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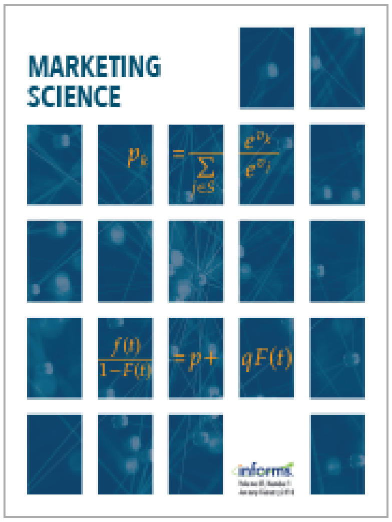

Marketing Science

Publication details, including instructions for authors and subscription information:
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Satisfaction Spillovers Across Categories

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To cite this article:
Xiaojing Dong, Pradeep K. Chintagunta (2016) Satisfaction Spillovers Across Categories. Marketing Science 35(2):275-283.
https://doi.org/10.1287/mksc.2015.0941

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MARKETING SCIENCE
Vol. 35, No. 2, March–April 2016, pp. 275–283
ISSN 0732-2399 (print) | ISSN 1526-548X (online)

http://dx.doi.org/10.1287/mksc.2015.0941
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Satisfaction Spillovers Across Categories

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We provide a descriptive study of the cross-category effects of satisfaction with financial services on retention behavior. Behavioral contrast and learning theories provide the bases for our understanding of these effects. Our empirical results reveal the following: (i) Across banking and investment categories, when customers have *different* providers, satisfaction with one lowers the retention probability in the other service. (ii) A customer who is dissatisfied with the investment service is more likely to stay with the current banking service. (iii) Significantly, we find that when the same firm is involved in both categories, dissatisfaction with the firm in the investment category spills over into the banking category thereby lowering its retention probability. We also find that: (a) among customers who are satisfied with banking (investment), more exposure to media increases retention probability; (b) although switching costs and order of acquisition affect retention, they do not show cross-category interactions with satisfaction. We then obtain implications for customer lifetime value (CLV) and show that it can increase satisfaction by leveraging both the within and across category effects. Bottom line: It is important for a company providing multiple services to measure satisfaction at the category level but to manage customers across categories.

Data, as supplemental material, are available at http://dx.doi.org/10.1287/mksc.2015.0941.

Keywords: Bayesian estimation; endogeneity; surveys and services
History: Received: May 27, 2013; accepted: April 13, 2015; Preyas Desai served as the editor-in-chief. Published online in *Articles in Advance* September 28, 2015.

1. Introduction

With the advent of cross-selling (Rust and Chung 2006, Bolton 1998), the satisfaction literature (e.g., Luo and Homburg 2008, Luo 2009, Fornell 1992, Anderson et al. 1994, Szymanski and Henard 2001) has moved into the multicategory domain, i.e., satisfaction wherein a provider influences outcomes across multiple categories. Verhoef et al. (2001) find no main effect of satisfaction on cross-buying. They do find that as the duration of the customer-firm relationship increases, the effect of satisfaction on cross-buying also increases. Li et al. (2005) show that overall satisfaction with a firm has an impact on consumers signing up for a variety of additional financial services. While overall satisfaction is an important driver of customer acquisition and retention, it might be less useful from the perspective of determining why a customer might have defected from a company's suite of services.

Consider a services firm that manages customer satisfaction across two categories by tracking an overall satisfaction measure for the firm and retention behavior in each category. Customer data shows that a reduction in overall satisfaction coincided with the customer defecting from both services, thus leading company investments in improving both services. However, the customer might have been extremely satisfied with one service and not at all with the other. Jointly these contribute to the reduction in overall satisfaction. For the service with the low satisfaction level, it is reasonable to expect defection. Yet there could also be spillover in satisfaction from the dissatisfied service to retention in the satisfied service leading to defection from both services. In this case, the firm should focus efforts and resources only on the dissatisfied category. Next, suppose the firm tracks satisfaction and retention separately by category and manages both categories independently. Because defection happens in both categories but satisfaction was low in only one, the firm would conclude that satisfaction affects retention in the dissatisfied category but does not influence retention in the satisfied category.

Our objectives here are to provide a descriptive study of the spillover of positive and negative satisfaction with one category on customer retention in that category and in *other* categories provided by the same firm, and to describe the consequences for CLV management. Rather than viewing the issue as a multicategory problem with provider or overall satisfaction driving retention in individual categories, we view the issue from a cross-category perspective, i.e., we seek to quantify the effects of (dis)satisfaction in one category on retention there and in other categories.

We use data from the 2010 and 2011 customer surveys conducted by Forrester Research, Inc. (Forrester 2010).

