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Customers have predictable life cycles. As a result of these life cycles, firms that sell multiple products or services frequently observe that, in general, certain items are purchased before others. This predictable phenomenon provides opportunities for firms to cross-sell additional products and services to existing customers. This article presents a structural multivariate probit model to investigate how customer demand for multiple products evolves over time and its implications for the sequential acquisition patterns of naturally ordered products. The authors investigate customer purchase patterns for products that are marketed by a large midwestern bank. Among the substantive findings are that women and older customers are more sensitive to their overall satisfaction with the bank than are men and younger customers when determining whether to purchase additional financial services, and households whose head has a greater level of education or is male move more quickly along the financial maturity continuum than do households whose head has less education or is female.

Cross-Selling Sequentially Ordered Products: An Application to Consumer Banking Services

Consumers frequently purchase multiple products and services from the same provider over time.[1] Often, these products can be naturally ordered in terms of complexity and functionality, leading to behavioral regularity such that, in general, the purchase of certain products precedes the purchase of others. This customer life-cycle effect may exist independently of any marketing activities, and it constitutes an exogenous effect on the overall customer life cycle.

For example, in general, a person establishes a checking account with a given bank before he or she establishes a brokerage account. A consumer may also sequentially purchase local and long-distance telephone service, cable television service, and Internet access from the same company. A person who purchases a personal digital assistant may then acquire Internet access, additional memory, and software from the same provider in the future. The common thread that runs through each of these examples is that consumers are more likely to purchase some products or subset of products before others. We term the development over time of consumers' complementary demand for multiple products and services "natural ordering," and in our application, we demonstrate the importance of this concept.

Markets that are especially prone to this behavioral regularity include those in which consumers' wants or needs evolve after some preliminary consumption, those in which consumers face some uncertainty about the quality of the product or service offering, and those in which consumer learning is required to receive the full benefit of the product. In such markets, the sequential purchase of multiple products or services from the same provider can enhance the relationship with the provider, raise switching costs associated with a move to a new provider, lower uncertainty about additional product purchases, and, in some cases, ensure proper technical compatibility with products that the consumer already owns (Kamakura, Ramaswami, and Srivastava 1991; Kamakura et al. 2003). The existence of sequentially developed demand for naturally ordered products offers substantial opportunities for companies that carry multiple products and services to "cross-sell" other products and services to their existing customer base.

There have been a few descriptive studies over the past four decades that probe consumers' sequential purchases (e.g., Bitner and Zeithaml 2000; Boulding et al. 1993;

[1]Throughout this article, we refer to products and services interchangeably. The model we develop is equally applicable to both.

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Hauser and Urban 1986; Mayo and Qualls 1987). To our knowledge, Kamakura, Ramaswami, and Srivastava's (1991) article is the first to model cross-selling opportunities formally. This research applies latent trait analysis to position financial services and investors along a common continuum. Kamakura, Kossar, and Wedel (2004) develop a split-hazard-rate model and focus on the prediction of each customer's (physician's) time of adopting a new product (drug) based on the timing of the customer's prior adoptions of multiple products. Knott, Hayes, and Neslin (2002) present four next-product-to-purchase models (discriminant analysis, multinomial logit, logistic regression, and neural net) that help predict what a customer is likely to purchase next and when. Kamakura and colleagues (2003) develop a mixed-data factor analyzer that is an extension of factor analysis to incorporate various types of data (i.e., choice, counts, or ratings), and they tailor their approach to identify the best prospects for each product on the basis of customer transaction data. They are not primarily interested in a behavioral interpretation of the latent dimensions but rather in a convenient, low-dimensional graphical display of the structure in the data. Edwards and Allenby (2003) propose a general approach to identify restrictions for the multivariate binomial probit model, and they develop an algorithm that is efficient especially for a large number of response options. One of their three applications is to survey data on ownership of financial products. Applicable to cross-sectional data, the preceding studies are aimed at the inference of cross-selling opportunities from the comparison of one-time measurements of current product ownership. The resulting recommendation of the next product to sell is usually consistent with the ranking of product market shares. This approach ignores the development over time of individual-level demand in favor of a cross-sectional approach. In a recent approach to this problem, Zhang and Krishnamurthi (2004) model sequential purchases in an online environment, modeling future purchase probabilities as a branching process. This approach provides a rich description of the different purchase paths that may describe the behavior of an individual consumer.

