Satisfaction Spillovers across Categories

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Abstract

We provide a descriptive study of the cross-category effects of satisfaction for financial services on retention behavior. Behavioral contrast and learning theories provide the bases for our understanding of these effects. Our main findings are (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) Importantly, 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) while switching costs and order of acquisition do affect retention they do not show cross-category interactions with satisfaction. We then obtain implications for customer lifetime value and show that it can be enhanced with increased 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 manage customers across categories.

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 multi-category domain - satisfaction with 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 diagnosing *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; leading to the company investing 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. But it could also be the case that there is 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 its efforts and resources only on the dissatisfied category. Next, suppose the firm tracks satisfaction and retention separately by category and manages both categories independently. Since defection happens in both categories but satisfaction was low only in one, the firm would conclude that satisfaction does affect retention in the dis-satisfied category but does not influence retention in the satisfied category.

Our objective in this paper is to provide a descriptive study of the spillover of positive and / or negative satisfaction with one category on customer retention in that category and in *other* categories provided by the same firm; and to describe consequences for customer lifetime value management. Rather than viewing the issue as a *multi*category problem with provider or overall satisfaction driving retention in individual categories our goal is to view the issue from a *cross*-category perspective, i.e., we seek to quantify the effects of (dis)satisfaction in one category on retention in that and in other categories.

We use data from a customer survey conducted by Forrester Research in 2010 and in 2011. 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 2 services in 2010 and the customer's other characteristics. We allow for spillovers of satisfaction from the banking category to the investment service and vice versa. Further, 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 acquisition of the services. In addition, we have information on respondents' exposure to media. As in Li et al (2005), we look at the influence of these three factors on the retention decision of respondents 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 runs the risk of losing a customer who might otherwise be quite satisfied with the service. Our descriptive analysis shows that it is necessary to manage customer satisfaction across categories rather than within silos. We compute the change in customer lifetime value 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 the satisfaction of its customers 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 that and the other category. 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 look at the economic impact of (dis)satisfaction by looking at the effects on customer lifetime value.

Theoretical underpinnings: When a customer is dissatisfied with his or 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 & Gutierres 1980, Kenrick et al., 1989, Flaherty 1996) refers to a change in the strength of one response that occurs 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.[2] 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 effect and the learning effect 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.

Data description

The data in our analysis are from surveys conducted by Forrester Research Inc. in 2010 and 2011. In each year, respondents are asked to rate their experiences with multiple service providers across various

[2] 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).

categories. In our analysis, we only use information on banking and investment services. In each of these two 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.[3] The survey also collects information on some demographic variables and consumer characteristics of each respondent. To obtain the actual switching behavior from the survey data in these two years, we compare the primary banking and investment companies reported by each respondent. There are 9 companies that offer both services to these respondents: Bank of America, Chase, Citi Bank, 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 from 2010, while only 43% stayed with the same investment company. In the 2010 survey, each respondent is asked a question regarding the satisfaction level with each service provided by the primary provider. A possible concern with variables of this nature is 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.

Besides satisfaction and demographic information, the survey also records other aspects of respondents' behaviors, four of which are included in our analysis. Each respondent reported the number of banking (checking, savings etc.), and the number of investment accounts (401K, investments, etc.) held; people 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 offline in each week. The differences in time spent between the two years' within respondent reflect the incremental exposure to these media, and potentially, to advertising

[3] All of the information in the data is related to the primary company for each service. The data does not record the information regarding 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 satisfactions with other companies, it is unlikely that we are capturing "should" expectations and more likely to be reflecting "will" expectations in our satisfaction measure (Boulding et al. 1993).

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, bigger is likely to be the switching cost vis-a-vis that firm. Since 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 $1M (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; else it is set to 0.

Table 1 lists the distribution of the three satisfaction levels[4]: 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.[5]

A key feature of the data is that respondents self-select into having 1 or 2 providers across the 2 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 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 "technology is important", and "life is to have

[4] The satisfaction scores are measured on a 5-point scale. We treat the bottom 2 as "negative" satisfaction, the top 2 as "positive" satisfaction and the mid-point as neutral. In principle we can estimate a "fixed effect" or a parameter for each level; however preliminary analyses suggested that 3 levels sufficed.
[5] While not reported here, our raw data provide prima facie evidence (available from authors) for satisfaction spillovers across categories and differential effects for those customers with the same provider across categories.

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.