Our study focuses on banking and investment services for which respondents report their primary service provider. Our dependent variable is the respondent's decision in 2011 to stay or switch from the provider used in 2010. This depends on the satisfaction for the two services in 2010 and the customer's other characteristics. We allow for satisfaction spillovers from the banking category to the investment service and vice versa. Furthermore, if the respondent uses the same provider in both categories, we incorporate this as an *incremental* source of spillover across categories. For a subset of respondents in our survey, we have information on switching cost-related factors as well as the order of services acquisition. In addition, we have information on respondents' exposure to media. As in Li et al. (2005), we examine the influence of these three factors on the respondents' retention decision as well as how these three factors interact with satisfaction in describing retention behavior.

Our results have implications for the service industry, especially for companies that tend to silo their customer service activities by category. Not integrating information across categories risks losing a customer who might otherwise be satisfied with the service. Our descriptive analysis shows the need to manage customer satisfaction across categories rather than within silos. We compute the change in CLV that can accrue from improving customer satisfaction and the extent to which cross-category effects contribute to this change. This provides a possible metric of the amount that the firm can invest to enhance customers' satisfaction within and across categories.

Our study builds on and complements the satisfaction literature in several ways. First, we have two distinct services and we quantify the effects of satisfaction in each category on retention decisions in both categories. Second, our data is across firms and categories. This enables us to study the incremental effects of having the same provider in the two categories. Third, we examine the economic impact of (dis)satisfaction by studying the effects on CLV.

Theoretical underpinnings: When a customer is dissatisfied with her bank such a perception could increase the likelihood of staying with the current investment service provider if, within the broader category of "financial services," the customer focuses on the *contrast between* the two providers in terms of the service that they provide. Behavioral contrast theory (see, e.g., Crespi 1942, Zeaman 1949, Simpson and Ostrom 1976, Bower and Hilgard 1980, Kenrick and Gutierres 1980, Kenrick et al. 1989, Flaherty 1996) refers to a change in the strength of one response when the rate of reward of a second response is changed. In our context, dissatisfaction (satisfaction) with one category results in increasing retention (defection) in the other category.[1] Satisfaction with the firm providing the banking service could also increase the retention probability for the (different) firm providing the investment service if, within the broader category of financial services, the customer *learns that all providers share* the feature of providing satisfying service (see for example, Markman and Ross 2003, Chin-Parker and Ross 2002). Such learning could also lead to lower retention of the investment service provider when there is dissatisfaction with the banking provider. The net effect of the contrast and learning effects is what we seek to quantify when the customer receives services from different providers.

What happens when the customer gets both services from the same company? In this case, the contrast effect no longer applies and only the learning effect remains. So (dis)satisfaction in one category will lead to retention/defection in the other category. A similar outcome when dealing with a single firm across categories can also be due to the halo effect (Beckwith and Lehmann 1975). Therefore, while we do not formally test these theories or make causal claims for the effects of satisfaction, the theoretical bases for the cross-category effects are grounded in behavioral contrast and learning theories.

2. Data Description

The data in our analysis are from surveys conducted by Forrester Research, Inc. in 2010 and 2011 (Forrester 2010). In each year, respondents are asked to rate their experiences with multiple service providers across various categories. In our analysis, we only use information on banking and investment services. In each of these categories, respondents report the primary banking and investment companies. Each respondent reports two companies, one in each category. Among them, some respondents use the same company for both services. The respondents also report their satisfaction levels with the primary company for each service.[2] The survey also collects information on some demographic variables and consumer characteristics of each respondent. To obtain actual switching behavior from the survey data in these two years, we compare the primary banking and investment companies reported

[1] Note that this effect is distinct from the notion of assimilation and contrast that has been recognized as a plausible mechanism for understanding (dis)satisfaction and product ratings since the work by Hovland et al. (1957).

[2] All of the information in the data is related to the primary company for each service. The data does not record the information about other companies for the same respondent in the same category. This limits our ability to study how satisfaction levels at non-primary companies influence retention decisions at the primary company. In addition, due to the lack of satisfaction with other companies, it is unlikely that we are capturing "should" expectations. More likely our results reflect "will" expectations in our satisfaction measure (Boulding et al. 1993).

Table 1 Distribution of the Three Satisfaction Levels

	Negatives	Neutrals	Positives
Banking	100	149	192
Investment	85	157	199

by each respondent. There are nine companies that offer both services to these respondents: Bank of America, Chase, Citibank, Charles Schwab, ING, TD Bank, US Bank, USAA, and Wells Fargo.

We have 441 customers in the data for estimation. Among them, 66% stayed with the same bank as their primary banking service provider in 2010, while only 43% stayed with the same investment company. In the 2010 survey, each respondent is asked a question about the satisfaction level with each service provided by the primary provider. It is possible that unobservable characteristics that drive behavior could also be correlated with the drivers we include. As our data is cross-sectional, we can only account for observable and some unobserved heterogeneity.

