Managing Adoption Barriers in Integrated Banking Services

Jonathan Lee
Associate Professor of Marketing
College of Business Administration
California State University, Long Beach
Long Beach, CA 90840
Phone (562) 985-4562 / Fax (562) 985-1588
jlee6@csulb.edu

Maureen Morrin
Associate Professor of Marketing
School of Business – Camden
Rutgers University
Camden, NJ 08102
Phone: (856) 225-6216 / Fax: (856) 225-6231
mmorrin@camden.rutgers.edu

Janghyuk Lee
Assistant Professor of Marketing
Korea University
An-am, Seong-book
136-701, Seoul, Korea
Phone (82) 17 239 2106
janghyuk.lee@korea.ac.kr

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Abstract

Service organizations such as retails banks are attempting to increase their customers' lifetime value through the introduction of service innovations such as integrated banking. To date, these efforts have met with mixed success. This research proposes that strategic consideration of barriers to adoption can significantly alter and enhance the effectiveness of segmentation and communication efforts for service innovations. The results of a latent class regression with concomitant variables on a large-scale multinational consumer survey (n = 2,702) demonstrate that incorporating barriers to adoption significantly alters the segments into which customers are classified, resulting in improved model fit and out-of-sample prediction. Strategic implications of our findings for the introduction of service innovations are discussed.

Advances in interactive technologies and regulatory changes have spurred retail banks into developing service innovations such as integrated banking in recent years. Their motivations have included increasing customer profitability and combating competition from alternative providers. A current banking innovation consists of the opportunity for integrated banking, also called asset management accounts, which involves the provision of a wide range of financial products “under one roof”. Banks now typically offer not only the traditional services of checking and savings accounts, but also brokerage accounts, IRA's, revolving credit, mutual funds, auto and home insurance, etc. Since the average consumer currently uses from seven to ten different financial service providers (e.g., a bank, a stock broker, a mortgage lender, a mutual fund company, an insurance company, and one or more credit card companies), there would appear to be significant cross-selling opportunities for banks by having their customers consolidate their accounts at their bank (Hitt and Frei 2002). Consolidating one's financial accounts at a single provider and receiving a single monthly statement might also make customers less likely to defect to competitors (Shapiro and Varian 1998), thus enhancing banks' ability to develop, maintain, and grow long-term relationships with their customers (Berger and Nasr 1998).

The provision of integrated banking services, however, has generated less than anticipated levels of customer adoption. According to a recent large-scale survey (Shevlin, Graeber and Sage 2005), integrated banking is considered appealing by just 17% of U.S. households (percent "interested" or "very interested" in purchasing multiple, different types of products from a single, preferred financial provider). In fact, prior technology-based banking innovations such as smart cards and ATM's initially exhibited similarly high levels of adoption resistance among consumers (Fain and Roberts 1997). How might retail banks enhance the likelihood of adoption of service innovations such as integrated banking? One aspect of the solution might involve more longitudinal promotional campaigns that involve step-by-step marketing efforts to encourage gradual consumer acceptance (Fain and Roberts 1997; Kestnbaum, Kestnbaum and Ames 1998; Peltier, Schibrowsky and Schultz 2002) or promotional efforts that exhibit a more integrated approach (Peltier, Schibrowsky and Schultz 2003). Indeed, to date most banks' efforts at promoting integrated banking services have focused on a single product at a time rather than offering bundled product pricing (Shevlin, Graeber and Sage 2005). Yet another aspect of the solution, and the one that is the focus of the present research, involves more effective segmentation and targeting strategies.