In this article, we explicitly model the development of customer demand for multiple products over time and derive a product acquisition sequence based on customers' individual level of demand maturity. Using a multivariate probit model applied to panel data, we implement the model in a hierarchical Bayesian framework. In contrast to previous work in the area, we study the behavioral reasons that underpin and drive these purchase patterns. Our empirical application demonstrates the value of this approach.

CONSUMERS' BANKING SERVICE ACQUISITION

Model Specification

At any point, consumers have demands for multiple products. Economic theory has shown that in the presence of finite resources, there is a "priority structure" among the demand objectives and that this priority structure can be transformed into a priority structure for products (Kamakura, Ramaswami, and Srivastava 1991). Our modeling approach orders multiple products and customers' demand for those products along a common continuum in a way that reflects the development of customer demand maturity. The closer a customer's demand maturity is to the position of a given product, the more likely this product is to satisfy the current need of the customer, and the more likely he or she is to purchase the product.

To formulate this idea in a random utility framework that is suitable for our panel data approach, we adopt an ideal point model (Lehmann 1971) in which the predicted choice probability inversely relates to the distance of an object (ratings of the actual brands that are being analyzed) from the ideal point (a consumer's rating of an ideal brand).[2] Formally, we assume that household i = 1, …, I makes binary purchase decisions (buy or not buy) on each of the products j = 1, …, J in the product set J, at each time period t. We specify the latent utility of a given household choosing product j = 1, 2, …, J at occasion t as

$$(1)\qquad U_{ijt} = \beta_i|O_j - DM_{it-1}| + \gamma_{1ij}COMPET_i + \gamma_{2ij}OVERSAT_i + \gamma_{3ij}SWIT_{it} + \varepsilon_{ijt},$$

where O_j defines the position of product j ranked along the same continuum as demand maturity, and DM_{it-1} denotes the demand maturity of consumer i at the end of time t – 1. These are parameters to be estimated. Thus, the term $|O_j - DM_{it-1}|$ represents the distance between demand maturity and product j. The term β_i measures how the development of customer demand maturity, relative to product j, affects the demand for product j. We allow the unobserved component of the utilities to be correlated.

$$(2)\qquad \varepsilon_{it} \sim MVN[0, \Sigma].$$

The correlations capture the "co-incidence" among different products in the sense that Manchanda, Ansari, and Gupta (1999) use the term, and the correlations take into account the contemporaneous product purchases.

Our model also includes variables that characterize a given customer's current relationship with the bank. Specifically, we define $COMPET_i$ as a dummy variable that is equal to one when household i has opened an account in category j with another bank in the past six months. This controls for the ease with which a given customer can acquire a new product or service from a provider other than this particular bank. We define $OVERSAT_i$ as household i's overall satisfaction with the bank as measured by the bank's customer satisfaction survey. This provides an important measure of the strength of the relationship between a given customer and the bank (Boulding et al. 1993).

We also included household-level switching costs ($SWIT_{it}$) in our analysis. This is defined as one if the account owner's profession is as a white collar worker, the household has at least one nonadult child, and the household owns more than the average number of accounts with the bank. We believe that such households have higher overall time costs, and thus their implicit costs associated with switching banks are greater. The logic of this inclusion follows Blattberg and colleagues' (1978) reasoning closely and Becker's (1965) work more primitively. Households that have a high cost of time, as evidenced by increasing levels of education or the presence of children, tend to spend less time shopping for banking services. People who have relatively complex relationships with the bank because of their large number of accounts also suffer greater inconvenience if they choose to switch banking service providers. Whereas

[2]For a detailed discussion of this modeling framework, see Lehmann (1971).

switching grocery stores is relatively easy, switching service providers often entails a significantly higher degree of discomfort. The reasons for this greater inconvenience are reasonably self-evident; they include such unpleasantness as filling out all the paperwork that is necessary for opening up a series of accounts at a new bank. We define a high-switching-cost household as the intersection of all three of these effects. At a practical level, this means that we define a household as having high switching costs only when these Becker-type switching costs are likely to be quite severe. However, we note that we have not directly elicited or measured switching costs. Whereas previous research (Becker 1965; Blatteberg et al. 1978; Narasimhan 1984) has argued that the same demographic variables used here are good proxies for a consumer's cost of time, we point out that we cannot definitively conclude that there is a one-to-one mapping between our demographic and account data and a consumer's overall switching cost.

