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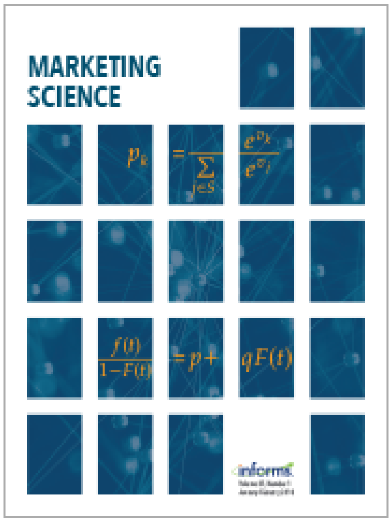

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An Empirical Study of the Impact of Nonlinear Shipping and Handling Fees on Purchase Incidence and Expenditure Decisions

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An Empirical Study of the Impact of Nonlinear Shipping and Handling Fees on Purchase Incidence and Expenditure Decisions

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Shipping-fee schedules are an important but underresearched element of the marketing mix for direct marketers. This paper provides an empirical study on the impact of shipping and handling charges on consumer-purchasing behavior. Using a database from an online retailer that has experimented with a wide variety of shipping-fee schedules, we investigate the impact of shipping charges on order incidence and order size. We use an ordered probability model that is generalized to account for the effects of nonlinear and discontinuous shipping fees on purchasing decisions, and to accommodate heterogeneity in response parameters. Results show that consumers are very sensitive to shipping charges and that shipping fees influence order incidence and basket size. Promotions such as free shipping and free shipping for orders that exceed some size threshold are found to be very effective in generating additional sales. However, the lost revenues from shipping and the lack of response by several segments are substantial enough to render such promotions unprofitable to the retailer. Heterogeneity across consumers also suggests interesting opportunities for the retailer to customize the shipping and other marketing-mix promotion offerings.

Key words: shipping fees; direct and Internet retailing; nonlinear pricing; promotions
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To be sure, understanding the connection between online consumer behavior and shipping costs is something of a Holy Grail for companies like Amazon and Buy.com. And both companies are largely in the dark as to where the sweet spot lies. "It's a test," says an Amazon spokesperson. "It's very expensive to do this. We'll find out if the customer response is great enough to make it work, but it's the right thing to do."—From CNN Online June 24, 2002

1. Introduction

Shipping charges are an important but underresearched element of the marketing mix for online and direct retailers. A characteristic of these businesses is that at the time of purchase the physical products are spatially separated from the customer. In contrast to traditional retailing where customers absorb many order assembly and transportation costs, when transactions take place with a distance between customers and products the firm incurs the costs of order assembly and delivery (Rosen and Howard 2000). Therefore, a key marketing decision for online retailers is how to charge for delivery services. This is a nontrivial task because the design of a shipping-fee schedule involves decisions about the level of fees and the relationship between fees and order size. These two aspects can impact both order incidence and order size, as shipping-fee schedules often involve nonlinear pricing that encourages or penalizes specific order sizes.

The importance of the remote shopping sector (Wood 2001) continues to grow as annual sales in catalog and Internet retailing now exceed $100 billion. Dissatisfaction with shipping fees is evidenced by survey data that over 60% of online shoppers have abandoned an order at the point when shipping fees are added (Jupiter Communications 2001) and over 50% of consumers list shipping fees as their main complaint about online retailing (Ernst and Young 1999). Academic research (Trocchia and Janda 2003, Janda et al. 2002, Pyke et al. 2001) has also identified order fulfillment issues as a key factor in customer satisfaction.

The relevance of shipping fees is also highlighted by the frequent use of "free shipping" and other shipping-related promotions (Lisanti 1999). However, reports are mixed regarding the profitability of shipping promotions (Quick 2000, Moore 2000). The profit implications of shipping policies are underscored by research showing that many e-retailers lost between \$4 and \$16 per order even while charging shipping fees (Barsh et al. 2000). These losses were largely due to fulfillment costs that ranged from \$15 for prescription drugs to \$28 for groceries. The importance of understanding how shipping fees influence consumer demand is also indicated by the level of experimentation occurring online. For example, Barnes and Noble and Amazon have tested policies that couple "free-shipping" benefits with order-size requirements (Courogen 2002, Wingfield 2003). In the case of Amazon, as the threshold for free shipping decreased from \$99 to \$25, the losses attributed to the shipping function grew from \$36 million in 2002 to \$139 million in 2003. Despite these losses, Amazon has continued the "free-shipping" offers (Amazon.com Annual Report 2003).

The shipping-fee schedule design is a relatively complex task that requires balancing the desire to recover shipping costs with the need to attract and retain a substantial customer base. In this paper we seek to develop an approach for estimating the relationship between consumer demand and nonlinear shipping fees and to provide empirical evidence of the magnitude of consumer response to shipping-fee levels and promotions. The study uses a database from an online grocer that includes transaction histories for individual customers and information on marketing activity related to pricing and promotions. The data set is especially suited to our purposes because the firm has actively experimented with shipping-fee schedules that vary in terms of the level of fees and the relationship between shipping charges and order size. The variation in shipping fees allows us to estimate how consumers alter their behavior in response to nonlinear shipping fees in terms of whether to buy and how much to spend.

Our empirical modeling approach is based on the notion that shipping fees introduce discontinuities and an element of discrete choice into the consumer's decision problem. Because the shipping-fee element of the decision is typically discrete, we use an ordered-choice model to predict the probabilities of order-size categories. Specifically, we use a generalized version of the ordered logit model that treats the category intercepts as functions of shipping fees. This approach accounts for the nonlinear effects of shipping charges while relaxing the restrictive proportional odds assumption. We also account for unobserved heterogeneity by specifying a nonparametric distribution of support points for the vector of estimated parameters (Kamakura and Russell 1989). This enables the identification of segments in the population that may vary in responsiveness to shipping charges.

Our results indicate that shipping fees significantly affect both order-incidence rates and expenditure levels. In terms of specific shipping policies, we find "free-shipping" promotions greatly increase order-incidence rates but lead to smaller order amounts. We also find policies that waive fees for larger orders often succeed in shifting customers to larger orders but have minor effects on order incidence. However, response to shipping fees is not uniform, as we find significant heterogeneity across households in responsiveness to shipping charges and marketing variables. Increased order incidence in response to free shipping ranges from over 35% to about 10% for different segments. A benefit of the segment-level analyses is that they suggest opportunities for the retailer to exploit heterogeneity in the population by customizing shipping charges. Finally, profitability calculations show that while shipping promotions can increase demand, the increased merchandise revenues are unlikely to offset the corresponding lost shipping revenues.

This paper contributes to the promotions and pricing literatures by describing a technique for measuring response to promotions involving nonlinear pricing and by empirically measuring the degree of consumer response to delivery-fee levels. The empirical results are salient because while the prevalence of shipping promotions suggests they are potent instruments, there is little data as to their efficacy, and firms continue to experiment with shipping fees (Wingfield 2003). We also find some evidence that consumers are more responsive to shipping fees than to merchandise prices. This result contradicts a finding in the partitioned-pricing literature (Morwitz et al. 1998) that consumers tend to underweight the second component of a total price. The emphasis on shipping fees in online retailing may have increased the salience of these fees to the point where consumers *overweight* shipping fees. More generally, the results add to the body of literature studying online consumer behavior (Danaher et al. 2003). Finally, our work is also applicable to response modeling in direct marketing (Elsner et al. 2004). The approach represents an important refinement to the common practice of using binary choice models to predict order incidence (Shepard 1999, Gönül and Shi 1998, Bult and Wansbeek 1995).

The remainder of the paper is organized as follows. Section 2 describes the modeling approach used for measuring the effects of shipping fees on order incidence and basket size. Section 3 describes the data used in the empirical implementation.