Model

We model the retention vs. switching decisions for all categories (indexed by $c = 1, \ldots, C$) simultaneously using a Binary Probit 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 $\{\epsilon_{ifc}, \forall c\}$ for each category follows a normal distribution. The common components across the two categories are captured by an individual specific intercept. As a result, we allow $\epsilon_{ifc}$to be independent across categories[6]. That is $\epsilon_{ifc} \sim N(0,1), \forall c$. Q_{ifc} is specified as follows

$$Q_{ifc} = \alpha_{ifc} + \sum_{l=1}^{L} X_{ifcl}\beta_{cl} + \left[\sum_{c' \neq c}\sum_{l=1}^{L} X_{if'c'l}\left(\beta_{c'l} + \sum_{c' \neq c} H_{ic'}\beta^{S}_{c'l}\right)\right]$$

$$+ \sum_{k=1}^{K} G_{ik} \times \left\{\sum_{l=1}^{L} X_{ifcl}\beta_{clk} + \left[\sum_{c' \neq c}\sum_{l=1}^{L} X_{if'c'l}\left(\beta_{c'lk} + \sum_{c' \neq c} H_{ic'}\beta^{S}_{c'lk}\right)\right]\right\} + \sum_{k=1}^{K} G_{ik}\beta_{ck} + Z_i\gamma_c \tag{2}$$

where *l* stands for 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 the individual's observations across

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

the two categories, banking and investment. α_{fc} is the firm-category-specific effect and is identified off respondents using the firm *f* in category *c*; $\alpha_{fc} = 0$, when $f = 1, \forall c$ for identification.

X_{ifcl} refers to the vector of 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} is 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 have 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 have 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 $\beta_{ck}, \forall k$ 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 Binary Probit 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 Binary Probit (BP) model is specified as

$$h_i = W_i\rho + u_i \tag{3}$$
$$Prob(H_i = 1|W_i) = Prob(h_i > 0|W_i)$$

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 a MBP-BP model using an individual level Multidimensional Binary Probit model and accounting for selection on a RHS variable using a Binary Probit choice model.

Estimation & Identification

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

$$\Delta = \left\{\alpha_i, \alpha_{fc}, \beta_{cl}, \beta_{c'l}, \beta^S_{c'l}, \beta_{clk}, \beta_{c'lk}, \beta^S_{c'lk}, \beta_{ck}, \gamma_c, \rho, \Sigma, \ \ \forall i, c, c', f, l, k\right\}$$

The full information likelihood function is

$$Prob(Y_i, H_i | X_i, G_i, Z_i, W_i, \Delta) = Prob(Y_i | H_i, X_i, G_i, Z_i, W_i, \Delta) \times Prob(H_i | W_i, \rho, \Sigma) \qquad (4)$$

Where Y_i denotes individual i's decisions to stay, which are observed dummy variables. 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 an 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 the parameters via Gibbs sampling and data augmentation techniques. The details of the Gibbs sampling are presented in Web Appendix.

Due to the inclusion of the G_{ik}variables in equation (2), we have a large number of interaction effects we need to estimate. We take two steps to alleviate that burden. The MORE_ACC variable is measured only at the category level (whereas all the other variables are measured at firm level). So rather than interact it with the firm-specific satisfaction levels, we use it as a shifter of the propensity 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 $1M in the banking (investment) company (CATG_GT1M). We reduce the number of associated parameters from 12 (including 2 categories, and within each category: 2 own category, 2 cross category for the baseline spillover effects, 2 cross category for the additional spillover effects due to the same firm) to 4 by first constraining the parameters to be the same across categories (reducing it to 6 parameters); and then combining the 2 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 4 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:

$$M_{ifc} = MORE\_ACC_{ic} \times \beta_{ic}^{KL} + CATG\_GT1M_{ifc} \times \sum_{l=1}^{L} \left(X_{ifcl} \times \beta_{l}^{SC} + X_{ifc'l} \times \beta_{l'}^{SC} \right)$$

$$+ FIRST\_CATG_{ifc} \times \sum_{l=1}^{L} \left(X_{ifcl} \times \beta_{l}^{FC} + X_{ifc'l} \times \beta_{l'}^{FC} \right) + MEDIA_{ifc}$$

$$\times \sum_{l=1}^{L} \left\{ X_{ifcl} \beta_{cl}^{AD} \sum_{c' \neq c} \sum_{l=1}^{L} X_{ifc'l} \left(\beta_{c'l}^{AD} + \sum_{c' \neq c} H_{ic'} \beta_{c'l}^{S,AD} \right) \right\}$$