In addition to satisfaction and demographic information, the survey records other aspects of respondents' behaviors, four of which are included in our analysis. First, each respondent reported the number of banking (checking, savings, etc.), and the number of investment accounts (401(k), investments, etc.) held. Customers with more banking (investment) accounts may have better knowledge about these services (MORE_ACC). Second, each respondent reported the number of hours spent reading newspapers/magazines and watching TV online and off-line in each week. The differences in time spent between the two years' within respondents reflects the incremental exposure to these media, and potentially, to advertising and other media coverage. We refer to these activities as media exposure (MEDIA). Third, each respondent reported the total amount of money they have with each firm; the larger the amount of money held, the larger the switching cost vis-á-vis that firm is likely to be. Because the amount of money in each category could be endogenous to the satisfaction levels, we try to minimize its influence by using a dummy variable, indicating whether the total amount of money exceeds $1 M (CATG_GT1M). Finally, for a subset of respondents, we can infer with which service (banking or investment) they initiated their relationship with each company (FIRST_CATG). This variable is created based on the following two pieces of information. First, all our respondents have banking and investment accounts. Second, a subset of them answered the question "which account did you open in the past 12 months?" Among the respondents who answered this question, if only a banking (investment) account was opened in the past month, FIRST_CATG for investment (banking) is set to 1; otherwise, it is set to 0.

Table 2 Summary Statistics for Demographic and Self-Reported Variables

	Mean	Std. dev
Age	52.79	(14.19)
Not a parent (1 = Yes, 0 = No)	0.35	(0.48)
Have a college degree or higher (1 = Yes, 0 = No)	0.63	(0.48)
Married (1 = Yes, 0 = No)	0.64	(0.48)
Low income (income level in the bottom 30%, 1 = Yes, 0 = No)	0.27	(0.45)
High income (income level in the top 30%, 1 = Yes, 0 = No)	0.28	(0.45)
Total number of accounts in the banking category (KNOWLEDGE—Banking)	1.54	(0.95)
Total number of accounts in the investment category (KNOWLEDGE—Investment)	1.08	(0.90)
More exposures to advertising in 2011 than in 2010 (1 = Yes, if spend more hours each week reading newspapers/magazine/TV/radio online and off-line, 0 = Otherwise) (ADVTG)	0.42	(0.49)
Having more than $1 M with the banking company (1 = Yes, 0 = Otherwise) (SWITCHING COST—Banking)	0.21	(0.41)
Having more than $1 M with the investment company (1 = Yes, 0 = Otherwise) (SWITCHING COST—Investment)	0.14	(0.35)
Having a bank account before the investment account (1 = Yes, 0 = Otherwise) (FIRST CATEGORY—Banking)	0.08	(0.28)
Having an investment account before the banking account (1 = Yes, 0= Otherwise) (FIRST CATEGORY—Investment)	0.06	(0.24)

Table 1 lists the distribution of the three satisfaction levels[3]: low satisfaction, which could have a negative effect on the dependent measure; high satisfaction, which could have a positive effect on the dependent measure; and neutral (neither high nor low) satisfaction, which could have no effect on the dependent measure. We estimate the relative effects of the negatives and positives vis-à-vis the neutral. We provide descriptive statistics for the demographic and other variables in Table 2.[4]

A key feature of the data is that respondents self-select into having one or two providers across the two categories. We need to account for such selection (Heckman 1979) and empirically we need information on variables that influence selection but are uncorrelated with our dependent variables of interest, i.e., we need *exclusion variables*. A Binary Probit (BP) model of the choice of same or different providers on various characteristics yielded the following as significant determinants of this decision: older people, having no kids, going online frequently; and those people who think

[3] The satisfaction scores are measured on a five-point scale. We treat the bottom two as "negative" satisfaction, the top two as "positive" satisfaction and the midpoint as neutral. In principle we can estimate a "fixed effect" or a parameter for each level; however preliminary analyses suggested that three levels sufficed.

[4] While not reported here, our raw data provide prima facie evidence (available from the authors on request) for satisfaction spillovers across categories and differential effects for those customers with the same provider across categories.

"technology is important," and "life is to have fun" and "family is very important." Of these we found that only the first two variables were significantly correlated with the decision to stay or switch (the "main" model). Consequently, while we include age and having kids (or being a parent) in both models, the other variables are excluded from the main model.

3. Model

We model the retention versus switching decisions for all categories (indexed by $c = 1, \ldots, C$) simultaneously using a BP model in each category. With C categories this requires a Multidimensional Binary Probit (MBP) model. The utility of individual i in staying with company f in category c is a latent variable y_{ifc}. This is decomposed into an observed to the researcher component (Q_{ifc}) and a random component unobserved to the researcher but not the consumer (ϵ_{ifc})

$$y_{ifc} = Q_{ifc} + \epsilon_{ifc}. \tag{1}$$

The random component ϵ_{ifc} for each category c follows a normal distribution. The common components across the two categories are captured by an individual specific intercept. As a result, we allow ϵ_{ifc} to be independent across categories.[5] That is $\epsilon_{ifc} \sim N(0, 1)$, $\forall c$. Q_{ifc} is specified as follows:

