Covariate coefficients

In the General Model, the price coefficient for the alternatives that involve the redemption of a coupon is significantly more negative than the price coefficient for the alternatives that do not involve the redemption of a coupon. That is, households tend to be more price sensitive when they shop with coupons than when they do not. The two nested models fail to show the difference in price sensitivities.

The coefficients on purchase background variables (past brand loyalty, past coupon proneness, recent brand loyalty, and recent coupon proneness) are positive and significant in all models ($p < 0.01$). Thus, brand choice and coupon redemption behaviors follow past patterns and display inertia. The coefficient on LOY_A is larger than the coefficient on LOY_C , which suggests asymmetry across brands in the impact of initial loyalty. Similarly, the coefficient on $BRECENT_C$ is twice as large as the coefficient on $BRECENT_B$, suggesting that the market leader enjoys a stronger repeat purchase tendency than the follower Brand B.

In preliminary models where we omitted purchase background variables, some demographic variables (in particular, female employment) appeared to be significant due to the omitted variables bias. (We do not show the results for space considerations.) However, when purchase background variables are added to the models, the demographic variables lost their significance. Hence, purchase background variables seem to be more powerful than demographics in explaining consumer behavior for brand choice and coupon use.

In the General Model, consumers' past and recent tendency to use coupons appear to be significantly associated with the present coupon choices. In contrast, if the coupon distribution environment is assumed to be restrictive (by assuming that either coupon distribution

decisions are independent across brands as in the Independent Model or that consumers are never deprived of coupons as in the Ordinary Model), the association of coupon-proneness on current coupon use is underestimated. Compare the larger coefficients on past and recent coupon proneness in the General Model with the coefficients in the nested models.

The relationship between brand loyalty and coupon proneness has been investigated before and is an important issue for brand managers. The evidence in the literature concerning this relationship is mixed.⁶ We vary the values of the brand loyalty variables, hold everything else constant, and compute the unconditional probability of redeeming a coupon. We find that neither past nor recent brand loyalty has any significant impact on the probability of coupon redemption. That is, whether or not brand loyal households redeem more coupons than other households is not clear from this data.⁷

Our findings can be summarized as follows:

1. We reject the hypotheses that (a) coupons are available all the time; and (b) brands act independently of each other regarding the availability policies of their coupons.
2. We find that price-sensitive shoppers are more likely to be coupon users.
3. We find that impact of past coupon use is underestimated when the coupon environment is constrained to yield independent coupon distribution decisions across brands.
4. We find no significant relationship between brand loyalty and coupon redemption.
5. We find that demographic variables lose their significance when purchase background variables are included in the model.

4.3. Simulated Scenarios

We simulate various coupon availability scenarios using estimates from the General Model and explore the impact of availability on market share and coupon redemption. Table 2 exhibits brand choice probabilities (that is, estimates of market shares), $P(y_i = j)$, and conditional coupon redemption probabilities $P(z_i = 1 | y_i = j)$ under each coupon distribution scenario.⁸

⁶ For example, Webster (1965) finds evidence for a negative relationship, while Bawa and Shoemaker (1987) find evidence for a positive relationship. However, the two works may not be in conflict since the “deals” measured in Webster are not necessarily the “coupons” in Bawa and Shoemaker.

⁷ The interaction effect can also be measured by multiplying the brand loyalty and coupon proneness variables. However, we calculate the interactive effect as described above, rather than estimate it with new parameters in order not to complicate the model further.

⁸ Brand choice probabilities are computed from our joint choice model as the marginal probabilities. Coupon redemption probabilities are calculated as the conditional probabilities.

When coupons for all three brands are always available, the market shares of the three brands change only slightly from the current allocation (compare simulations #0 and #1): the leading brand's market share falls from 57% to 51% while the market share of Brand A increases from 24% to 28% and the market share of Brand B remains roughly constant. The brand that eliminates coupons suffers a dramatic drop in market share (see simulations #2, #3, and #4): Brand A's market share is cut in half, Brand B's market share is cut by a factor of 6, and Brand C's market share is cut by a factor of 3). If two brands eliminate coupons (simulations #5, #6, and #7), the third brand that issues coupons benefits considerably (Brand A's market share increases to 68%, Brand B's market share increases to 62%, and Brand C's market share increases to 83%).

When all brands eliminate coupons, the brands' market shares remain virtually unchanged from the market shares that would obtain if coupons for all three brands were always available (compare simulations #1 and #8). Thus, the results suggest that couponing is a Prisoners' Dilemma. (Shaffer and Zhang, 1995, also find strong support for Prisoners' Dilemma in their work on competing target coupons). Among the three brands, Brand B appears to rely on coupons for survival more than the other two brands. For example, when Brand B eliminates its coupons, it virtually eliminates itself from the market by suffering a dramatic drop in market share. Hence, the relationship between coupon availability and market share is asymmetric across brands.