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

$$M_{ifc} = \sum_{k=1}^{K'} \left[\sum_{l=1}^{L} X_{ifcl} \beta_{clk} + \left\{ \sum_{c' \neq c} \sum_{l=1}^{L} X_{ifc'l} (\beta_{c'lk} + \sum_{c' \neq c} H_{ic'} \beta_{c'lk}^{S}) \right\} \right] \times G_{ik}$$

<u>Identification</u>: We estimate the following set of parameters: (a) An overall individual-specific intercept (α_i) – this is identified off the 2 observations we have for each consumer – one 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 effect of satisfaction (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 and stay. A similar argument holds for the dissatisfied customers. (d) Cross category effect of satisfaction ($\beta_{c'l}$ and $\beta_{c'l}^{S}$) – 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 the identification of the main effects of the demographic and behavioral variables can be argued in a similar way – based on the share of respondents in each group that stays with the previous service.

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} in the banking category show that Bank of America, Citibank, Chase, TD Bank and US bank are not statistically distinguishable from zero (Wells Fargo, the base brand is 0); Charles Schwab, ING and USAA have significant negative intercepts. The former group's customers are indifferent between staying and switching while the latter's customers are inclined to switch. The results for 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 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 – 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. Further, it is easy to assess whether this percentage is greater than 90% or 95% - a useful feature vis-à-vis the assessment of statistical significance. We base our discussions below on the 90% level. Using the 95% level will leave our implications unchanged but a few of the parameters will no longer be significant.

- **Base line effect of customer satisfaction**

We find statistically significant effects only for positive experiences. When customers are satisfied with the banking (0.570) or investment (0.612) service, they are more likely to stay with the corresponding firm. However, when they are dissatisfied, it does not always translate into switching behavior. Turning to 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), we see 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 provided by 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* that was 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: 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); and has a greater than 90% chance of being negative. 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 the table). 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 to a customer with less exposure. 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*.

Across categories, among those who are not satisfied with a different firm's banking service, people with more exposure to media and advertising are more likely to stay with the investment service, compared to those with less exposure. This parameter (0.964) is close to the 90% cut-off (89% chance of being positive). Once again, media exposure seems to highlight the contrast effect for these customers since the have different providers for the two services.

The results of the cross-category spillover effects indicate that more exposure to advertising enhances positive spillover when 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). Different from 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 (0.551 and 0.672 for banking and investments respectively), which demonstrates the existence of higher switching costs among customers with over $1M with the firm; respondents are more likely to stay with their current providers if they feel more invested in them. This is consistent with research that has looked at the role of switching costs in financial services (Li et al 2005). Our results also show that the 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 first signing 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 out the satisfaction at the own- versus cross-category level. When it comes to retention, the mechanism by which satisfaction has an affect is by strengthening 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 bank and investment companies. Customers with no kids are more likely to stay with the investment firm; low income customers are more likely to stay with their current bank; and high income customers tend to stay with both their current bank and investment firms. 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 Binary Probit model are presented in Table 6. The results show that older customers, customers with no kids and customers who go online frequently 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 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. (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 people 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. (e) A model that neglects unobserved heterogeneity.

The results (not reported) 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, but 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_{bank} =\$119 and the profitability of investment as $m_{Investment}$ =\$111); and (iv) the cost of acquisition. Our calculations here ignore (a) acquisition costs; (b) the possibility that the margins the company makes could vary with the satisfaction level of the customer; 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 for banking (investment) is improved from negative to neutral, the CLV related to banking (investment) improves by 45% (58% for investment); (ii) if satisfaction for 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 the 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 vs. 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 the customer satisfaction. When satisfaction for 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 for the investment category has higher impact on the overall CLV than the improvement in banking service; and the improvement from negative to neutral has higher impact on the overall CLV than the improvement from neutral to positive.

Summary

We provide a descriptive analysis of the effects of (dis)satisfaction in one category on outcomes both in that category and also in other categories of financial services. Additionally, we look at 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 of the contrast across categories driving behavior, we find 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 at the existing banking service. We therefore find asymmetries both across categories as well as across satisfaction and dissatisfaction in the cross-category effects. Importantly, we find that when the same firm is involved in both categories, dissatisfaction with the firm in the investment category lowers banking's retention probability. Switching costs, media exposure and order of acquisition of services have different roles to play 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 both the within as well as across category effects. The bottom line on the results of our study is that multi-product service firms need to integrate customer service and satisfaction departments across these services that currently are in separate silos. Doing so would alert the firm to potential customer defections due to dissatisfaction with any of the services being 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; if the customer is dissatisfied with any category, it 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 need to be viewed as descriptive rather than causal in nature. Nevertheless, we believe that it serves as a useful starting point for service organizations managing customer satisfaction across product categories.