$$\begin{aligned} Q_{ifc} = {} & \alpha_{ifc} + \sum_{l=1}^{L} X_{ifcl}\beta_{cl} + \left[\sum_{c'\neq c}\sum_{l=1}^{L} X_{if'c'l}\left(\beta_{c'l} + \sum_{c'\neq c} H_{ic'}\beta^{S}_{c'l}\right)\right] \\ & + \sum_{k=1}^{K} G_{ik}\cdot\left\{\sum_{l=1}^{L} X_{ifcl}\beta_{clk} \right. \\ & \left. \qquad + \left[\sum_{c'\neq c}\sum_{l=1}^{L} X_{if'c'l}\left(\beta_{c'lk} + \sum_{c'\neq c} H_{ic'}\beta^{S}_{c'lk}\right)\right]\right\} \\ & + \sum_{k=1}^{K} G_{ik}\beta_{ck} + Z_i\gamma_c, \end{aligned} \tag{2}$$

where l denotes the level of the driver variable (positive, neutral, negative). The first term α_{ifc} contains the intercept or intrinsic intention of staying with the current service. Since α_{ifc} is the dimensionality of our data, we decompose the intercept into two components as: $\alpha_{ifc} = \alpha_i + \alpha_{fc}$. $\alpha_i \sim N(m_1, \sigma_1^2)$, $\forall i$ is a random effect and reflects the overall differences across customers in their retention decisions. The parameters of its distribution across individuals are identified using all of the individual's observations across the two categories, i.e., banking and investment. Firm-category specific effect α_{fc} is identified off respondents using the firm f in category c; $\alpha_{fc} = 0$, when $f = 1$, $\forall c$ for identification.

[5] Allowing ϵ_{ifc} to be correlated across the categories gave a correlation of -0.04 (Std. Dev $= 0.07$) so we set it to 0.

The vector X_{ifcl} denotes satisfaction levels for firm f in category c, as reported by individual i. l indexes the level of satisfaction, which could be positive (satisfied), neutral (base case for identification) or negative (dissatisfied). β_{cl} denotes the vector of parameters for the within-category satisfaction effect. $X_{if'c'l}$ is the satisfaction level for the other categories $c' \neq c$. $\beta_{c'l}$ is the cross-effect on the decision to stay with firm c, when different companies are used in these two categories. $H_{ic'}$ is an indicator variable that takes the value 1 if the same firm is used in both categories c and c'. $\beta^{S}_{c'l}$ measures the *incremental* cross-category effect of satisfaction with the firm in c' when the firms are the same across categories. Next, we show the interactions between the satisfaction variables (within and across categories) and MORE_ACC, MEDIA, CATG_GT1M, and FIRST_CATG (denoted as G_{ik}, where $k = 1, 2, 3, 4$, indexing these four variables). We also show the main effects of the behavioral variables G_{ik}, the demographic variables, and consumer characteristics Z_i. Their effects are accounted for via the parameters β_{ck}, $k = 1, 2, 3, 4$, and γ_c. These variables account for observed heterogeneity across respondents.

How a consumer determines $H_{ic'}$ is the basis for accounting for self-selection in the data. We use a BP model to understand how various factors drive the choice of the same or different providers across categories. As only two categories are present in our data, there is only one c'. In the following, c' is removed from the subscripts. The BP model is specified as

$$\begin{aligned} h_i &= W_i\rho + u_i \\ \text{Prob}(H_i = 1 \mid W_i) &= \text{Prob}(h_i > 0 \mid W_i). \end{aligned} \tag{3}$$

Among this, W_i represents individual specific factors that drive selection and ρ denotes the effect of these factors on selecting the same company for both services. The random error term u_i is assumed to follow a standard normal distribution, i.e., $u_i \sim N(0, 1)$. We allow the error terms in the two models to be correlated, so the distribution of ϵ_{ifc} in the MBP model (Equation (1)) and u_i in the BP model (Equation (3)) is

$$\begin{Bmatrix} \{\epsilon_{ifc}\} \\ \{u_i\} \end{Bmatrix} \sim N(0, \Sigma).$$

In summary, our model specification is an MBP-BP model using an individual level MBP model and accounting for selection on a right-hand side variable using a BP choice model.

4. Estimation and Identification

We develop a likelihood-based approach to estimate all of the model parameters while simultaneously using Bayesian methods. Define Δ as the set of all of the parameters to be estimated, i.e.,

$$\Delta = \{\alpha_i, \alpha_{fc}, \beta_{cl}, \beta_{c'l}, \beta^{S}_{c'l}, \beta_{clk}, \beta_{c'lk}, \beta^{S}_{c'lk}, \beta_{ck}, \gamma_c, \rho, \Sigma\}.$$

The full information likelihood function is

$$\begin{aligned}&\mathrm{Prob}(Y_i, H_i \mid X_i, G_i, Z_i, W_i, \Delta)\\&=\mathrm{Prob}(Y_i \mid H_i, X_i, G_i, Z_i, W_i, \Delta)\cdot \mathrm{Prob}(H_i \mid W_i, \rho, \Sigma), \quad (4)\end{aligned}$$

where Y_i denotes individual i's decisions to stay, which are observed dummy variables. And H_i denotes whether the customer uses the same or different providers in the categories.