Section 4 details estimation results, marginal effects, and profitability implications. Section 5 concludes the paper with a discussion of managerial issues, caveats to the current study, and suggestions for future work.

2. Model

In this section we develop a model to investigate the role of different shipping-fee schedules on buyer behavior in terms of order incidence and the distribution of order sizes. A complicating factor to estimation is that shipping-fee schedules often involve nonlinear pricing (Bohman 1999). In practice, shipping fees often impose two types of nonlinear pricing. Flat or fixed shipping fees are an example of the first part of a two-part tariff. The level of the shipping fees may impact order-incidence rates because shipping surcharges represent a transaction cost that can dissuade customers from ordering (Tyagi 2004). Similarly, the relationship between order size and shipping fees can influence purchase amounts. When shipping fees change according to a step function, shipping fees impose a second element of nonlinear pricing that can encourage or penalize specific order sizes by changing the marginal costs associated with incremental items.

Although nonlinear pricing is commonly employed in practice (Dolan and Simon 1996), it is an empirically difficult topic to study (Allenby et al. 2004). Previous empirical work on nonlinear pricing schedules includes papers by Train et al. (1987, 1989) that study the selection of telephone calling plans by consumers. These papers use nested logit models of the multilevel decisions of consumers first selecting a rate plan and then choosing a level of calling. A main finding is that self-selection can make it difficult to increase revenues because customers often switch to flat-rate plans in response to increasing usage charges.

The decision that we model is different in structure from the sequential choice of a pricing plan and then an amount. In the case of shipping fees, the choice of merchandise quantity and shipping fee occurs simultaneously. In particular, nonlinear shipping fees may cause customers to alter order quantities by changing the marginal costs of incremental items. One common practice is to waive shipping fees for orders that exceed some dollar threshold. For instance, consider the case of a shipping schedule that charges \$5 to ship orders of less than \$75 and waives shipping fees for orders exceeding \$75. If a customer adds a \$2 item to a basket with \$74 of merchandise, the final total cost would be \$76 rather than \$79 if the item is not added. In this case the marginal cost of the last item is negative. Another common tactic is graduated schedules that increase fees according to a step function as order size increases. Graduated schedules may constrain order size by imposing penalties when orders reach certain thresholds.

To account for such discrete jumps, we estimate the likelihood of order-size categories. The approach adopted is reduced-form estimation that treats the size decision as a dependent variable in an ordered-probability model. Thus, rather than treat order size as a continuous variable, our strategy is to estimate the likelihood of observing ranges of order sizes. While the dollar value of an order is often interpreted as a continuous measure, the construction of a basket is not the result of a decision process involving a continuous variable, but rather a variable that increases via a step function. Consumers typically do not construct an order by selecting the magnitude of buying, but rather through a process of adding incremental items. The use of shipping-fee thresholds exacerbates this issue because penalties, or benefits, associated with reaching order-size thresholds result in discontinuities in the consumer's maximization problem. The approach of converting dollar amounts into categories is a compromise between reducing the precision of the dependent variable and the benefits of accounting for nonlinear effects.

The model formulation begins with a standard ordered-choice model designed to predict the probability of observing categories of order sizes. For instance, one possible categorization could be options of no purchase, small basket, and large basket.[1] The model is based on a latent regression of the form, $y_{it}^* = \beta_i' X_{it} + \varepsilon_{it}$, where X_{it} is a vector of individual factors and marketing variables for household i at time t, β_i is a vector of unknown parameters to be estimated, and ε is the vector of disturbances. The dependent variable y corresponds to the observed order size. In this example involving three order categories, y would be set equal to 1 to indicate a decision not to buy, equal to 2 to indicate a small order, and equal to 3 to indicate a large order. With J mutually exclusive and exhaustive order-size categories, the observed dependent variable y is related to the latent variable y^* as follows (individual and time subscripts suppressed):

$$y = \begin{cases} 1 & \text{if } y^* < \alpha_1, \\ 2 & \text{if } \alpha_1 \le y^* < \alpha_1 + \alpha_2, \\ \cdots & \\ J & \text{if } \sum_{i=1}^{J-1} \alpha_i \le y^*, \end{cases} \tag{1}$$

where the α_js are unknown threshold parameters such that for all $j > 1$, $\alpha_j > 0$. The probability of

[1] The cut-offs used in the empirical study are based on the firm's shipping schedules and are discussed in §4.

a particular order size is given by:

$$\Pr[y=j]=\begin{cases}\Lambda(\alpha_1-\beta'X) & \text{if } j=1,\\ \Lambda\left(\sum_{i=1}^{j}\alpha_i-\beta'X\right)-\Lambda\left(\sum_{i=1}^{j-1}\alpha_i-\beta'X\right) & \\ & \text{if } 2\le j\le J-1,\\ 1-\Lambda\left(\sum_{i=1}^{J-1}\alpha_i-\beta'X\right) & \text{if } j=J,\end{cases} \tag{2}$$

where Λ is the (logistic) cumulative distribution function of the error term.

The model described above is the standard ordered-logit model and possesses two major shortcomings. First, it suffers from the proportional odds or parallel regression assumption which restricts the coefficients to be the same for all threshold points. However, it is possible to adapt the model to better represent the decision process that occurs in the presence of a graduated shipping-fee schedule. Specifically, the ordered logit may be generalized so that the category intercepts (α_js) are parameterized to be a function of observed and unobserved factors:

$$\alpha_{ki}=\alpha_{k-1,\,i}+\Delta(T_k,\zeta), \tag{3}$$

where Δ may be a function of observed factors like shipping fees (T_k) and unobserved factors, ζ. The generalization we use is to model the intercepts as functions of relevant shipping fees.

A second flaw of the model is that it does not allow for consumer heterogeneity. Previous research has found extensive evidence of parameter heterogeneity in preferences and marketing-mix sensitivity, and that ignoring heterogeneity can result in biased estimates (Abramson et al. 2000). Some households may be sensitive to shipping charges, while others may discount or overlook these fees. To account for heterogeneity in individual preferences, we estimate models that treat the population as a mixture of unobserved types (Kamakura and Russell 1989). In this formulation, a vector of parameters is estimated for each type in the population, and the likelihood function is a finite mixture, or weighted average, of the type-specific likelihoods. For a sample of N individuals, each making t_n choices, the likelihood function under an assumption of M types is

$$\prod_{n=1}^{N}\sum_{m=1}^{M}\Pr\left(Y_{1n}^{m},Y_{2n}^{m},\ldots,Y_{t_n n}^{m}\mid \text{type}=m\right)*\pi_m, \tag{4}$$

where π_m is the proportion of type m in the population.

3. Data

The data for the study is from an online retailer specializing in nonperishable grocery and drugstore items. The data set contains records of all customer transactions through the first 14 months of operations. This period of operation includes histories for over 25,000 unique customers making 50,000-plus transactions. Average order size is in excess of \$50, and the typical basket contains greater than 10 items. Each transaction record contains the time of purchase, prices of all items purchased, shipping charges, promotional discounts, and communications with customer service. Table 1 presents the set of covariates that are expected to influence consumer decision making. These covariates are classified into three broad categories: *Marketing-Mix*, *Household-Specific*, and *Shipping and Handling*.