References

Anderson, Eugene W., Claes Fornell and Donald R. Lehmann (1994), "Customer Satisfaction, Market Share and Profitability: Findings from Sweden," *Journal of Marketing*, 58 (July).

Beckwith, Neil E. and Donald R. Lehmann, "The Importance of Halo Effects in Multi-Attribute Attitude Models," *Journal of Marketing Research*, 12 (August 1975), 265-275.

Bolton, Ruth N. (1998), "A Dynamic Model of the Duration of the Customer's Relationship with a Continuous Service Provider: The Role of Satisfaction," Marketing Science, 17 (1), 45-65.

Boulding, W., A. Kalra, R. Staelin and V. A. Zeithaml, "A Dynamic Process Model of Service Quality: From Expectations to Behavioral Intentions," *Journal of Marketing Research*, Vol. 30, 7-27.

Bower, G. H., & Hilgard, E.R. (1980). *Theories of Learning* (5th ed.) Englewood Cliffs, NJ: Prentice-Hall

Chin-Parker, Seth and Brian H. Ross (2002), "The Effect of Category Learning on Sensitivity to within-Category Correlations," *Memory and Cognition*, 30 (3), 353-362.

Crespi, Leo P. (1942), "Quantitative variation of incentive and performance in the white rat," *American Journal of Psychology, 55,* 467-517

Flaherty, C.F. (1996), *Incentive Relativity*, New York, NY: Cambridge University Press

Fornell, Claes (1992), "A National Customer Satisfaction Barometer: The Swedish Experience," *Journal of Marketing*, 56 (January), 1-18.

Forrester Research (2010, 2011), North American Technographics Online Benchmark Survey.
Gupta, Sunil, and Donald R. Lehmann (2006), "Customer Lifetime Value and Firm Valuation," *Journal of Relationship Marketing* 5 (2/3).
Heckman, James J. (1979), “Sample Selection Bias as a Specification Error,” *Econometrica*, 47, 153-161.
Hovland, Cabl I., W. Mandell, E. H. Campbell, T. Brock, A. S. Luchins, A. R. Cohen, W. J. McGuire, I. L. Janis, R. L. Feierabend, and N. H. Anderson (1957), *The Order of Presentation in Persuasion.* New Haven: Yale Univ. Press.
Kenrick, D.T., Gutierres, S.E. (1980), “Contrast effect and judgements of physical attractiveness,” *Journal of Personality and Social Psychology, 38,* 131-140.
Kenrick, D.T., Gutierres, S.E., and Goldberg, L.L. (1989), “Influence of popular erotica on judgments of strangers and mates,” *Journal of Experimental Social Psychology, 25,* 159-167.
Li, Shibo, Baohong Sun, and Ronald Wilcox (2005), "Cross-Selling Sequentially Ordered Products: An Application to Consumer Banking Services," *Journal of Marketing Research*, 42(2), 233-239.
Luo, Xueming (2009), “Quantifying the Long-Term Impact of Negative Word of Mouth on Cash Flows and Stock Prices,” Marketing Science, 28(1), 148-65.
Luo, Xueming and Christian Homburg (2008), “Satisfaction, Complaint, and the Stock Value Gap,” *Journal of Marketing*, 72(4), 29-43.
Markman, Arthur B. and Brian H. Ross (2003), “Category Use and Category Learning,” *Psychological Bulletin*, 129 (4), 592-613.
Rust, Roland T. and Tuck Siong Chung (2006), "Marketing Models of Service and Relationships," *Marketing Science*, 25 (6), 560-80.
Simpson, D. D. & Ostrom, T. M. (1976), “Contrast effects in impression,” *Journal of Personality and Social Psychology*, 34 625 -29.
Szymanski, David M. and David H. Henard (2001), “Customer Satisfaction: A Meta-Analysis of the Empirical Evidence,” *Journal of the Academy of Marketing Science*, 29 (1), 16-35.
Verhoef, Peter C., Philip Hans Franses, and Janny C. Hoekstra (2001), "The impact of satisfaction and payment equity on cross-buying: A dynamic model for a multi-service provider," *Journal of Retailing*, 77 (3), 359.
Zeaman, D. (1949), “Response Latency as a Function of Reinforcement,” *Journal of Experimental Psychology*, 39(4), 466-483.