The likelihood function in Equation (4) consists of two likelihood functions from two models, i.e., the MBP switching (the first probability) and the BP selection models (the last probability). We develop a Markov Chain Monte Carlo (MCMC) algorithm to estimate the model parameters in this likelihood function, by augmenting the latent variables y_{it} as in Equation (1) and h_{it} as in Equation (3). In doing so, we put the parameters and the latent values into groups, and obtain the posterior distributions of all of the parameters via Gibbs sampling and data augmentation techniques. Details of the Gibbs sampling are presented in the Web Appendix (available as supplemental material at http://dx.doi.org/10.1287/mksc.2015.0941).

Because of the inclusion of the G_{ik} variables in Equation (2), we have a large number of interaction effects to estimate. To address this problem, we take two steps. The MORE_ACC variable is measured only at the category level (whereas all other variables are measured at the firm level). So rather than interact it with the firm-specific satisfaction levels, we use it as a propensity shifter to stay with the current provider; i.e., we only estimate β_{ck} (in Equation (2)) for this variable. Only 92 (63) of 441 respondents report over \$1 M in the banking (investment) company (CATG_GT1M). We reduce the number of associated parameters from 12 (including two categories, and within each category: two own category, two cross category for the baseline spillover effects, two cross category for the additional spillover effects due to the same firm) to four by first constraining the parameters to be the same across categories (reducing it to six parameters), and then combining the two sets of cross category effects parameters (baseline and additional). Similarly, 39 (26) participants report having a banking (investment) account before an investment (banking) account. We reduce the number of parameters to estimate for the FIRST_CATG variable from 12 to four in the same way. For the MEDIA variable we have 184 respondents from whom we estimate all effects for interactions with this variable. The final specification is

$$\begin{aligned}M_{ifc} &= MORE\_ACC_{ic}\cdot\beta^{KL}_{ic}\\&\quad + CATG\_GT1M_{ifc}\cdot\sum_{l=1}^{L}(X_{ifcl}\cdot\beta^{SC}_{l} + X_{ifc'l}\cdot\beta^{SC}_{l'})\\&\quad + FIRST\_CATG_{ifc}\cdot\sum_{l=1}^{L}(X_{ifcl}\cdot\beta^{FC}_{l} + X_{ifc'l}\cdot\beta^{FC}_{l'})\\&\quad + MEDIA_{ifc}\cdot\sum_{l=1}^{L}\Big\{X_{ifcl}\beta^{AD}_{cl}\sum_{c'\neq c}\sum_{l=1}^{L}X_{ifc'l}\\&\qquad\Big(\beta^{AD}_{c'l}+\sum_{c'\neq c}H_{ic'}\beta^{S,AD}_{c'l}\Big)\Big\},\end{aligned}$$

where M_{ifc} refers to the part related to the interaction variables in the second row of Equation (2), that is

$$\begin{aligned}M_{ifc} = \sum_{k=1}^{K'}\Big[&\sum_{l=1}^{L}X_{ifcl}\beta_{clk}\\&+\Big\{\sum_{c'\neq c}\sum_{l=1}^{L}X_{ifc'l}\Big(\beta_{c'lk}+\sum_{c'\neq c}H_{ic'}\beta^{S}_{c'lk}\Big)\Big\}\Big]\cdot G_{ik}.\end{aligned}$$

Identification: We estimate the following set of parameters: (a) An overall individual-specific intercept (α_i) (this is identified off the two observations we have for each consumer) for each category; (b) A firm-category intercept (α_{fc}) (this is identified by the share of each firm in each category); (c) Within category satisfaction effect (β_{cl}) (for "satisfied" respondents this is identified off the difference in the share of respondents who are satisfied and stay, and the share of respondents with a neutral evaluation who stay). A similar argument holds for the dissatisfied customers. (d) Cross category effect of satisfaction ($\beta_{c'l}$ and $\beta^{S}_{c'l}$). Here we distinguish between those who use the same company across categories (group A) and those who use different companies (group B). Within each group the cross-category effect on banking (investment) for those "satisfied" with the investment (banking) service is identified off the difference in share of banking (investment) respondents who are satisfied with investment (banking) and stay relative to those who are neutral and stay. A similar argument holds for dissatisfied customers. Finally identification of the main effects of the demographic and behavioral variables can be similarly argued based on the share of respondents in each group that stays with the previous service.