The probability that a coupon is redeemed, conditional on the purchase of a specific brand, $P(z_i = 1 | y_i = j)$, is another measure of a brand's reliance on coupons to build market share. In our sample these conditional probabilities are 53%, 72%, and 56% for Brands A, B, and C, as reported in the first row of Table 2. We find that as a brand's coupon availability increases relative to its competitors the proportion of its purchases made with a coupon also increases. We note the interesting case of Brand B. If Brand B is the only brand issuing coupons, our simulations predict that 94% of its purchases would be made with a coupon (see simulation #6), as compared to 72% in the data. At the time our data was collected Brand B was a relatively new brand in the vicious diaper market. Hence, the evidence we present suggests the vulnerability of a new warrior in a mature product market engaged in coupon wars.

In summary:

1. We find that although any one brand's market share would fall substantially if it eliminated coupons unilaterally, the brands' market shares would remain essentially unchanged from the observed market shares if all three brands were to eliminate coupons simultaneously. This phenomenon resembles the Prisoners' Dilemma in the game theoretic literature.

Table 2
Impact of coupon availability on purchase behavior

Simulation number	Market shares			Proportion of purchases made with a coupon		
	Brand A	Brand B	Brand C	Brand A	Brand B	Brand C
Data	0.24	0.19	0.57	0.53	0.72	0.56
0	0.24	0.19	0.57	0.50	0.71	0.57
1	0.28	0.20	0.51	0.79	0.89	0.75
2	0.10	0.28	0.62	0	0.90	0.76
3	0.35	0.03	0.62	0.81	0	0.76
4	0.42	0.37	0.21	0.84	0.92	0
5	0.12	0.05	0.83	0	0	0.81
6	0.12	0.62	0.26	0	0.94	0
7	0.68	0.05	0.27	0.88	0	0
8	0.25	0.15	0.60	0	0	0

Notes: The first row, labeled “Data”, gives the observed frequencies in the estimation sample. In simulation #0, the environment probabilities are set at the maximum likelihood estimates from our General Model. In simulation # n ($n \geq 1$), the probability of environment n is set to 1 and the probabilities for the remaining environments are set to 0.

2. We report evidence for an asymmetric effect of couponing on brands. That is, while one brand maintains market lead in most of the scenarios, another is most vulnerable in coupon wars.

5. Conclusion

Better forecasts for competing brands are desirable for a retailer in order to manage category sales and plan for inventory. Coupon availability, if measured accurately, can help predict brand market shares more satisfactorily. This study presents a way to infer unbiased estimates of availability from redemption data and to predict market shares for each brand in a supermarket product category. The method helps circumvent the upward bias in measuring the effect of coupons on brand choice, that typically occurs when coupon redemption is used instead of availability. In addition, the method we propose to some extent obviates the need to search for exogenous sources of data on coupon availability. Our model uses information on brand choice and coupon redemption, and therefore, is applicable with any scanner panel data set. Recently Gonul and Srinivasan (1996) used our model to generate 0–1 coupon distribution variables for each household in each week for their dynamic purchase incidence model by simulating draws from the estimated availability probabilities.

In sum, our work shows an analytically correct way of inferring coupon availability from redemption and brand choice data by the enumeration of all possible coupon environments. However, there are some limitations in our work as in all studies:

- (1) We have adopted the multinomial logit model for computational simplicity. A brand's coupons may

draw disproportionately from its loyal users, hence, using a multinomial logit model may be restrictive (Neslin, 1990). Conceptually, our methodology is applicable to the multivariate probit model as well. However, our efforts to obtain convergence in probit with the method of simulated moments were not successful even for the simplest (Ordinary) model. This is possibly due to the modest sample size we have and the difficulty in estimating probit with the current state of the technology. However, our proposed model does not suffer from the independence from irrelevant alternatives limitation at the aggregate level, since the environments that are common to various choice alternatives capture potential correlation across alternatives.

- (2) In order to build dependence across choice alternatives, one may consider a model with a common intercept for couponed alternatives. We have estimated such a model as well which is in fact a nested version of our model. (In our models intercepts are free from restrictions). However, the model fit was not satisfactory ($\log L = -1856$; $CAIC = 3745$) and hence we drop the model from further consideration.
- (3) In this paper, we focus on the probability of availability as a dimension of coupon attractiveness. We do not consider other aspects of coupons such as the depth of discount and a later expiration date.

We hope to address these issues in future research.

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