We define a household's latent financial maturity as a function of cumulative ownership, monthly balances, and the holding time of all available accounts weighted by the corresponding importance of each product. That is,

$$(3)\qquad DM_{it-1} = \sum_{j=1}^{J}[O_j D_{ijt-1}(\lambda_1 ACCTNBR_{ijt-1} + \lambda_2 BAL_{ijt-1} + \lambda_3 Holding_{ijt-1})],$$

where D_{ijt-1} is a dummy variable indicating that household i purchased product j during the previous month. The term $ACCTNBR_{ijt-1}$ captures the cumulative number of purchases up to and including the past month. Previous research has shown the importance of using ownership as a predictor variable (see Knott, Hayes, and Neslin 2002). In addition, we also include the monthly balances (BAL_{ijt-1}) and the time elapsed since first opening this type of account ($Holding_{ijt-1}$) as additional explanatory variables. These three variables indicate the purchase experience or satisfied needs for product j and can be interpreted as the realization of consumer demand for j at the beginning of time t. We then weight the satisfied demands for all the products by product order to construct the latent variable, or the financial maturity of household i at time t. To obtain easily interpretable estimates of O_j, we rescaled all three variables to have zero mean and unit variance.

To mitigate the well-known problems associated with not controlling for consumer-level heterogeneity (Allenby and Rossi 1999; Gönül and Srinivasan 1996; Heckman 1981; Kamakura and Russell 1989; Krishna, Currim, and Shoemaker 1991), we write the utility coefficients as linear functions of basic demographic information. This allows for household characteristics to influence the weight that certain factors play in the utility function. Formally, we specify coefficient heterogeneity as follows:

$$(4)\qquad \begin{cases} \beta_i = \mu_0 + \mu_1 EDUCAT_i + \mu_2 SEX_i + \mu_3 AGE_i \\ \qquad + \mu_4 INCOME_i + e_i \\ \gamma_{ki} = \omega_{0k} + \omega_{1k} EDUCAT_i + \omega_{2k} SEX_i + \omega_{3k} AGE_i \\ \qquad + \omega_{4k} INCOME_i + \xi_{ki} \end{cases},$$

where we assume that $e_i \sim N[0, \sigma^2]$ and $\xi_{ki} \sim MVN[0, M_\xi]$.

The μs capture how customers' information costs vary when they make the adoption decision for product j, and μ_4 reveals the resource constraint. For example, we believe that better-educated and male household heads believe themselves to be more knowledgeable and better informed about the financial products. They are also more confident in managing their investments (see Barber and Odean 2001). Thus, we conjecture that adoption speed or movement along the financial maturity continuum may be faster for households that are better educated and headed by a male. Higher-income people may move along the continuum more quickly because they are more motivated to pay attention to and find solutions for their financial needs. Households may also respond differently to competition, satisfaction, and switching costs. This is captured in the ω parameters.

To solve the identification problem, we normalize one of the O_j's to 1. We divide the utility by its corresponding standard deviation, transforming Σ to a correlation matrix. We use a hierarchical Bayesian approach to estimate the model. We refer readers who are interested in the details of the estimation procedure to the work of Allenby and Rossi (1999), Gelfand and Smith (1990), and Manchanda, Ansari, and Gupta (1999).[3]

A Description of the Banking Transaction Data

We use this model and household-level data collected by a large midwestern bank to explore consumers' acquisition of financial services. Specifically, we obtained holding and transaction information for eight products of 1201 randomly selected households that have stated that they used this bank as their primary bank from July 1997 to June 1998.[4] The data include monthly observations on which accounts and products the customer had purchased or held as an investment. We also had access to demographic information for each customer. Finally, the bank provided the results of a customer satisfaction survey that each customer in the sample completed just before July 1997. Because our data were at the household level, we also observed repeat purchases. We cannot determine whether these repeat purchases represent true repeats by the same person or were new purchases by someone else in the household, so our analysis is at the household level. A brief description of the variables that we used appears in Table 1.

Comparing our Model with Other Plausible Specifications

In the interest of comparing our model with other plausible specifications, we estimated four competing models and our own. The first is a first-order Markov model using conditional purchase probabilities. Assuming independence among products, it predicts purchases in the next period on

[3]We have conducted a simulation to study the identification and statistical properties of this model. We have also compared the scale of the estimated product-ranking coefficients with the estimated demand maturity on the basis of both simulated data and our data. The two variables are measured on similar scales, and the distances between product positions and demand maturity explain purchases well (details on the simulation, prior distributions, and the estimation of the model are available on request).