5. Results

Intercepts. From the estimates for the individual-specific intercept α_i, we find considerable heterogeneity in the intrinsic propensity to switch to a different provider. The results for the mean of α_{fc} (Table 3) in the banking category show that Bank of America, Citibank, Chase, TD Bank, and US Bank are not statistically distinguishable from zero, indicating their customers are indifferent between staying and switching. Wells Fargo, the base brand is 0. Charles Schwab, ING, and USAA have significant negative intercepts, indicating their customers are inclined to switch. The results for

Table 3 **Population Mean for Firm-Category Specific Intercepts α_{fc}**

	Banking	Investment
Bank of America	0.075 (−0.55, 0.71)	−0.739 (−1.23, −0.27)
Chase	−0.072 (−0.69, 0.57)	−1.235 (−1.91, −0.56)
Citibank	−1.231 (−2.58, 0.08)	−0.787 (−1.86, 0.28)
Charles Schwab	−1.871 (−3.59, −0.29)	−0.678 (−1.21, −0.17)
ING	−3.563 (−4.93, −2.32)	−1.047 (−1.69, −0.41)
TD Bank	−0.463 (−1.88, 0.98)	−0.590 (−1.11, −0.09)
US Bank	−0.357 (−1.32, 0.61)	−1.565 (−2.80, −0.46)
USAA	−1.162 (−2.14, −0.21)	−0.838 (−1.50, −0.19)
Wells Fargo	0	0

the investment services are mostly negative, except for Citibank and Wells Fargo (base) customers who have the highest probability of staying with their companies. The correlation in α_{fc} between the two categories is 0.07, and is not statistically significant, with a standard error of 0.29.

Satisfaction and Interactions. Estimates for the effects of customers' overall satisfaction levels and their interactions with the behavioral variables (media exposure and advertising (i.e., MEDIA; switching cost—CATG_GT1M; and order of category acquisition—FIRST_CATG)) and the main effects of these latter variables are in Table 4. In parentheses are the percentages of times each parameter is positive when simulated from its posterior distribution. This information is especially useful given the large number of parameters (52 in addition to the intercepts) estimated using a relatively small size of our sample (441 respondents). Providing the percentages of times each parameter is positive helps us to gauge the relative strength of each model estimate.[6] We base our discussions in the next section on the 5% significance level.

• *Baseline effect of customer satisfaction.* We find statistically significant effects only for positive experiences with the investment service. When customers are satisfied with the investment (0.612) service, they are more likely to stay with the investment firm; the finding for banking is qualitatively similar (0.570) although the estimate is less precise. However, customer dissatisfaction does not always translate into switching behavior. In Table 4, the baseline cross-category effects (the "Banking" ("Investment") column refers to the effects of satisfaction/dissatisfaction with the investment (banking) service provided by company A on the retention of banking (investment) services from company B). Note that at the 5% significance level, none of these four parameters are statistically significant. At the 10% significance level, however, three of them are. In particular, this shows that if a customer is dissatisfied (satisfied) with the investment service (0.778 if dissatisfied and −0.644 if satisfied), she is more (less) likely to stay with her current banking service provider. Similarly, greater satisfaction with the banking services from the current provider lowers the retention of the other firm providing investment services. These results appear to *provide support for the contrast theory rather than the learning theory* previously discussed. Finally, if a customer is not satisfied with the investment service provided by a firm, she is less likely to stay with the banking service provided by that same company. The net negative spillover effect can be calculated as the sum of the two spillover effects, i.e., the baseline spillover (0.778) and the additional spillover effects when using the same company (−1.713). The net effect is −0.935 (= −1.713 + 0.778). This is an important finding as it characterizes the spillover or halo effect of a bad experience in one category (i.e., investment services) on retention in a different category (i.e., banking).

• *Main effects of behavioral variables and their interactions with satisfaction*

Media and Advertising Exposure (*MEDIA*). The main effects of the exposure variable are not statistically significant (−0.242 and 0.012 in the top row of Table 4). For the interactions, we find that for both banking and investment, a satisfied customer with more media exposure is less likely to stay with her current service provider, as compared with a customer with less exposure. While these effects are not precisely estimated at the 5% level, they are significant at the 10% significance level. In effect, *media exposure might be successful in highlighting the potential benefits of other providers even for those customers who are satisfied with their current providers*.

The results of the cross-category spillover effects indicate that more exposure to advertising enhances positive spillover when the customer is satisfied with the other service provided by the *same* firm. In particular, among customers who are satisfied with the banking (investment) service provided by the same company, more media exposure makes them more likely to stay with the company (estimates of 1.171 and 1.707, respectively). Contrary to the results noted above, our findings here suggest that the halo effect across categories is being enhanced due to media and advertising exposure. This could come about if the advertising messages reinforce the many different services being provided by the financial institutions.

Switching cost (*CATG_GT1M*). The main effect of this variable shows a positive and statistically significant effect (0.672) for the investment service, which demonstrates the existence of higher switching costs among customers with over $1 M with the firm; respondents are more likely to stay with their current providers if they feel more invested in them. We find a smaller (0.551) and less precisely estimated effect for the banking service. This is consistent with research into the

[6] This percentage for each parameter is similar to the concept of $(1-p)$-value.