Retail banks are keenly aware of the need to target innovative service offerings to appropriate customer segments to optimize the likelihood of product adoption. Researchers have noted how critical appropriate segmentation strategies are in cross-selling efforts (Parsons, Zeisser and Waitman 1998). Historically, demographic characteristics such as gender, age, income, education, and household composition as well as some attitudinal and behavioral variables have been used as key characteristics upon which to segment customer groups (Gilbert and Warren 1995). For example, one study found that early adopters of ATM's tended to be younger and more educated, had higher incomes, were more likely to possess other financial products such as credit cards, and were more likely to hold favorable attitudes toward computers and change (Swinyard and Ghee 1987). And recent research suggests that consumers who express interest in integrated banking tend to be younger, more affluent, urban males who own more financial products and use the web often for their banking needs (Shevlin, Graeber and Sage 2005). Implicit in such segmentation schemes is the assumption that customers possessing particular demographic, behavioral, or attitudinal characteristics are more likely to benefit from the services offered and that such characteristics therefore account for a large proportion of differences between product adopters and non-adopters. However, recent research (Hitt and Frei 2002) found that demographic characteristic account for only a small proportion of the difference in lifetime value between customers who adopted on-line banking and those who did not.

In the present paper, we propose that a key characteristic that is lacking from previous retail bank customer segmentation approaches is the consideration of barriers to new product adoption. Our argument extends the theorizing of Peltier and Schibrowsky (1997, p. 54) who argued for the inclusion of need-satisfying motives and benefits in marketers' segmentation schemes in order to address the issue of "why" consumers respond, in addition to "who" responds. Significant advances have been made in the use of psychographics to segment banking customers for cross-selling purposes (Gilbert and Warren 1995; Peltier, Schibrowsky, Schultz, and Davis 2002; Peltier, Schibrowsky and Davis 1998). In the case of service innovations, barriers to adoption would seem to take on a particularly salient role in determining which consumers will versus will not adopt the innovation.

It has been suggested that the banks most successful in attracting customers to their on-line services are those that have stressed the safety and security of their services, that is, barriers (ABA Bank Marketing 2002), rather than the benefits of the new product. These banks recognized that while many customers of a particular demographic profile might desire the various benefits provided by on-line banking, a large number might be hesitant to adopt such behavior due to concerns about online security. We build on prior research (Ram and Sheth 1989; Fain and Roberts 1997) that has identified two major types of consumer-related barriers to adoption for technologically driven banking innovations: functional barriers (such those related to usage, value, and perceived risk) and psychological barriers (such as those related to tradition and image). Knowing what are the key barriers to adoption for service innovations for various consumer segments should allow for more focused and effective targeting and communication efforts. Also, we investigate the extent of customer segment dispersion when barriers to adoption are added to a segmentation model. By customer segment dispersion we mean the degree to which the members of one customer segment are distributed proportionately across the segments of an alternative model, such as one that incorporates an additional variable. We show that there is a pattern of relationship between consumer characteristics and barriers.

What barriers to adoption do consumers perceive as being the most difficult to overcome, and how do these perceptions vary across different consumer segments? In this paper we examine these issues and propose segmentation strategies for integrated banking services focusing on barriers to adoption. Once information on the barrier patterns for each segment of consumers has been obtained, and differences in consumer characteristics such as demographics, ownership, and information sources, are examined, it may then be possible for managers to more effectively target each segment with more compelling promotional and product-oriented efforts.

Prior research in direct marketing underscores the advantages associated with segmenting a market in order to be able to target promotional efforts to those with a higher probability of exhibiting the desired behavioral responses (Fain and Roberts 1997). We demonstrate that when firms introduce service innovations, it is critical to consider barriers to adoption that are not adequately reflected in traditional bases of segmentation such as demographic, behavioral, and psychographic criteria. Enhancing traditional segmentation approaches with barriers to adoption can not only significantly alter segment membership, but also improve model fit, and thus potentially enhance managers' decisions regarding targeting and tailoring communication efforts.