Marketing-Mix Environment

Our first priority for constructing variables that describe the marketing environment is to create a measure that reflects the overall pricing environment. However, creating variables that capture the overall store-pricing environment is a nontrivial task because the retailer in question sells over 14,000 distinct products that are classified into several hundred categories. Previous papers focused on modeling basket size have used prices for a subset of salient categories (Bell and Lattin 1998) or constructed a measure that reflects the prices of a household's consideration set

Table 1 **Variable Descriptions**

Variable names	Definitions
PRICEB	Price of a basket of the 50 top-selling items divided by 50 for average item price.
EMAIL	1 if an e-mail-based coupon is available in a given week, zero otherwise. Three e-mail promotions were used during the data collection period.
FREQ%	Order frequency percentage. Computed by dividing the total number of orders placed up until time t by the number of weeks in the system.
AMT	Average dollar amount (for merchandise) of previous orders.
TDUR	Time (in weeks) since last purchase.
PSER (previous service incident)	1 if the previous order was filled with less than 100% accuracy, 0 otherwise.
CHILD	1 if a household includes a child, 0 otherwise. Inferred from initialization data.
BABY	1 if a household includes a baby, 0 otherwise. Inferred from initialization data.
PET	1 if a household includes a pet, 0 otherwise. Inferred from initialization data.
T_S	Price to ship an order with a retail price of less than \$50.
T_M	Price to ship an order with a retail price of at least \$50 but less than \$75.
T_L	Price to ship an order with a retail price of at least \$75.

(Dreze et al. 2004). A measure that reflects the consideration set is appealing, but is not feasible given our data. While the database records the price and promotion information for every UPC sold on a given day, for many low-volume items price histories are relatively incomplete. Our strategy is therefore to use an aggregate measure that is designed to capture the overall price environment on a given day. The price variable (PRICEB) used in the model is the average price of the 50 top-selling items, over the entire data collection period, in each week.

The second marketing-mix variable is an indicator of an e-mail-based promotion (EMAIL). On several occasions the retailer distributed promotional coupons via e-mail to the existing customer base. These coupons provided the recipient with a 10% discount on total expenditures if a purchase is made in a specified weekly period. This variable is operationalized as an indicator variable that takes on a value 1 if there is a coupon available in that week and 0 otherwise. For these two marketing-mix variables we expect high prices (PRICEB) to deter order incidence, while the e-mail coupons (EMAIL) are expected to have the opposite effect.

Household-Specific Variables

Household transaction histories are used to construct individual measures of past behavior that may be useful for predicting future purchasing activity. The next three variables in Table 1 are measures of past behavior: weekly ordering rate (FREQ%), average order size (AMT), and time since last order (TDUR). These measures are similar to the RFM (recency, frequency, and monetary value) measures employed in direct marketing (Hughes 2000). In our empirical application, we also utilize several interaction terms to account for dynamic purchasing patterns. For instance, the interaction of the previous amount and time duration helps capture inventory effects that may lead big-basket buyers to purchase with lower frequency.

The next household-specific variable (PSER) is an indicator taking a value 1 if there was a problem with the fulfillment of the previous order for a household. Examples of such service failures include incorrect order filling and incomplete orders due to stockouts. Overall, 16% of the total shipments experienced service problems.

The detailed transaction histories are used to infer several demographic traits. For instance, a purchase of baby products such as diapers is taken to indicate the presence of an infant in the family. Similarly, purchase of dog food or cat litter indicates the presence of a pet and purchases of products such as prepackaged kids' lunches indicate the presence of children. Based on these definitions, we find that 22% of households have an infant in the family (BABY = 1), 56% have children (CHILD = 1), and 39% of the households have a pet (PET = 1). In general, we do not have prior expectations of the impact of these household-specific variables except for the service failure indicator (PSER), which is expected to deter future ordering.

Table 2 Shipping- and Handling-Fee Structures

	Small order ($0 to $50) ($)	Medium ($50 to $75) ($)	Large ($75 plus) ($)	Order incidence[1] (Std. dev.)	Average order (Std. dev.)
Structure 1	4.99	6.99	0	8.9% (0.035)	$64.68 (11.93)
Structure 2	4.99	6.99	8.95	8.2% (0.019)	$56.05 (7.79)
Structure 3	2.99	4.99	4.99	9.3% (0.029)	$48.28 (5.01)
Structure 4	0	0	0	14.0% (0.037)	$46.05 (3.67)
Structure 5	5.99	7.99	9.99	2.6% (0.002)	$54.17 (8.47)

[1] To account for customer-base growth, the number of orders is given as a percentage of the existing customer base.

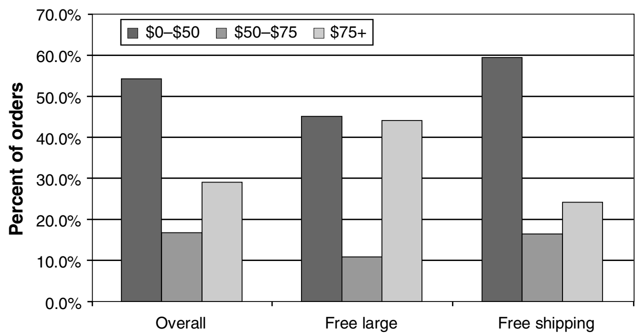
Shipping and Handling Fees

The focal variables for the analysis are the shipping and handling fees. Table 2 describes the various shipping-fee schedules used by the firm. Schedules 2, 3, and 5 represent increasing fee structures with shipping charges that rise as order size grows. Structure 4 is a free-shipping promotion that includes no size incentives or penalties. Structure 1 charges more for medium orders relative to small orders, but waives shipping fees for large orders.

Two of the policies presented in Table 2 are particularly notable. As discussed in the introduction, online and catalog retailers often use promotions that waive shipping fees for all or some subset of order sizes. Structures 1 and 4 represent instances of these practices. Table 2 also includes measures of the effects of each policy on order incidence and order size. The "free-shipping" policy generates the highest ordering rate but the smallest order amounts. The "free-large" policy has a small impact on order incidence but leads to the largest average expenditures.

Figure 1 provides greater detail on size effects by illustrating the distribution of order sizes for Schedules 1 and 4 as well as the average numbers for the entire time period. The distribution of order sizes shifts quite dramatically due to shipping charges. For example, with an incentive of free shipping for orders over $75, approximately 45% of the orders received by the firm are over $75 (compared to an average of 29%). Free shipping for all orders, in contrast, tends to shift the distribution towards the smaller categories.

Figure 1 **Impact of Shipping-Fee Schedules on Distribution of Order Size**



4. Empirical Analysis

The sample for our empirical estimation was selected as follows. First, we drew a random sample of 3,000 customers (approximately 10% of the total) from the entire database. Next, we removed all customers with only a single purchase, because the first purchase is used to infer demographics. Finally, the first five weeks from the point of the customer's first purchase are used to initialize the transaction history measures and are not used in the estimation. This process resulted in a set containing 2,026 customers. The mean number of purchases for this sample is approximately 8.5, and the average order size is just over $57.

For the order-size categories we define the categories based on the shipping-fee thresholds that exist in the data. Specifically, we classify basket size as small, medium, or large as follows: small baskets are defined as orders with a dollar value of between zero and $50; medium baskets as orders with a dollar value of at least $50 but less than $75; large baskets are orders of at least $75. To study order incidence a no-purchase category is also included.

4.1. Estimation Results

Table 3 provides the number of parameters, log-likelihoods, and Bayesian information criteria (BIC) fit measures for a variety of model specifications that differ in how shipping fees are incorporated and the number of support points for the unobserved heterogeneity. The first three rows in the table show the fit criteria for different specifications of the shipping-fee variables. The first model is a standard ordered logit that does not include the shipping-fee covariates. The second model includes shipping fees as standard covariates. The third model is a generalized version that models the category intercepts as linear functions of the shipping fees as follows:

$$\alpha_0 = \gamma_0 + \gamma_{0,\,\mathrm{sm}} * T_S + \gamma_{0,\,\mathrm{med}} * T_M + \gamma_{0,\,\mathrm{lrg}} * T_L, \quad (5)$$

$$\alpha_1 = \gamma_1 + \gamma_{1,\,\mathrm{med}} * T_M + \gamma_{1,\,\mathrm{sm}} * T_S, \quad (6)$$

$$\alpha_2 = \gamma_2 + \gamma_{2,\,\mathrm{lrg}} * T_L + \gamma_{2,\,\mathrm{med}} * T_M, \quad (7)$$

where (T_S, T_M, T_L) are the shipping fees associated with small, medium, and large orders, and the γs are the associated parameters. The generalized model is the best-performing specification as comparisons with the "no fees" and "shipping fees as standard covariates" versions yield χ^2 statistics of 442.8 and 353.6, respectively, versus corresponding critical values of 11.3 and 18.5.