Table 4 Estimation Results for the Main Model (Probability of Staying with the Current Firm)

Estimation results for the parameters of satisfaction and interaction variables								
			Interactions between satisfaction and behavior variables					
			More exposure to advertising in 2011 than in 2010		More than \$1 M in banking	More than \$1 M in investment	Bank account first	Investment account first
	Impact on this service		ADVTG		SWITCHING COST		FIRST CATEGORY	
Satisfaction variables	Banking	Investment	Banking	Investment	Banking	Investment	Banking	Investment
Main effects of three of the behavior variables			−0.242 (29%)	0.012 (51%)	0.551 (90%)	**0.672 (95%)**	−0.703 (13%)	−0.195 (37%)
Within category								
Not satisfied	−0.237 (31%)	−0.240 (31%)	−0.023 (49%)	−0.313 (35%)	−0.940 (19%)		0.041 (52%)	
Satisfied	0.570 (91%)	**0.612 (95%)**	−0.995 (7%)	−0.810 (9%)	−0.771 (16%)		**1.640 (97%)**	
Across categories, different companies								
Not satisfied	0.778 (90%)	−0.284 (28%)	0.102 (54%)	0.964 (89%)	0.546 (69%)		0.324 (62%)	
Satisfied	−0.644 (7%)	−0.535 (9%)	0.788 (87%)	−0.546 (22%)	0.491 (74%)		−0.363 (35%)	
Additional cross-category spillover, same company								
Not satisfied	**−1.713 (1%)**	0.336 (68%)	0.601 (70%)	−0.714 (22%)				
Satisfied	−0.655 (13%)	−0.023 (48%)	**1.171 (96%)**	**1.707 (100%)**				

Note. Bold indicates statistically significant at 5% confidence level.

role of switching costs in financial services (Li et al. 2005). Our results also show that interactions with the satisfaction variables do not have any statistically significant effects on retention behavior.

Sequence of accounts (*FIRST_CATG*). We do not find statistically significant main effects for the initial customer sign up with either banking or investment services (estimates of −0.703 and −0.195, respectively) on service retention. The results for the interaction variables, on the other hand, demonstrate that being the first among these two services enhances the positive experience with a firm. If customers are satisfied with their banking/investment services, the effect of this satisfaction is enhanced if that service was also the first one that customers signed up for with the firm. This "enhancement of satisfaction effect" (1.640 in Table 4) complements the previous literature (e.g., Li et al. 2005) by separating the satisfaction at the own- versus cross-category level. As to retention, customer satisfaction strengthens retention for the account that is opened first at the institution. Yet we do not find significant cross-category effects of these interactions indicating the "within" category nature of this interaction.

Demographic Variables. Results for the effects of demographic variables on retention are in Table 5. Older customers are more likely to stay with the current investment company. Low-income customers are more likely to stay with their current bank. These results highlight the importance of heterogeneity in retention across consumers. Finally, the MORE_ACC variable shows that greater knowledge facilitates retention.

Selection Model. The estimation results from the BP model are presented in Table 6. These results show that customers with no kids are more likely to use the same company for the two services. In addition, customers who think "technology is important" and "life is to have fun" are less likely to have the same

Table 5 Estimation Results for the Parameters of the Demographic Variables

	Stay with bank	Stay with investment firm
Customer demographic variables		
Age/10	0.094 (90%)	**0.224 (100%)**
With no kids	0.295 (87%)	0.298 (91%)
With at least a college degree	0.194 (78%)	0.056 (60%)
Married	0.130 (69%)	0.045 (57%)
Low income dummy	**0.803 (100%)**	0.051 (58%)
High income dummy	0.334 (90%)	0.373 (93%)
The other customer behavior variable (*no interactions with the satisfaction variables*)		
Total number of banking/investment accounts (*KNOWLEDGE*)	**1.028 (100%)**	**0.269 (99%)**

Note. Bold indicates statistically significant at 5% confidence level.

Table 6 Estimation Results for the Selection Model

	Use the same company
Intercept	−0.681 (19%)
Age/10	0.067 (93%)
No kids	**0.407 (100%)**
Go online frequently	0.117 (91%)
"Technology is important to me"	**−0.937 (0%)**
"Life is to have fun"	**−0.822 (0%)**
"Family is very important"	**0.053 (96%)**

Note. Bold indicates statistically significant at 5% confidence level.

firm. Customers who think "family is very important" are more likely to use the same firm. The covariance between the error term from the selection model and that from the main model for banking is 0.486, with a 96% chance of being positive. The covariance between the selection model error term and the investment model is −0.497, with a 98% chance of being negative. These parameters provide some evidence of selection in the data.

Model Comparisons. We estimated several alternative models. These include: (a) A model that uses the average satisfaction levels across the two categories as a proxy for overall satisfaction rather than category-specific satisfaction; (b) A model that ignores the incremental cross-category spillover effects for customers using the same company for both services; (c) A model that completely ignores the cross-category effect of customer satisfaction; (d) A model that neglects the selection issue; and (e) A model that neglects unobserved heterogeneity.

The results (not reported here) show that our model fits the data the best. Among the within-sample tests, the log-marginal density value of the base model is slightly better than alternative model (b) with no incremental spillover and model (d) that ignores selection. Our model is, however, much better than model (c) with no cross-category effects. In the out-of-sample tests, the base model performs better than models (b) and (c) and is marginally better than (d). Thus both from the perspective of insight (comparison with model (a)) as well as fit (models (b), (c), and (d)), our proposed specification reveals some advantages.