EMPIRICAL STUDY

Description of the Data

The data were provided by Forrester Research, which conducted a large-scale mail survey among consumers in the European Union during the fall of 2002[1]. The survey asked consumers a number of questions including which types of banking products they currently used, such as checking and savings, as well as whether or not they used more innovative services such as integrated banking. The vast majority of respondents did not use this service. Nonusers were asked about the reasons for not using integrated banking. They were also asked about their intention to adopt this service innovation. For the purposes of the present research, we include in the analyses all survey respondents who checked one or more reasons for not adopting integrated banking. This resulted in a total sample size of 2,702 consumers from six countries in the European Union (Great Britain, France, Germany, Sweden, the Netherlands, and Italy), from which we randomly chose 400 consumers for a holdout sample.

For this analysis, we included a set of variables representing the types that might be used in a traditional segmentation analysis to generate customer segments: demographics, attitudes, behavior, and media usage. Five demographic variables were included in the model: gender, age (low, middle, high), education (low, middle, high), income (low, middle, high), and household size (one, two, three, four, five or more). A potentially important individual difference variable that may impact the likelihood of innovative banking product adoption is a consumer's overall optimism about technology, which was captured in the survey in a binary format. Consumers were also asked whether they currently owned a number of financial products. We collapsed these options into two major categories of financial products: basic (credit card, checking

[1] Based on the Forrester European report (2004), the penetration rate of integrated banking service is still very low (11%). Also, they use the same items for measuring barriers and the summary statistics of barriers do not show any significant change.

account, and savings account) and advanced (mortgage, personal loan, stocks/mutual funds, and pension). Respondents also indicated which of several alternative media sources they used to obtain information regarding financial products and services. We collapsed the media sources into three categories as follows: broadcast (television + radio), print (newspapers + magazines) and internet.

There were a total of five responses consumers could check off as reasons for not using integrated banking in the mail survey:

- I don't want to give one company full view of my financial life.
- No one company could have all the best products.
- My financial life is not complicated enough to benefit from consolidation.
- I don't want all my assets tied to the fate of one company.
- No one company could have the products that are best for me.

Figure 1 illustrates the heterogeneity in responses regarding barriers to adoption across the countries surveyed. We find that there are significant differences across countries and also the barrier pattern for each country differs. We collapsed these five reasons into three major types of barriers: No need recognition (uncomplicated financial life), Perceived risk (company would know too much + assets tied to the fate of one company), and Inadequate product (can't have all products + can't have right products). Finally, for the second stage of analysis in this paper, which measures the predictive accuracy of the models, we utilized the survey responses regarding intention to adopt integrated banking services in the future.

FIGURE 1 ABOUT HERE

Barriers-Based Segmentation with Concomitant Variables

Mixture regression models relate a dependent variable to a set of independent variables, in our case, adoption intention to perceived barriers. If we have a subset of consumers that differ in terms of the importance of barriers on adoption, we would like to identify those groups from the data, and estimate the regression model for each group. The analytical model used in this research is one form of the mixture regression model that defines prior segment membership probabilities as functions of concomitant (i.e., demographic) variables (Gupta and Chintagunta 1994; Kamakura, Wedel, and Agrawal 1994). In order to make the segments accessible and insightful, managers often want to profile them with demographic variables. That is, we can include the concomitant variables into the mixture model as descriptors of segment membership. Thus, in addition to the parameters from mixture regression for each segment, the concomitant variable model also provides the means of the concomitant variables for each segment. Those means provide the researcher with a description of the segments in terms of the concomitant variables, which may be important for targeting and other decisions.

The concomitant variable mixture model provides one way of analyzing consumers' intent-to-adopt in relation to perceived barriers and consumer characteristics. A shared pattern of barriers among consumers can then be transformed into a strategic focus regarding how to remove those barriers for a well-defined group of consumers, and also provide a benchmark for the evaluation of new financial products.

Results of the Base Model (Latent Clustering without Barriers)

The purpose of the base model is to find out whether there is a non-random relationship between barriers and consumer characteristics. It is based on a latent class (LC) cluster analysis, in which objects are assumed to belong to one of a set of K latent classes, with the number of classes and their sizes not known a priori (Vermunt and Magidson 2002; Jorgenson and Hunt 1996). An important difference between standard cluster analysis techniques and LC clustering is that the latter is a model-based clustering approach. More precisely, it is assumed that the data are generated by a mixture of underlying probability distributions. LC analysis is a probabilistic approach and therefore, although each object is assumed to belong to one class or cluster, it takes into account that there is uncertainty about an object's class membership.