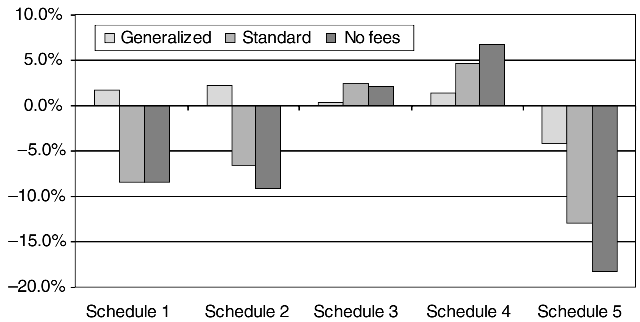
It is useful to consider the intercept equations in more detail, as the form of these equations illuminates the logic of the model. Equation (5) defines the likelihood of the no-buy option. Inclusion of all three shipping fees allows order incidence to be a function of the entire shipping schedule. This may be relevant if policies that waive fees for larger order sizes impact order incidence in addition to order size. Similarly, the likelihood of small orders is determined by the size of α_1 relative to α_0. For example, a positive coefficient for the medium-order fee variable means that α_1 becomes larger as T_M increases. Given the model structure in Equation (2), this implies the likelihood of smaller orders increases as the fee associated with medium orders grows. We discuss interpretation issues in more detail when we report the estimation results.

Note that by allowing the shipping-fee coefficients to vary by expenditure category, the specification represents a partial relaxation of the proportional odds assumption. In principle, separate coefficients could be estimated for all covariates. However, for our data, models with other marketing-mix variables included in the intercept terms did not significantly improve the model fit. For example, including the PRICEB and EMAIL variables in the intercept terms yields a likelihood ratio test statistic of 0.56, which is nonsignificant ($\chi^2_{4,\,0.05} = 9.488$). An additional concern is that the number of parameters grows quickly when we allow for consumer heterogeneity. A fully generalized four-segment model would require over 200 parameters.

Table 3 **Comparison of Model Specifications**

Model description	Parameters	BIC	LL	BIC
Homogenous models				
No shipping fees	14	116,548.1	−58,194.0	116,548.1
Shipping fees as covariates	17	116,454.3	−58,129.9	116,454.3
Generalized model	21	115,992.4	−57,876.0	115,992.4
Heterogeneous models				
2 segments	43	112,039.1	−55,773.5	112,039.1
3 segments	65	110,838.2	−55,047.1	110,838.2
4 segments	87	110,424.7	−54,714.5	110,424.7
5 segments	109	110,468.7	−54,610.6	110,468.7

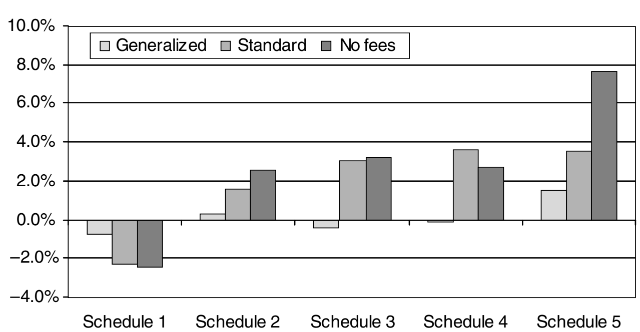
Figure 2 **Holdout Sample Analysis: Error in No-Buy Rates**



The lower section of Table 3 shows fit statistics for models that vary in terms of the number of unobserved types within the population. The four-segment model provides the best fit in terms of BIC and yields intuitive parameter estimates. The merits of the modeling approach are also illustrated by comparing the forecast errors for our partially generalized model versus specifications that treat the shipping fees as standard covariates, or do not include shipping fees in any form. Figures 2 and 3 show the forecast error for the three ordered-choice models across the various fee schedules using a randomly selected 1,000-member holdout sample. Figure 2 shows the average error (average predicted probabilities versus actual probabilities) for the no-buy option and Figure 3 shows the error for the percentage of large orders. The generalized model performs better because the other models have difficulty forecasting the impact of shipping fees that significantly deviate from the overall average fees. Forecast error is relatively low for the alternative models for Policy 3, which is the most frequent shipping structure, but is very large for Schedule 5, which involves dramatically higher shipping fees.

Table 4 provides the parameter estimates and the standard errors for the population and four-segment models. The parameter estimates for the population model are presented in the first column of Table 4. The majority of the estimated coefficients for the shipping fees and marketing-mix instruments are significant and of the expected signs. For example, the

Figure 3 **Holdout Sample Analysis: Error in Large-Order Rates**



positive sign associated with the price variable suggests that higher prices deter ordering. While this may be somewhat nonintuitive, the reason covariates that negatively impact ordering have positive signs is clear given the expressions for the probability of each outcome (Equation (2)). To illustrate this, consider the probability of the no-purchase option ($y=0$) in Equation (8):

$$P(y=0)=\frac{\exp(\beta Z+\alpha_0)}{1+\exp(\beta Z+\alpha_0)}. \tag{8}$$

This probability increases when covariates with positive signs increase. Conversely, the negative coefficient for the e-mail coupon suggests that these discounts increase order incidence.

The shipping and handling variables are also of the expected signs and are significant with the exception of the $\gamma_{0,\,\mathrm{med}}$ and $\gamma_{0,\,\mathrm{lrg}}$ terms. Thus, only the shipping fee associated with "small" orders seems to impact order incidence. The role of the shipping fees is best understood by examining the equations for the intercepts (nonsignificant parameters are set to zero):

$$\alpha_0 = -1.126+0.045*T_S, \tag{9}$$

$$\alpha_1 = 1.015-0.541*T_S+0.332*T_M, \tag{10}$$

$$\alpha_2 = 0.678-0.059*T_M+0.041*T_L. \tag{11}$$

As per Equation (8), we see that as the shipping fee for a small order (T_S) increases, the probability of not buying increases. The effects on the probabilities of the other categories can be analyzed in a similar fashion. The equation for α_1 largely determines the probability of observing a small order. The coefficient associated with the cost to ship a medium order is positive, while the coefficient for the cost to ship a small order is negative. The marginal effect of increasing the cost to ship a medium order is, therefore, an increase in the likelihood of small orders. This means that an increase in T_M results in fewer medium orders and more small orders. In contrast, an increase in T_S penalizes small orders and shifts demand to medium orders. The equation for α_2 involves a similar structure. Increasing T_L leads to fewer large orders, while increasing T_M causes some fraction of medium orders to shift towards bigger purchases. These results are intuitive as they indicate that consumers alter behavior based on order-size incentives and penalties.