Implications for Customer Lifetime Value. The calculation of the simple version of CLV (Gupta and Lehmann 2006) requires: (i) the interest rate ($\delta = 10\%$); (ii) the retention rate or the future probability of purchase (this comes directly from the dependent variable of our main model); (iii) the profitability of each future purchase or margin; we use Li et al. (2011) to compute profitability for banking per account as $m_{\text{bank}} = \$119$ and the profitability of investment as $m_{\text{Investment}} = \$111$; and (iv) the cost of acquisition. Our calculations here ignore (a) acquisition costs, (b) the possibility that company profit margins could vary with the customer satisfaction level, and (c) effects on recommendation and the "network" effect of improving satisfaction. Using these values for m_{bank}, $m_{Investment}$, and δ, together with our estimates, we obtain the mean CLV across all customers to be \$675.68 (\$480.22 for banking and \$195.46 for investment).

We find that, among the within-category effects, (i) if satisfaction with banking (investment) is improved from negative to neutral, the CLV related to banking (investment) improves by 45% (58% for investment); (ii) if satisfaction with banking (investment) is improved from neutral to positive, the CLV related to banking (investment) improves by 34% (26% for investment). In other words, improving customer satisfaction from negative to neutral has a much higher impact on the customer's CLV for that service than improving from neutral to positive. This is true for both banking and investment services. We also find that among the cross-category effects for customers who use different companies for these services, if a customer's satisfaction level for *investment* is improved from negative to neutral (from neutral to positive), she is less likely to stay with the current (different) banking company. Her CLV with the banking company is reduced by 45% (16%). If her satisfaction with *banking* is improved from neutral to positive, she is less likely to stay with the current (different) investment firm. Her CLV with the investment company is reduced by 42%. This step demonstrates the asymmetric effect across categories for customers using different companies. These two steps illustrate the asymmetric results of customer satisfaction effects, both between satisfaction versus dissatisfaction; and across categories.

To provide a measure in dollars, we calculated, among the customers using the same firm for both services, the incremental dollar values in the overall CLV as a result of one step improvement in customer satisfaction. When satisfaction with the banking (investment) service increases from neutral (negative) to positive (neutral), customers using the same firm show a 9.7% (14.5%) increase in average CLV. If satisfaction increases from negative to neutral for banking, the average CLV across categories increases by 57%, which is higher than the change from negative to neutral in satisfaction of the banking service. Similarly, if satisfaction for investment services improves from negative to neutral, the increase in the average CLV is the highest, 93%. Overall, we find an improvement in satisfaction with the investment category has a higher impact on the overall CLV than the improvement in banking service; the improvement from negative to neutral has a higher impact on the overall CLV than the improvement from neutral to positive.

6. Summary

We provide a descriptive analysis of the effects of (dis)satisfaction in one category on outcomes in that category and in other financial services categories. Additionally, we examine the interaction effects of satisfaction with other factors (identified by previous research as potential drivers of the adoption of financial services) such as switching costs, acquisition sequence of services, etc.

Consistent with the behavioral notion that the contrast across categories drives behavior, we find some evidence that when consumers have different providers in the two categories, satisfaction with one service lowers the retention probability in the other service for both categories. However dissatisfaction only works from investments to banking: A customer who is not satisfied with the investment service is more likely to stay with the existing banking service. We therefore find some evidence of asymmetries across categories as well as across satisfaction and dissatisfaction in the cross-category effects. Significantly, we find that when the same firm is involved in both categories, dissatisfaction with the firm in the investment category lowers banking retention probability. Switching costs, media exposure, and order of acquisition of services have different roles in terms of direct effects on retention as well as interaction effects with satisfaction.

We find that CLV can be enhanced with increased satisfaction by leveraging the within as well as the across category effects. The bottom line on the results of our study is that multiproduct service firms need to integrate customer service and satisfaction departments across these services, which are currently in separate silos. Doing so would alert the firm to potential customer defections due to dissatisfaction with any of the services provided. Thus, it is important for a company providing multiple services to manage customers at the customer level across categories, rather than at the category level: Customer dissatisfaction with any category could lead to churn from the current provider. A key limitation of our data and hence, our analysis, is that in the absence of panel data our conclusions should be viewed as descriptive rather than causal. Nevertheless, we believe that this research is a useful starting point for service organizations managing customer satisfaction across product categories.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mksc.2015.0941.

Acknowledgments

The second author thanks the Kilts Center of Marketing at the University of Chicago for financial support and the Graduate School of Business, Stanford University, where part of this project was completed. The authors thank K. Sudhir whose discussion with one of the authors triggered this research. The authors also thank Thomas Otters, Elisabeth Honka, seminar participants at Santa Clara University, participants at the 2012 Marketing Science Conference in Boston, and participants at the 2013 University of Texas at Dallas Frontiers of Research in Marketing. Comments from the editor-in-chief, associate editor, and two reviewers at the Marketing Science conference are also gratefully acknowledged.

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