The best-fitting cluster analysis model without barriers to adoption resulted in a four-segment solution, with one very large segment accounting for nearly half the customers, and smaller segments accounting for the remainder. Members of segment 1 ("older educated males"), who in this model account for nearly half of all customers (48.5%), tend to be older, highly educated males who are more likely to live in smaller households (alone or with one other person). These customers are more likely than average to already possess both basic and advanced financial products and thus would seem to represent a good target for innovative banking products. To reach these customers, banks would likely use print vehicles such as newspapers and magazines, rather than broadcast media such as TV and radio, based on the where these customers say they normally obtain such information.

Members of segment 2 ("lower income females"), who accounted for about a third of the customers (33.4%), are more likely to be lower-income females with less education. They are less likely than average to obtain information about financial products from print vehicles. This segment does not appear to be a very good target for innovative financial products. Members of the relatively small segment 3 ("net-savvy educated males"), who accounted for about a tenth of the customers (11.2%), tend to be educated males who are more likely than average to already possess both basic and advanced financial products. This segment is unique in that it is much more likely than others to obtain information about the financial products from the internet. This segment, although small, would appear to be a very good target for innovative financial products and could possibly be reached with low-cost internet strategies. The members of the fourth and smallest segment ("big families," 6.9%) exhibit higher incomes and education levels, and tend to live in the largest household sizes. However, customers in this segment are least likely to own even basic financial products, and almost none possess advanced financial products. For these reasons, this segment does not seem to represent a very good target for the marketing of innovative financial products.

TABLE 1 ABOUT HERE

Managers utilizing the results from a traditional segmentation model without the inclusion of barriers to adoption would likely choose to target segments 1 and 3. Segment 1 is a large segment representing older, educated males who use many financial products and who would be best reached with newspaper and magazine advertisements. A secondary target would be the much smaller net-savvy group of educated males in segment 3, which could probably be efficiently reached via the internet.

Results of Latent Clustering including Barriers

We then conducted the cluster analysis including the three major types of barriers to adoption. Based on the information criteria, the best model resulted in a 5-segment solution as shown in Table 1. Managers utilizing barriers to adoption as segmentation bases for integrated banking could target customers with more information that matches consumer demographics with barriers in a structured manner.

Segment 1 represents an older, educated, wealthy male segment that has both risk concerns and needs to be convinced that the bank offers a competitive product assortment. Interestingly, this segment, while similar to the large segment 1 of the model without barriers, differs from that segment in that it exhibits higher income levels and has a higher propensity to utilize the internet. Consumers belonging to this segment have unique barrier concerns and thus, managers can respond in terms of different media choice and message contents, knowing that they are amenable to more efficient communication vehicles such as via the internet. Segment 2, which is demographically similar to segment 1, differs from it in that this segment does not have major doubts as to product superiority. The communication effort against this segment would be need to be tailored to focus primarily on perceived risk issues, rather than product superiority issues, and would need to utilize non-broadcast communication vehicles. There is a third, future growth segment of interest, segment 5, which represents a youthful target that could pay dividends in terms of customer lifetime value in future years. Consumers in this segment are highly educated but do not yet own many financial products.

TABLE 2 ABOUT HERE

We next conducted a cross-tabulation of the segment membership of the two models (without/with barriers) to assess the degree of difference due to perceived barriers, shown in Table 2. It shows there is a non-random relationship between consumer characteristics and perceived barriers. A Chi-Square test confirms there are significant associations in segment membership in the two models beyond what would be expected from random variation (Chi-Square (12) = 4190.1, $p < .0001$). More specifically, we see that at least two of the segments from the model without barriers were replicated nearly intact in the second model (e.g., 74.6% of segment 2 moved to segment 3, accounting for 96.4% of that segment; and 96.4% of segment 4 accounts for 63.5% of segment 5).