The parameter estimates for the four-segment model may be interpreted in a similar fashion. In general, the coefficients are of the expected signs and most are significant. In terms of the shipping-fee terms we observe a similar pattern, as in the population results. With the exception of a few intercepts, all terms are significant except for several of the $\gamma_{0,\,\mathrm{med}}$ and $\gamma_{0,\,\mathrm{lrg}}$ terms. It is notable that the $\gamma_{0,\,\mathrm{lrg}}$

Table 4 Estimation Results

	Homogeneous population Coefficient (Std. err.)	Heterogeneous population results Segment 1 Coefficient (Std. err.)	Segment 2 Coefficient (Std. err.)	Segment 3 Coefficient (Std. err.)	Segment 4 Coefficient (Std. err.)
CHILD	−0.209***	−0.270***	−0.252***	−0.044	−0.501***
	(0.026)	(0.093)	(0.050)	(0.071)	(0.072)
PET	−0.047**	0.181**	−0.047	−0.094	0.070
	(0.022)	(0.087)	(0.045)	(0.068)	(0.061)
BABY	−0.177***	−0.221***	−0.020	−0.341***	−0.045
	(0.026)	(0.085)	(0.048)	(0.068)	(0.073)
PRICEB	1.59***	1.393**	2.196***	1.769***	1.825**
	(0.253)	(0.686)	(0.451)	(0.549)	(0.806)
EMAIL	−0.136***	−0.158**	−0.072	−0.309***	−0.092
	(0.043)	(0.061)	(0.081)	(0.089)	(0.136)
PSER	−0.015	−0.040	−0.022	−0.069	0.147**
	(0.034)	(0.092)	(0.066)	(0.073)	(0.070)
TDUR	0.034***	−0.111***	0.053***	0.015**	0.245***
	(0.006)	(0.009)	(0.006)	(0.006)	(0.012)
FREQ%	−2.057***	−1.952***	−2.124***	1.683***	1.514***
	(0.080)	(0.364)	(0.105)	(0.219)	(0.220)
AMT/100	−0.051	−0.236**	−0.365*	−0.456***	−0.495***
	(0.050)	(0.098)	(0.214)	(0.110)	(0.191)
AMT × TDUR	−0.005	0.063***	0.018*	0.062***	−0.737***
	(0.0038)	(0.006)	(0.010)	(0.006)	(0.020)
FREQ% × TDUR	0.125***	−0.148**	−0.076***	−0.806***	−0.844***
	(0.025)	(0.061)	(0.017)	(0.043)	(0.039)
γ_0	−1.126**	0.142	−2.139**	−1.168	−1.132
	(0.491)	(1.341)	(0.924)	(1.072)	(1.600)
$\gamma_{0,\,sm}$	0.045***	0.042***	0.054***	0.041***	0.060***
	(0.015)	(0.012)	(0.006)	(0.009)	(0.009)
$\gamma_{0,\,med}$	−0.007	0.010	−0.009	−0.027	−0.001
	(0.009)	(0.023)	(0.014)	(0.020)	(0.024)
$\gamma_{0,\,lrg}$	0.008	−0.018	0.008	0.035*	−0.011
	(0.009)	(0.023)	(0.014)	(0.019)	(0.0236)
γ_1	1.015***	0.156**	2.615***	0.503***	0.767**
	(0.0521)	(0.064)	(0.236)	(0.082)	(0.160)
$\gamma_{1,\,sm}$	−0.541***	−0.454***	−0.799**	−0.885***	−0.327*
	(0.051)	(0.102)	(0.291)	(0.095)	(0.184)
$\gamma_{1,\,med}$	0.332***	0.261**	0.507**	0.593***	0.222*
	(0.039)	(0.154)	(0.209)	(0.071)	(0.122)
γ_2	0.678***	0.094***	0.747***	0.551***	0.774***
	(0.059)	(0.030)	(0.166)	(0.134)	(0.212)
$\gamma_{2,\,med}$	−0.059***	−0.014**	−0.062**	−0.101***	−0.073*
	(0.010)	(0.061)	(0.030)	(0.022)	(0.039)
$\gamma_{2,\,lrg}$	0.041***	0.023***	0.252***	0.050***	0.063***
	(0.007)	(0.008)	(0.065)	(0.015)	(0.019)
Segment sizes		0.0096***	0.925***	0.857***	0.0
		(0.0017)	(0.140)	(0.140)	

*Significant at a 10% level; **significant at a 5% level; ***significant at a 1% level.

term for Segment 3 is positive and marginally significant. This is not surprising, as we do not expect the shipping fee for larger orders to dramatically impact order incidence. The positive sign for the effect of T_L for Segment 3 suggests higher fees for big-basket purchases can have a negative impact on order incidence for this segment.

The marketing-mix variables are of the expected sign, but two of the e-mail terms are insignificant. This is salient because it means that we do not possess strong evidence that Segments 2 and 4 are positively influenced by the e-mail-based promotions. Another interesting effect is the impact of service failures. The impact on Segment 4 is negative and significant, while the other segments are not meaningfully affected by stockouts.

The transaction history measures and associated interaction terms are designed to account for intricate purchasing patterns. For example, for Segment 1 the signs of the RFM variables are all negative. This means that purchasing is positively correlated with time since last purchase, higher ordering frequency, and order size. This is an interesting pattern because recency is often negatively correlated with buying (Hughes 2000). However, because Segment 1 has a tendency to purchase large orders, time duration since last purchase likely is more related to inventory levels than an indicator of attrition. In addition, the interaction terms moderate the main effects. For instance, the estimated effect of order amount interacted with recency is positive. This means that larger purchases will be associated with slightly larger future interpurchase times.

4.2. Marginal Effects

The behavioral characteristics of the segments are best illustrated by computing the marginal effects of various marketing tactics. Table 5 provides several summary measures that characterize the segments in terms of incidence rates and order-size preferences. These characterizations are developed assuming a shipping policy that charges $3 for a small order, $5 for a medium order, and $7 for a large order. E-mail promotions and stockouts are set to zero, while other variables in the model are set at the mean values observed in the data.

Segment 1 comprises 14.7% of the population and may be characterized as big-basket buyers, as almost 80% of purchases are in the large category. The order-incidence rate implies this segment purchases about one time every six weeks. Segment 2 also has a strong size preference, but favors small baskets and orders relatively infrequently. Segments 3 and 4 are less distinct in terms of basket size. Segment 3 purchases small baskets 52.3% of the time, while Segment 4 selects small baskets 42.7% of the time. Segment 4 exhibits a much greater order-incidence rate than the other segments. Segment 4's order-incidence rate is 48.5% versus 16.9% for Segment 1, 12.0% for Segment 3, and 13.0% for Segment 2. Therefore, while Segment 4 comprises less than 15% of the customer base, it generates approximately 38% of all orders from existing customers. Table 6 describes the segments in terms of the demographic measures by assigning households to segments based on posterior probabilities. The most interesting finding from the segment descriptions is the high rate of baby-product purchases (43%) in Segment 1.

In addition to incidence rates, size preferences, and demographics, the segments also differ in their responsiveness to shipping fees and other promotions. Table 7 provides marginal effects of several alternative shipping policies relative to the base policy used to generate the segment descriptions in Table 5. The table lists the order-incidence rates and the distribution of sizes for each segment and for the overall population. The table also gives the percentage change in order incidence relative to the base level. The first promotion detailed is free shipping for all order sizes. The "free-shipping" promotion is predicted to increase total order incidence by 17.9%, from 18.4% to 21.7%. The effect is strongest for Segment 3, as the rate increases by 36.6%, from 13.0% to 17.8%. The other segments' rates increase by between 10% and 15%.