[4]The bank provided access to holding and transaction information for 20 financial products that it offered for 1201 households. However, there are 11 products without any purchase or very little purchase information in this short observation window. There is also 1 product with only 16 purchase observations. To avoid the problem of data scarcity, we focus only on products with more than 29 purchases in the observation period.

the basis of current ownership. The second model also assumes that product choices are independent. This model specification comprises product-specific binary probit models, one for each category. It ignores potential unobserved correlation across categories, the allocation of assets, switching costs, and heterogeneity. We include this model because it is a specification that firms commonly adopt to predict probabilities of cross-selling. This model is also similar to that of Kamakura, Ramaswami, and Srivastava (1991) and Knott, Hayes, and Neslin (2002) insofar as the models assume that consumers make independent decisions about the purchases of different products. The third model is a multivariate probit model that is similar to Manchanda, Ansari, and Gupta's (1999). It captures the contemporaneous (non-over-time) complementary relationship among products on the same purchase occasion. The fourth model adds the impact of switching costs to the third model. Although not directly comparable, this model can be likened to that of Edwards and Allenby (2003) insofar as the predicted purchase order is derived from the order of intrinsic preferences. Finally, our proposed model adds demand maturity to the fourth model, thereby allowing us to take into account customers' previously satisfied financial needs.

We estimated the independent model using the probit procedure in SAS. We estimated the remaining four models using a Markov chain Monte Carlo approach. For model comparison, we used both the Bayes factor criterion and the deviance information criterion, which penalizes a complex model for additional parameters (Spiegelhalter et al. 2002). Both methods indicate that our proposed model (Model 5) fits the data better than do any of the competing models, and as such, our model demonstrates that taking into account the development of customer financial demand is important in determining service adoption.[5]

The Substantive Results of Our Consumer Banking Application

We turn our attention to the application and the substantive results that arise from it. We begin with the ordering among products by examining the ranking of O_j that we report in Table 2. The ranking of the parameters indicates the following product sequence: checking → saving → debit card → credit card → installment loan → certificate of deposit (CD) → money market (MM) → brokerage. This is consistent with our intuition that customers usually invest more aggressively in financial instruments that promise stable returns (e.g., CD, MM) only after they obtain basic financial services (e.g., checking, saving, debit, credit, loan) and that they usually invest in high-risk, high-return brokerage accounts only after they invest in other low-risk products. The implied order of the eight financial products is consistent with Kamakura, Ramaswami, and Srivastava's (1991) idea of the development of financial maturity from convenience products, to stable income products, to risky income products. The ordering that our model recovered is exactly what we a priori expected. It is also consistent with our conversations with bank managers.

Beyond a simple rank ordering, the estimated O_j's also provide a distance metric that indicates each product's relative distance from all other products along a common maturity continuum. Each product's estimated position on the continuum appears in Figure 1.

Referring to the parameter estimates that appear in Table 2, the slope parameter β indicates how the distance between

[5]The exact fit statistics for each model and a discussion of those statistics are available on request.

Table 1
VARIABLE SPECIFICS

Variables	*Definitions*	*Mean or Frequency*
COMPET	1 if the household opens an account in another bank during the past six months, 0 if otherwise.	13.3%
OVERSAT	A household's overall satisfaction (on a scale from 1 to 7) with the bank as reported on the bank's customer satisfaction survey.	4.3
SWIT	1 if the account owner's profession is white collar and the household has at least one nonadult child and the household owns a more than average number of accounts with this bank, 0 if otherwise.	6.6%
EDUCAT	The household head's education is measured on a 1–5 scale (1 = some high school, 5 = post graduate).	2.76
SEX	1 if the account owner is a male, 0 if otherwise.	82.5%
AGE	Account owner's age.	67
INCOME	Household's income is measured on a scale from 1–7, where 1 < $15,000, 2 = $15,000–$24,999, 3 = $25,000–$34,999, 4 = $35,000–$49,999, 5 = $50,000–$74,999, 6 = $75,000–$99,999, AND 7 = $100,000+.	3.34