Barriers-Based Segmentation and Strategic Implications

Table 3 reports the estimation results of concomitant variables latent class model. Based on the best fitting model, which resulted in a six-segment solution, we can infer the potential profitability and accessibility of each segment. In general, *perceived risk* seems to be the most difficult barrier across segments in adopting integrated banking service. For about 40% of the sample, we also find that perceived risk is accompanied by negative tech attitude, which can be taken into account when setting the advertising objectives.

TABLES 3 ABOUT HERE

Consumers belonging to segment 1 ("older educated product concerned," 26.4%) and segment 4 ("older high income high usage," 12.9%) also present another challenge to marketers. Though customers in these segments are wealthy and already possess both basic and advanced financial products, they don't believe in one bank having all the best products. Since they clearly represent a good target for consolidation, banks may provide incentives such as reduced fees for buying multiple products and differentiate their service from what they are currently getting from multiple providers. Simply giving them a price break may not be enough and banks can also provide tailored offerings to their changing needs. To reach these customers, marketers should use print vehicles such as custom catalogs and magazines, rather than broadcast media or internet. Consumers in segment 3 ("younger educated male net users" 12.5%) and 5 "no need females" (14.1%) are more likely to turn to the online channel for a host of financial activities than other consumers. For their product decisions, they depend heavily on the online research across a range of products. In terms of barriers, it seems consistent that their only concern is about the risk involved in consolidating assets. The remaining segments are less attractive or accessible targets because of technological and risk barriers in segment 2 ("old fashioned female pessimists" 24.8%), and small size lacking profitability in segment 6 ("young male pessimists" 9.3%). Considering the size of segment 2, marketers may think of it as a "must seek" segment but the consumer characteristics combined with the type of barriers suggest otherwise.

TABLES 4 ABOUT HERE

In addition to the model fit in the calibration sample, we also investigated the predictive validity of the concomitant variable latent class model relative to 1) a base model without barriers, 2) a base model with barriers, and 3) a mixture model without barriers. In assessing the predictive validity we used the barrier ratings of the hold-out sample, and calculated the membership probabilities on the basis of the parameters obtained from the estimation set. The results are shown in Table 4. The hit ratio is the percentage of 400 subjects correctly classified based on the estimated parameters compared to the actual segmentation. The model with a better fit in the estimation sample also produced better predictive fit in the hold-out sample. Also, both in pure clustering and mixture regression models, the models including barriers outperformed those without barriers. Table 4 shows that the predictive fit (84% hit ratio) obtained with the concomitant variable model is much better than the one obtained with the simpler models, thus indicating its predictive validity.

DISCUSSION

The results of our study suggest that the inclusion of barriers to adoption can significantly enhance the effectiveness of customer segmentation and targeting efforts. Though we used the data from integrated banking services, our main goal is to provide some empirical support of a more general discipline, managing adoption barriers for successful service innovations. We show that marketers can benefit from incorporating perceived barriers besides looking into consumer demographics. Adding barriers to adoption in the segmentation analysis helped to uncover the unexplained heterogeneity and in turn resulted in the improved fit as measured by intention to adopt. The proposed approach not only produced a managerially relevant set of consumer segments with distinct barriers and demographic characteristics, but also significantly improved predictive ability, as demonstrated by the model's application to a hold-out sample.

The implications of barrier segmentation for managers concern the selection of customers or prospects for targeting promotional efforts, the nature of those efforts (e.g., which barrier(s) to focus on), as well as the basket of products that should be offered to each segment as part of the integrated banking service. Different segments would likely prefer not only different products but also different contact channels, for example, traditional media, internet, telemarketing, etc. (Peltier, Schibrowsky and Schultz 2003). As pointed out by previous researchers, segments as small as one could be efficiently reached using web-enabled interactive technologies driven by customer database-driven segmentation models (Peltier, Schibrowsky and Schultz 2003).