Table 5 Segment Descriptions

			Order-size distribution (conditional on purchase)		
	Percentage (%)	Incidence (%)	Small (%)	Medium (%)	Large (%)
Segment 1	14.7	16.85	7.96	13.49	78.55
Segment 2	36.6	12.02	92.82	6.38	0.80
Segment 3	34.2	13.03	52.27	14.94	32.79
Segment 4	14.5	48.50	42.75	28.16	29.10
Population	100	18.37	52.38	17.76	29.86

Table 6 Segment Demographic Descriptions

	Baby (%)	Child (%)	Pet (%)	Average order size ($)
Segment 1	43.7	77.7	53.9	103.70
Segment 2	17.9	63.1	42.8	26.60
Segment 3	19.8	69.5	45.7	50.67
Segment 4	28.2	79.0	52.7	56.40

Table 7 Marginal Effects of Alternative Shipping Policies

			Order-size distribution (conditional on purchase)		
	Incidence rate (%)	% Change	Small (%)	Medium (%)	Large (%)
Free shipping to all order sizes					
Segment 1	18.79	11.54	12.06	6.69	81.26
Segment 2	13.85	15.30	91.61	4.39	4.00
Segment 3	17.80	36.57	52.27	14.94	32.79
Segment 4	53.31	9.92	35.00	28.14	36.86
Total	21.65	17.90	50.21	16.11	33.68
Free shipping to large orders only					
Segment 1	16.85	0.00	7.96	1.85	90.18
Segment 2	12.02	0.00	92.82	2.52	4.66
Segment 3	16.04	23.08	51.39	2.02	46.59
Segment 4	48.50	0.00	42.75	15.31	41.94
Total	19.40	5.06	52.12	6.94	40.94
10% reduction in shipping fees ($2.70, $4.50, $6.30)					
Segment 1	17.03	1.11	8.39	12.79	78.82
Segment 2	12.19	1.45	92.71	6.35	0.94
Segment 3	13.45	3.24	50.74	15.87	33.39
Segment 4	48.98	0.99	41.98	28.21	29.81
Total	18.67	1.63	51.77	17.88	30.34

The second analysis reports marginal effects for a policy that provides an incentive for large orders. This policy charges $3 for small orders, $5 for medium orders, but waives shipping fees for large orders. This structure leads to a minor increase in overall ordering, as the only segment that possesses a significant order-incidence effect is Segment 3. The primary impact of this schedule is a shift in the distribution of order sizes. The large category is predicted to grow from 29.9% of all orders to 40.9%, while the medium category shrinks from 17.8% to 6.9%. As in the case of the "free-shipping" promotion, Segment 3 is the most responsive group. The third change evaluated is a 10% across-the-board reduction in shipping fees. This change is predicted to increase order incidence by 1.6% and to slightly shift orders to larger sizes.

In addition to the effects of shipping fees, the results yield several insights relevant to direct marketing and customer relationship management. Table 8 reports the marginal effects of two price promotions and of stockout-based service failures. The first price promotion is an e-mailed coupon that grants a 10% discount on the total dollar value of an order. The second price effect is the impact of a 1% decrease in average prices (PRICEB). An additional motivation for evaluating the marginal effects of alternative promotional instruments is that the relative impact of shipping-fee promotions can be compared with similarly valued traditional price promotions. These comparisons are useful for deciding how promotional discounts should be administered.

There are several reasons why we might expect merchandise discounts to be a more powerful promotional instrument than a shipping-fee promotion with a similar dollar value. First, based on the partitioned-pricing experiments conducted by Morwitz et al. (1998), there is reason to suspect that consumers may systematically underweight shipping fees. Second, a 10% discount similar to the e-mail coupon allows customers to select the value of the offer through their selection of basket size. For example, waiving the shipping fee on large orders is worth $7 no matter what the order size actually is, while the dollar value of a 10% coupon continues to increase as order size increases. However, a comparison of the predicted effects of the "free-shipping" promotion to the 10% discount coupon suggests that the shipping promotion has a slightly greater impact. It may be that the emphasis on shipping fees in online retailing has increased the salience of these fees to the point where consumers *overweight* shipping surcharges.

The table also evaluates the impact of fulfillment failures (Ricker and Kalakota 1999). While stockouts have an insignificant impact on three of the four segments, this type of service failure has a significant negative effect on the high-frequency customers in Segment 4. While Segment 4 represents just 14.5% of all customers, the segment places 38% of all orders received from the existing customer base. The lack of significant negative effects for the other three segments suggests it may be advisable to base fulfillment priorities on customer characteristics. For instance, when inventories of specific items are low, it may make sense to selectively ration by customer type to minimize the probability that high-frequency customers suffer stockouts.

The inclusion of RFM measures and associated interactions in the specification allow the estimation results to be used to consider multiperiod effects. The measures of duration since last purchase and most-recent order size, as well as the interaction between the two, allow the estimation results to account for inventory and attrition effects. The inclusion of these factors in the model provides a means for analyzing the dynamic effects of shipping-fee pro-

Table 8 **Additional Marginal Effects**

			Order-size distribution (conditional on purchase)		
	Incidence rate (%)	% Change	Small (%)	Medium (%)	Large (%)
E-mailed 10% discount					
Segment 1	19.18	13.83	7.76	13.22	79.02
Segment 2	12.80	6.51	92.76	6.43	0.81
Segment 3	16.95	30.07	51.12	15.07	33.81
Segment 4	50.80	4.74	41.63	28.32	30.05
Total	20.67	12.52	51.28	17.59	31.14
1% merchandise price decrease					
Segment 1	17.24	2.34	7.93	13.44	78.63
Segment 2	12.49	3.94	92.78	6.41	0.81
Segment 3	13.44	3.17	52.15	14.95	32.89
Segment 4	49.41	1.89	42.31	28.22	29.47
Total	18.87	2.72	52.33	17.73	29.94
Stockout (service failure)					
Segment 1	16.85	0.00	7.96	13.49	78.55
Segment 2	12.02	0.00	92.82	6.38	0.80
Segment 3	13.03	0.00	52.27	14.94	32.79
Segment 4	44.84	−7.54	44.43	27.86	27.70
Total	17.84	−2.88	53.28	17.34	29.38

Table 9 **Dynamic Effects**

	Segment 1 (%)	Segment 2 (%)	Segment 3 (%)	Segment 4 (%)
Free shipping (1 week)				
4-week change (orders)	1.4	3.6	9.2	2.9
4-week change ($s)	0.6	4.7	9.8	4.4
Free shipping (4 weeks)				
4-week change (orders)	8.4	15.1	30.3	5.6
4-week change ($s)	5.3	17.6	42.5	11.3

motions. Table 9 describes the results of simulation experiments that evaluate the effects of a one-week free-shipping promotion and a permanent shift to a free-shipping policy. The simulations are useful for assessing how much of the promotional lifts are due to purchase acceleration and how much are a true expansion of demand.

For Segment 1, a one-week free-shipping promotion (in Week 1) results in a cumulative increase in order incidence of 1.4% over a four-week period, while a permanent shift to free shipping increases order incidence by 8.4%. These projections indicate the promotion pulls demand forward because the marginal impact of free shipping when the RFM variables are at their average levels is an 11.5% increase (see Table 7). If no demand was pulled forward, the four-week cumulative effect of a one-week promotion would be an increase in incidence of 2.9%, while for the permanent policy change the increase would be equivalent to the 11.5% marginal effect. In contrast, Segment 2 exhibits almost no purchase acceleration. For Segment 2, the weeks following a one-week promotion do not exhibit reduced demand, and in the case of a permanent policy shift, demand remains relatively constant. For Segments 3 and 4, short-term promotions do not pull much demand forward, but the permanent policy change does yield diminishing benefits.

4.3. Contribution Analysis

We now shift from characterizing the relationship between demand measures and shipping fees to analyzing profitability implications. For this analysis, we compare a standard increasing-fees structure, a policy with order-size incentives, and free shipping. The analysis assumes a 10,000-member customer base and is detailed in Table 10. For the contribution calculations we assume a 25% gross margin for all merchandise. The row representing the total merchandise contribution (middle of the table) shows that the two shipping promotions are effective in generating additional revenues for the firm over the baseline policy.