Table 2
ESTIMATION RESULTS OF PROPOSED MODEL

Product/Covariate	*COMPET*	*OVERSAT*	*SWIT*	*ORDER* (O_j)
Installment loan	–11.60	2.55	2.55	.71
	(.06)	(.01)	(.10)	(.03)
Debit card	–9.59	2.01	2.38	.57
	(.03)	(.01)	(.10)	(.03)
Checking	–12.04	2.77	4.40	–.09
	(.05)	(.01)	(.12)	(.03)
Credit card	–8.92	2.49	1.39	.69
	(.07)	(.01)	(.10)	(.03)
Savings	–11.21	2.77	2.71	–.03
	(.08)	(.01)	(.18)	(.01)
CD	–8.40	2.33	1.80	.79
	(.07)	(.01)	(.08)	(.11)
MM	–9.54	3.10	1.20	.84
	(.05)	(.01)	(.16)	(.03)
Brokerage	–14.63	3.44	5.05	1
	(.06)	(.01)	(.06)	

Estimates	*ACCTNBR* (λ_1)	*BAL* (λ_2)	*DURATION* (λ_3)
Maturity	.13	.03	.06
	(.03)	(.00)	(.01)

Notes: The numbers in parentheses are standard errors.

the financial maturity and the corresponding product affects the probability of purchase as the customer's latent financial maturity changes. The sign of the coefficient is negative, indicating that the closer the distance to a product, the more likely that product is to be purchased. This is consistent with Lehmann's (1971) interpretation. The terms λ_1, λ_2, and λ_3 are all positive and significant, indicating that the cumulative number of account purchases, cumulative balances, and holding times increases financial maturity. Some notable results center on the impact of overall satisfaction and household switching costs. Overall satisfaction with the bank increases the bank's ability to sell its products to existing customers. This effect is more potent in the demand for advanced financial services than for lower-end products. This result is intuitive in that advanced financial services (e.g., brokerage) require much more interaction with the bank than does a simple CD account, which requires much less human interaction.

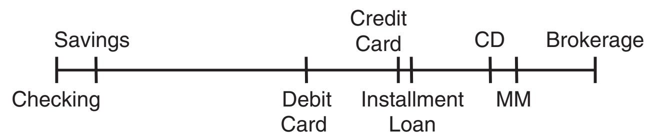
It is apparent that switching costs play an important role in providing companies with opportunities to cross-sell their products to existing customers. Switching costs play a powerful role in influencing households for all eight products. Following the preceding logic, we expect that this effect is more potent for convenience and advanced services than for cash reserves, and indeed this is the case. This result raises some questions about which customers are most important for the bank to satisfy. Although conventional wisdom certainly dictates that the bank should place more emphasis on satisfying its wealthier customers, our results indicate that some customers may be "trapped" by the bank because of the substantial implicit costs a given customer might face in switching from one bank to another.

We now turn our attention to the consumer heterogeneity expressions and examine how demographic variables, such as education, sex of the head of the household, age, and income, affect the acquisition pattern of sequentially ordered products.[6] These estimates describe how knowledge, risk bearing, life stage, and financial resources characterize the speed of adoption for financial products. Most of the estimates are significant. The coefficients of education and sex in the heterogeneity equation for β_i are negative and indicate that for any given level of financial maturity, people with a higher level of education or with male household heads are likely to progress more quickly along the financial continuum than are other customers. These results are consistent with the research findings of Barber and Odean (2001), who find that men are more confident about their ability to manage risky assets. Similarly, we found that older customers and higher-income customers are also more likely to progress more quickly along the continuum.

The estimated coefficient of education in the heterogeneity equation for competition directly suggests that highly educated households are less likely to be cross-sold other products after they have opened an account with the bank's competitors. Notably, highly educated customers seem to care more about customer service and switching costs as determinants of future purchases than do customers with an average or below-average level of education.

[6]The estimates from the heterogeneity expression are available on request.

Figure 1
FINANCIAL MATURITY CONTINUUM



Male household heads seem to care less than their female counterparts about both satisfaction and switching costs in determining future purchases. This result may be at least partially explained by the influence of education and sex on a customer's organizational ability, an ability that would impact the customer's sensitivity to service quality and the propensity to switch or patronize multiple financial institutions.

Owning an account at a competing financial institution is more likely to deter older customers from cross-buying other products from the bank than to deter their younger counterparts. These same customers are much more sensitive to satisfaction and less sensitive to switching costs. We speculate that these results arise because older, and often retired, customers have more time to shop for the best alternative. If older customers are not satisfied, it is relatively easy for them to switch banks. This is a potentially important finding because older customers also have the potential to be some of the bank's best customers. Together, these results strongly suggest that a bank's top priority should be to satisfy older customers.