Prior researchers have shown not only that customers can be effectively segmented into groups with different probabilities of response, but that segments with higher probabilities may warrant more resource-intensive or long-term, step-by-step promotional efforts (Kestnbaum, Kestnbaum and Ames 1998; Fain and Roberts 1997). Segments with higher projected lifetime values have implications for the timing, context and extent of communication efforts, and product offerings (Blattberg, Getz, and Thomas 2001). Prior segmentation research applied to the retail banking context has linked results to cross-selling profitability (Peltier, Schibrowsky, Schultz and Davis 2002). Further research in this area should attempt to measure potential segment profitability for actionable results. Another set of barriers that this research does not address is that of organizational barriers (Sciulli 1998), such as the determination of which bank unit receives lower profit margins when a reduced price is offered to reward integrated banking customers for signing up for another service (Shevlin, Graeber and Sage 2005).

We note that the present conclusions, while based on a relatively large sample (n=2,702), are nonetheless limited in that they are based on a sampling of European consumers, who may differ in their adoption patterns from consumers in other parts of the world. In addition, the present research is limited in that we have not discussed the flexibility and co-creation of such services in fuelling the marketing strategies. Our study requires replication across other industries with other types of product and service innovations for additional support. Future research could further build upon the current findings if conducted in alternative markets such as in the domain of business-to-business marketing or the marketing of professional services.

Table 1. Latent Clustering without/with Barriers to Adoption

Base Model	Segment 1	2	3	4
Demographics				
Gender	2.74	-2.40	3.19	ns
Age	2.20	ns	ns	ns
Education	2.04	-7.13	2.19	3.45
Income	ns	-5.30	ns	2.42
Household Size	-4.41	ns	ns	2.50
Technology Optimism	ns	3.28	ns	ns
Ownership				
Basic	4.65	ns	2.03	-6.59
Advanced	2.63	ns	3.47	-2.52
Info Sources				
Broadcast	-2.11	ns	ns	ns
Print	2.21	-3.65	ns	ns
Internet	ns	ns	2.82	ns
Segment Size	48.5%	33.4%	11.2%	6.9%

	Segment 1	2	3	4	5
Demographics					
Gender	3.92	2.01	-3.03	ns	ns
Age	2.17	3.65	2.94	3.37	-3.06
Education	3.58	3.57	-5.67	ns	5.34
Income	2.07	ns	-4.03	ns	2.63
Household Size	ns	ns	ns	-3.40	4.06
Tech. Optimism	3.72	3.87	4.07	-3.84	3.61
Ownership					
Basic	2.82	ns	-2.56	ns	-6.84
Advanced	4.17	2.21	ns	ns	-2.19
Info Sources					
Broadcast	ns	-2.15	ns	ns	ns
Print	ns	ns	-3.72	ns	ns
Internet	2.07	ns	ns	ns	ns
Barriers					
No Need	-4.94	-2.35	ns	2.90	-2.23
Perceived Risk	5.59	4.83	ns	-3.58	ns
Inadequate Product	2.49	ns	ns	ns	ns
Segment Size	28.8%	24.4%	23.1%	14.6%	8.9%

Table 2. Cross Tabulation of Segment Membership Based on Latent Clustering

		w/ Barrier Segment					
		S1	**S2**	**S3**	**S4**	**S5**	**Total**
Base Segment	1	314	722	21	390	42	1489
	2	118	4	558	9	59	748
	3	261	1	1	20	4	287
	4	2	1	0	5	186	193
Total		695	726	579	424	293	**2717**