Next, we incorporate revenues from the shipping fees and account for costs associated with shipping the orders. The shipping costs incurred by the firm are assumed to be \$6.50 for a small order, \$7.50 for a medium order, and \$10.00 for a large order.[3] Consideration of shipping revenues and costs vividly clarifies the situation. The weekly net contribution from existing customers is about \$21,100 for the base policy, \$18,800 for the "free-large" policy, and \$16,000 for the "free-shipping" policy. Thus, the increase in demand due to shipping promotions is not sufficient to offset lost shipping revenues. In fact, assuming no changes in the distribution of order sizes, a 55.5% increase in order incidence from the baseline of 18.7% to 28.5% would be needed for the "free-shipping" policy to be profitable. We conclude that while shipping-fee promotions can change order incidence and order size, these structures may be difficult to profitably implement. Shifts in buying patterns within the existing customer base are not sufficient to make up for the lost shipping revenue and higher shipping costs.[4]

Table 10 Contribution Analysis

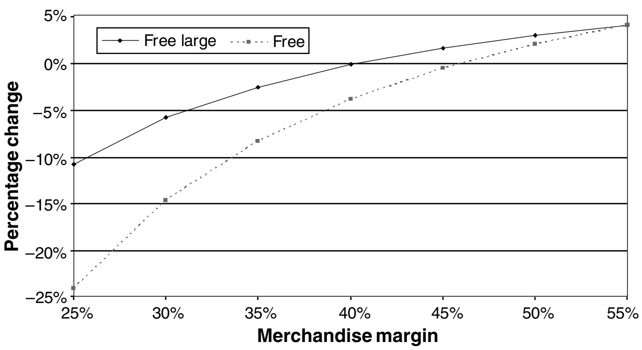
	Base policy	Free large	Free shipping	10% E-mail
Existing customers				
Initial customer base	10,000	10,000	10,000	10,000
Order incidence (%)	18.37	19.40	21.65	20.67
Small orders	962.20	1,011.10	1,086.80	1,060.00
Medium orders	326.30	134.60	348.60	363.60
Large orders	548.50	794.20	729.60	643.70
Average order size (\$):	58.61	63.13	60.91	59.51
Merchandise contribution (25% gross contribution) (\$)	26,917	30,620	32,968	18,452
Average shipping revenue (\$)	4.55	1.91	0	4.60
Total shipping revenue (\$)	8,358	3,707	0	9,503
Estimated shipping costs (\$)	14,151	15,490	16,925	16,009
Net shipping contribution (\$)	(5,794)	(11,784)	(16,925)	(6,506)
Net contribution (existing) (\$)	21,123	18,836	16,042	11,946

The contribution analysis includes an estimate of gross margin of 25%. This margin is consistent with the actual margins, which ranged from the low to the high twenties in the actual data. However, because the profitability projections are in some respects the result of trade-offs between shipping revenue and merchandise revenues it is useful to evaluate the sensitivity of the recommendations to the merchandise margins. Figure 4 shows the relative performance of the Free-Shipping and Free-Large schedules relative to the base fee schedule for different assumed margins. We observe that the Free-Large schedule, which encourages larger baskets, overtakes the base schedule at a margin rate of about 40%. The free-shipping promotion exceeds the contribution of the base policy at around 45% and reaches equivalence with the Free-Large schedule at a margin rate of about 55%. This sensitivity analysis is of potential interest when considering the appropriate shipping-fee schedule in

[3] These costs estimates are based on discussions with the manager who provided the data. Note that the firm was subsidizing the shipping charges under most schedules.

[4] While the analysis reported is only concerned with existing customers, the addition of customer acquisition projections, developed using aggregate-level data, does not change the rank ordering of the policies. We find that while shipping promotions increase customer acquisition, these increases are not enough to overcome the profitability advantage of the base policy. The customer acquisition analysis is available upon request.

Figure 4 **Margin Sensitivity Analysis: Incremental Contribution Relative to Base Fee Schedule**



high-margin categories. The intuitive result is that as margins become increasingly large, it may be advisable to subsidize shipping.

It is also instructive to perform the contribution analysis at the segment level. Table 11 shows the expected contribution associated with each policy for each segment. The segment-level analyses show the profitability of the policies varies by segment. The base policy is the best for Segments 1 and 4 while the "free-large" policy is the best for Segments 2 and 3. In more descriptive terms, the recommendation is to use an order-size incentive policy with the segment that is most oriented towards buying small baskets (Segment 2) and with the most price- and promotion-sensitive customers (Segment 3). In contrast, the segments that already have preferences for larger baskets (Segment 1) and who are relatively insensitive to marketing actions (Segment 4) are more profitably served using the base fee schedule.

This is an intuitive set of recommendations. The segments that are more responsive or that have a large potential for growth are better served using promotions designed to change behavior, while price-insensitive consumers are best marketed to with relatively high shipping fees. The advice to use promotions that influence expenditure levels as well as incidence is an important addition to the promotions literature. While the majority of the promotions literature (Neslin 2002) studies response to fixed per-item discounts, our findings recommend a promotion structure (for two segments) that requires consumers to increase order size to receive the discount.

Table 11 **Segment-Level Profitability for Various Promotions**

	Customers	Base ($)	Free large ($)	Free shipping ($)	10% E-mail ($)
Segment 1	1,466	5,072	3,785	3,856	3,152
Segment 2	3,662	2,078	2,095	962	676
Segment 3	3,420	5,250	5,443	4,369	3,441
Segment 4	1,452	8,723	7,512	6,854	4,678

5. Discussion and Conclusions

A primary goal of the research was to develop an accessible method for measuring response to nonlinear pricing schemes. The use of an ordered-response model that is generalized to consider nonlinear shipping fees is a significant advance relative to the use of binary discrete-choice models that predict order incidence. The method provides a forecast of incidence *and* the distribution of order sizes from the existing customer base. In direct-marketing contexts, the additional detail provided by this forecast could be used to refine mailing and promotions decisions. From a technical standpoint, while the partial generalization we use is not a standard method in statistical packages, implementation is fairly straightforward. Also while we choose to account for unobserved response heterogeneity using a finite mixture model, Bayesian methods that estimate individual- rather than segment-level parameters may also be worthwhile.

Our empirical results demonstrate that shipping fee schedules influence both order-incidence rates and expenditures. Specifically, we find that "free-shipping" promotions can greatly increase order-incidence rates, but this increase is at the expense of a significant reduction in shipping-fee revenues. We also find schedules that involve incentives for large orders can successfully induce customers to shift to larger order sizes. However, while the use of order-size-based shipping discounts are an increasingly popular technique, our results suggest these types of fee schedules should be closely scrutinized, as the loss of shipping-fee revenue and incremental shipping costs can make these promotions economically unattractive. The results also indicate the presence of significant, unobserved heterogeneity in responsiveness to shipping fees. In the four-segment model a "free-shipping" promotion is predicted to increase order incidence by at least 10% for all customers, but by over 35% for the most responsive segment.

This last result suggests there is a significant opportunity to customize. Using purchase histories, a firm could classify its customers into various segments and then set shipping fees to maximize profits for each segment. In our data, we would recommend offering "free shipping on large baskets" only to two of the four segments. Such a customized shipping-fee schedule is predicted to increase the firm's net contribution by 4.4% relative to the increasing-fee base policy, while a blanket promotion would result in losses relative to the base policy.

Our results suggest that shipping-fee promotions are unprofitable for the firm under study, and there is substantial evidence that shipping promotions have failed to be profitable for many firms (Barsh et al.