Following the same reasoning and also arising from our estimated model, higher-income customers have less time to spend searching for the best product, the best service, or the lowest price. They are more likely to be cross-sold other convenience products after they become customers of the bank. They are less sensitive to satisfaction and more sensitive to switching costs. These are customers who are somewhat "trapped" and seek convenience to save time. However, for nonconvenience products, such as CD's, MM's, and brokerage accounts, these customers alter their behavior and are more sensitive to competition and satisfaction. We speculate that this is because higher-income customers are more sensitive to the return on investment and to the availability of specific investment choices. They are also more likely to have better knowledge of the options that competing banks and other service providers offer.

Predicting Cross-Selling Opportunities

Because part of the focus of this application is to predict the probability of acquiring new products to help bank managers more efficiently allocate their targeting efforts, we now compare the predictive ability of our proposed model with the other benchmark models. To accomplish this, we divided our original sample of 1201 households into an estimation sample and a holdout sample. The estimation sample has three-quarters of the households, and the holdout sample has the remaining quarter.

Figure 2 depicts the mean absolute error between the predicted purchase probability and the actual purchase realization for each of the five models, using the holdout sample. The worst predictive accuracy arises from the independent model (Model 2). Including "co-incidence" to allow for the copurchase of multiple products and heterogeneity, Model 3 increases the predictive accuracy. Thus, the approach that Manchanda, Ansari, and Gupta (1999) suggest, though developed in the study of complementary demands (shopping basket) for frequently purchased products, captures unobserved factors that cause multiple purchases at the same purchase occasion in this setting. Comparing Model 4 with our model (Model 5), we find that a multivariate probit model with sequential ordering effects provides a much more accurate description of households' future purchase decisions. The predictive accuracy of our proposed model is fairly remarkable. For example, the mean absolute error rate of convenience services is less than .5%. Although we do not claim that all applications will achieve such a high degree of accuracy, we believe that the evidence weighs in favor of including order effects in attempts to model choice formally in this type of environment.

Given the customer-relationship-management nature of our application, a gains chart is a common approach to the evaluation of predictive performance when there are low response rates. Figure 3 includes gains charts for each of the tested models, again using the holdout sample. The gains chart approach begins by the selection of 10% of the customers from our holdout sample who, according to the model, are most likely to make a purchase. This is done for each model. Next, we compute the number of accurately predicted responses relative to the total number of responses in the entire sample; this percentage is the gain due to using the model, and it represents the value of sorting the data by the predictions from the models. The "No Model" line depicts a situation in which customers are grouped randomly. Thus, if we have a randomly drawn group that constitutes 10% of the sample, on average it will contain 10% of the overall number of purchases and so forth. We compute analogous values for each percentile of the holdout sample (top 20%, top 30%, etc.). The greater the difference between the gains curve and the baseline model, the better is the model. Note that the gains chart and mean absolute error approach give somewhat different results. Although both methods support the conclusion that the predictive accuracy of our proposed model is superior to that of the baseline case and each of the competing models we examined, the gains chart approach suggests that Model 4, which excludes demand maturity, does a significantly better job in predicting future purchases than do the other three benchmark models.

Figure 2
MODEL COMPARISON: MEAN ABSOLUTE ERROR ACROSS MODELS (HOLDOUT SAMPLE)

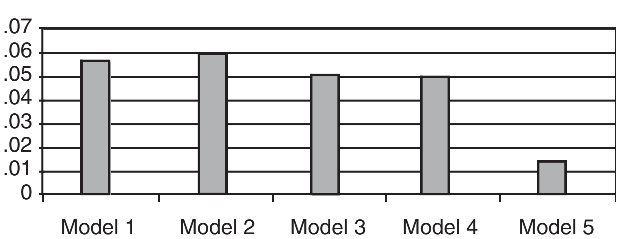
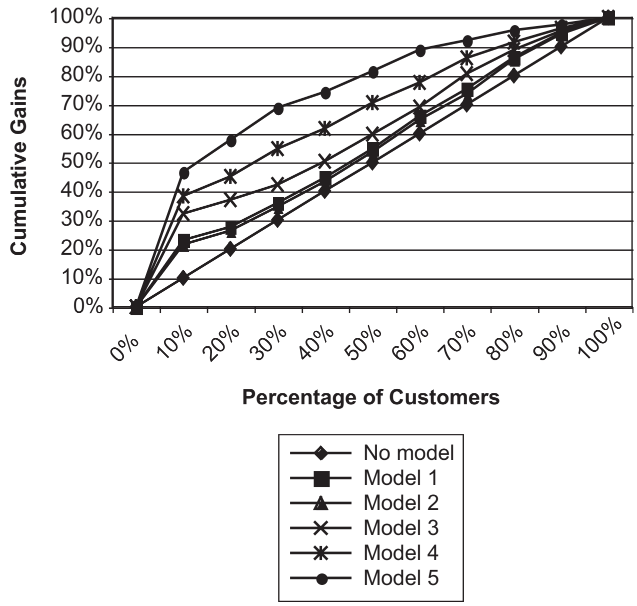