Table 1 Number of observations for different levels of the drivers of intentions

	Negatives	Neutrals	Positives
Banking	100	149	192
Investment	85	157	199

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 offline, 0=otherwise) (ADVTG)	0.42	(0.49)
Having more than $1M with the banking company (1=Yes, 0=otherwise) (SWITCHING COST – banking)	0.21	(0.41)
Having more than $1M 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 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)
Citi	-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)

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

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

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 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%)**

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%)**

Web Appendix: The Gibbs Sampler to Estimate the Model Parameters

1. $[y_i|\cdot]$ draw the latent values y_i, for the two categories simultaneously conditional on all other model parameters.Knowing the full covariance matrix Σ among the three error terms, which is

$$\begin{Bmatrix} \{\epsilon_{ifc}\} \\ \{u_i\} \end{Bmatrix} \sim N(0,\Sigma), for\ c = 1,2$$

we can derive the conditional covariance matrix of $\Sigma_{\epsilon|\mu} = var\left(\{\epsilon_{ifc=1}, \epsilon_{ifc=2}\}|u_i\right) = \Sigma_{\epsilon\epsilon} - \Sigma_{\epsilon\mu}\Sigma_{\mu\mu}^{-1}\Sigma_{\mu\epsilon}$.

In this equation,

$$\Sigma = \begin{bmatrix} \Sigma_{\epsilon\epsilon} & \Sigma_{\epsilon\mu} \\ \Sigma_{\mu\epsilon} & \Sigma_{\mu\mu} \end{bmatrix}$$

where $\Sigma_{\epsilon\epsilon}$ is a 2x2 matrix, with the diagonals constrained to be 1, and $\Sigma_{\mu\mu}$ takes the value of 1.

With the conditional covariance matrix $\Sigma_{\epsilon|\mu}$ and the conditional mean of y_{it} for both categories, we can simulate the values of y_{it} from truncated normal distribution. The truncation depends on the value of the corresponding Y_{it}.

2. $[h_i|\cdot]$ simulate the latent values h_i, as in equation (3)

As h_i enters both parts of the full likelihood function, including the likelihood related with the decision on stay vs. switching; and the likelihood related with the decision of using the same vs. different companies for the two services. In the first model, h_i enters the two dimensional Binary Probit model on the right hand side of the equation, and the likelihood function is

$$y_i - Q_i(h_i) \sim N\left(0, \Sigma_{\epsilon|\mu}\right)$$

In this specification, $Q_i(h_i)$ refers to the specification in equation (2), which is a function of h_i.

In the second model, h_i enters the selection model on the left hand side of the equation, and the likelihood function is a combination of:

$$h_i - W_i\rho \sim N(0,1)$$

$$Prob(H_i = 1|W_i) = Prob(h_i > 0|W_i)$$

This is a truncated normal with mean 0, variance 1, and the truncation is determined by the value of H_i.

3. $[\Sigma|\cdot]$ draw the covariance matrix of all the three error terms, including $\epsilon_{ifc=1}$, $\epsilon_{ifc=2}$ and u_i

With a conjugate prior, this is just a simulation from an inverted-Wishart distribution. As discussed in the paper, for identification purposes, we constrained the diagonals of this matrix to be 1, therefore, we need to rescale the simulated values of y_i and h_i, based on the estimated diagonals in Σ. Using σ_{11}, σ_{22} and σ_{33} to denote the values of the diagonal, we need to calculate

$$\widetilde{y_{i1}} = \frac{y_{i1}}{\sigma_{11}}, \widetilde{y_{i2}} = \frac{y_{i2}}{\sigma_{22}}, \widetilde{h_i} = \frac{h_i}{\sigma_{33}}$$

4. $[\beta|\cdot]$ draw the model parameter in the stay/switch model.

With a conjugate prior, this is a simulation from multi-variant Normal posterior distribution, as in a regular multi-dimensional regression model with multi-variant normal error terms. The value of the dependent variable, however, needs to be calculated. In particular, we need to subtract the firm-category specific intercept, and the conditional means of the error term, due to the fact that we estimate these parameters conditional on the error terms from the selection model, i.e. knowing the values of u_i.

5. $[\alpha | \cdot]$ draw the intercepts in the stay/switch model

   The simulation draw in this step is very similar to that in the step of obtaining β.

6. $[\rho | \cdot]$ draw the parameters from the selection model, as in equation (3).

Knowing the latent value of h_i, and the variance of the error term being constrained to be 1, this step is the same as simulating from a single dimension regression model.