2000). However, there may be dynamic, competitive, and operational factors beyond managing demand from existing customers that influence shipping policies.[5] For example, free shipping may be an effective tool for customer acquisition. Specifically, given the heightened attention to shipping fees, shipping promotions may be an effective instrument for growing a customer base. Subsidized shipping policies may also be motivated by competitive forces. If competitors offer free or reduced shipping rates, firms may lower shipping fees as a defensive strategy. The previous two reasons are based on the idea that shipping fees are particularly salient to consumers. Along these lines, a firm may choose to offer free shipping by shifting shipping costs into higher merchandise prices.[6] Shipping fees and fulfillment rates may also affect customer retention by impacting satisfaction levels (Trocchia and Janda 2003).

Shipping-fee policies may also be motivated by operational costs. For example, shipping schedules can be designed as price-discrimination mechanisms that provide quantity discounts. This may be important if a firm's logistics system can more efficiently process larger orders (Dolan 1987). More generally, shipping schedules can be used to manage distribution costs by influencing order frequency and order size (Dolan 1987, Nightingdale 2000). Another aspect of delivery schedules that we have not considered is the timing of delivery. Firms may be able to lower logistics costs by trading shipping discounts for timing flexibility. Shipping policies can also affect post-purchase costs by affecting return rates (Hess and Mayhew 1997).

Based on these types of concerns firms may view shipping subsidies as beneficial despite the associated direct losses. Given these myriad rationales for subsidizing shipping, methods for measuring the impact of shipping fees on demand are of critical importance. Specifically, tools for assessing the direct consequences of shipping fees on consumer demand can be vital for balancing customer revenue goals with the aforementioned factors. Furthermore, many of these additional shipping-related factors are topics for future research. For example, an open question is how shipping schedules affect the types of customers that are acquired. Customers with preferences for large orders who are acquired under a policy that waives shipping fees for large orders may react more negatively to an increasing-fee structure, than would a customer acquired under a fixed-fee schedule. Delivery speed is another important issue not addressed in our model. Our data does not afford an opportunity to study consumer willingness to pay for faster delivery.[7]

[5] The authors thank the editor and area editor for several of these suggestions.

[6] This is not the case in our data. In fact, we find shipping fees are positively correlated with merchandise prices.

[7] The firm obtained discounts from a national shipper in exchange for allowing the delivery service flexibility as to delivery dates. Delivery speed is described as "likely between 1 and 4 business days."

References

Abramson, Charles, Rick Andrews, Imran Currim, Morgan Jones. 2000. Parameter bias from unobserved effects in multinomial logit models of consumer choice. *J. Marketing Res.* **37**(4) 410–426.

Allenby, Greg M., Thomas S. Shively, Sha Yang, Mark J. Garratt. 2004. A choice model for packaged goods: Dealing with discrete quantities and quantity discounts. *Marketing Sci.* **23**(1) 95–108.

Barsh, Joanna, Blair Crawford, Chris Grosso. 2000. How E-tailing can rise from the ashes. *McKinsey Quart.* **3** 98–109.

Bell, David R., James Lattin. 1998. Shopping behavior and consumer preferences for store price format: Why "large basket" shoppers prefer EDLP. *Marketing Sci.* **17**(1) 66–88.

Bohman, Ray. 1999. A closer look at catalog S&H charges. *Logistics Management Distribution Rep.* **38**(11) 27.

Bult, Jan Roelf, Tom Wansbeek. 1995. Optimal selection for direct mail. *Marketing Sci.* **14**(4) 378–395.

CNN.com. 2002. Domino's pizza ending free delivery. CNN Online, www.cnn.com/2002/us/08/10/pizza.delivery.ap/index.html.

Courogen, Chris. 2002. Amazon.com once again offers free shipping to online customers. *Knight Ridder Bus. News* (Oct. 2) 2000.

Danaher, Peter J., Isaac W. Wilson, Robert A. Davis. 2003. A comparison of online and offline consumer brand loyalty. *Marketing Sci.* **22**(4) 461–476.

Dolan, Robert. 1987. Quantity discounts: Managerial issues and research opportunities. *Marketing Sci.* **6**(1) 1–22.

Dolan, Robert, Hermann Simon. 1996. *Power Pricing*. The Free Press, New York.

Dreze, X., P. Nisol, N. Vilcassim. 2004. Retailer promotions and within-store household expenditures: An empirical analysis. *Quant. Marketing Econom.* **2**(1) 59–92.

Elsner, Ralf, Manfred Krafft, Arnd Huchzermeier. 2004. Optimizing Rhenania's direct marketing business through dynamic multilevel modeling (DMLM) in a multicatalog-brand environment. *Marketing Sci.* **23**(2) 192–206.

Ernst and Young. 1999. Third annual online retailing report.

Gönül, F., Meng Ze Shi. 1998. Optimal mailing of catalogs: A new methodology using estimable structural dynamic programming models. *Management Sci.* **44**(9) 1249–1262.

Hess, James, Glenn Mayhew. 1997. Modeling merchandise returns in direct marketing. *J. Direct Marketing* **11**(2) 20–35.

Hughes, Arthur. 2000. *Strategic Database Marketing*. McGraw Hill, New York.

Janda, S., P. Trocchia, K. Gwinner. 2002. Consumer perceptions of Internet retail service quality. *Internat. J. Service Industry Management* **13**(5) 412–421.

Jupiter Communications. 2001. Creating loyalty: Building profitable relationships. Jupiter Vision Report: Digital Commerce, Vol. 2.

Kamakura, Wagner, Gary Russell. 1989. A probabilistic choice model for market segmentation and elasticity structure. *J. Marketing Res.* **26**(November) 379–390.

Lisanti, Tony. 1999. The 15 laws of cyberretailing. *Discount Store News* **38**(4) 11.

Moore, John. 2000. The death of free delivery. *Business* 2.0 (Sept. 21).

Morwitz, V. G., E. A. Greenleaf, E. J. Johnson. 1998. Divide and prosper: Consumers' reactions to partitioned prices. *J. Marketing Res.* **35**(November) 453–463.

Neslin, Scott. 2002. *Sales Promotion*. Marketing Science Institute, Cambridge, MA.

Nightingdale, Tom. 2000. Oh no! Free shipping! *Traffic World* (March 6). www.trafficworld.com.

Pyke, D., M. E. Johnson, P. Desmond. 2001. E-fulfillment, it's harder than it looks. *Supply Chain Management Rev.* (Jan./Feb.) 26–32.

Quick, Rebecca. 2000. Days of freebies disappear for Web shoppers; too good to last E-retailers money dries up with free shipping, giveaways. *Wall Street J.* (June 26) R8.

Ricker, F., R. Kalakota. 1999. Order fulfillment: The hidden key to E-commerce success. *Supply Chain Management Rev.* **Fall** 60–70.

Rosen, K., A. Howard. 2000. E-retail: Gold rush or fool's gold? *California Management Rev.* **42**(3) 72–100.

Shepard, David and Associates. 1999. *The New Direct Marketing*, 3rd ed. McGraw-Hill, New York.

Train, Kenneth, Daniel McFadden, Moshe Ben-Akiva. 1987. The demand for local telephone service: A fully discrete model of residential calling patterns and service choices. *RAND J. Econom.* **18** 109–123.

Train, Kenneth, Moshe Ben-Akiva, Terry Atherton. 1989. Consumption patterns and self-selecting tariffs. *Rev. Econom. Statist.* **25**(2) 62–73.

Trocchia, P., S. Janda. 2003. How do consumers evaluate Internet retail service quality. *J. Services Marketing* **17**(2/3) 243–251.

Tyagi, Rajeev. 2004. Technological advances, transaction costs, and consumer welfare. *Marketing Sci.* **23**(3) 335–344.

Wingfield, Nick. 2003. Leading the news: Amazon boosts forecasts as sales soar. *Wall Street J.* (Jan. 24) A.3.

Wood, Stacey. 2001. Remote purchase environments: The influence of return policy leniency on two-stage decision processes. *J. Marketing Res.* **38**(May) 157–169.