Figure 3
GAINS CHART FOR MODEL COMPARISON ACROSS ALL PRODUCT CATEGORIES (HOLDOUT SAMPLE)



In summary, the most important lessons from our application are as follows:

- A household's evolving financial maturity drives the sequential purchase of multiple products.
- Households with a greater level of education or male household heads move more quickly along the financial maturity continuum than do households that are headed by a person with less education or by women. Households that are older and have higher incomes also move along this continuum more quickly.
- The switching costs associated with owning multiple products create opportunities to cross-sell other products to the same customer.
- Customer satisfaction or service quality has a significant influence on a customer's future purchase decisions, especially for more advanced financial products (e.g., brokerage). This effect is particularly strong for older customers.
- A multivariate probit model with heterogeneity, switching costs, and sequential ordering effects provides a more accurate description and prediction of households' future purchase decisions than do other plausible specifications.

DISCUSSION, LIMITATIONS, AND DIRECTIONS FOR FURTHER RESEARCH

This research explicitly models the development of customer demand for multiple products over time and derives a product-purchase sequence under the assumption that different products are designed to meet the requirements of customers at different stages of their demand maturity. As the first cross-selling model applicable to panel data, this article provides a behavioral explanation for the development over time of customer demand and for the purchase of multiple products from the same provider. Our research also shows that sequential demands for naturally ordered products develop differently across different customers, and it points to some of the antecedents of these differences. Our findings provide guidance to managers who are charged with allocating marketing dollars to customers with the greatest incremental profit potential.

Our model directly suggests that it is important for a company to collect information to determine its customers' stages of demand maturity before it spends money to market to customers who may not be ready to adopt a new product or service. In addition, it appears that in this particular market, it is more effective to target customers with higher education, males, and customers with higher incomes, because these customers move more quickly along the demand maturity continuum.

Our banking application uncovered several behavioral findings that may be instructive of consumers' service adoption in general. We use the word "may" here because the study was limited in several ways. First, we do not have detailed information on competition. Further research might consider the ownership information with competitors when calculating demand maturity. This would enable a more accurate ordering of the products. Second, although we obtained relatively detailed information on customer-level account activity, we did not have access to data that detailed the marketing activity that each person in our sample was exposed to over this time period. If such information were available, it would be possible to explore more formally the impact of marketing variables (e.g., price, advertising) on cross-selling tactics and opportunities. This would be a valuable contribution to the knowledge of these markets. Third, our data only covered the span of one year. In an environment such as banking in which a customer relationship may last for many years but new service acquisitions are relatively infrequent, one year may not be sufficient to capture the richness of the phenomenon. We expect that data that span a longer time period would yield even greater differences between our modeling approach and those that do not account for temporal ordering. Finally, a product or service provider is interested not only in whether an additional service can be sold to an existing customer but also in the amount of profit such a sale is likely to generate. We did not have access to data that would allow such analysis. Further research should more explicitly model the flow of funds, type of usage, and cost to examine the impact of cross-selling on profit.

The market for services is a large and growing segment of the U.S. economy. Even the more narrowly defined market for financial services is a truly enormous segment of the economy. It has been shown that there are benefits of predictive modeling in the arena of packaged goods. The state of knowledge in this market has increased dramatically over the past two decades. In contrast, disproportionately little attention has been paid to the market for services. There is no doubt that the relative difficulty of obtaining quality and timely data from service providers at least partially explains this neglect. Data from service providers tend to be more convoluted than data generated by scanner technology. Yet despite such challenges, the benefits of exploring this marketplace are truly remarkable. We believe our research is one step in that direction.

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