Table 3. Results of Mixture Regression with Concomitant Variables

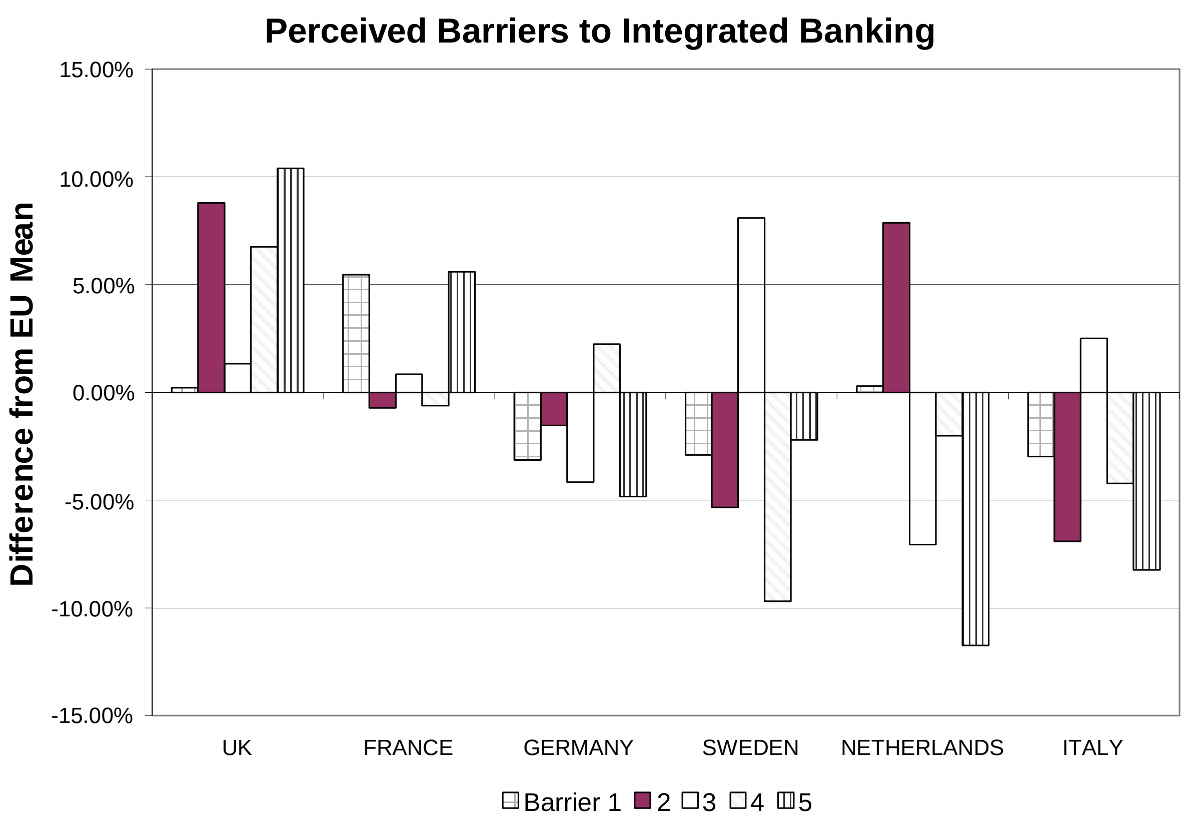
	Segment 1	2	3	4	5	6
Barriers						
Intercept	2.52	ns	-1.92	ns	ns	ns
No Need	ns	ns	3.50	ns	ns	1.48
Perceived Risk	-3.63	-2.94	ns	-1.51	-3.16	ns
Inadequate Product	1.62	ns	ns	-3.98	ns	ns
Tech. Optimism	ns	-4.32	1.74	ns	-2.04	-5.05
Concomitant Variables						
Demographics						
Gender	ns	-2.46	-3.11	ns	2.35	-4.12
Age	1.14	1.51	-3.03	2.14	-1.67	-1.89
Education	3.05	ns	5.17	-6.03	3.11	ns
Income	3.11	ns	ns	1.91	ns	2.15
Household Size	ns	-0.11	ns	2.37	-3.07	ns
Ownership						
Basic Products	ns	-1.39	ns	0.18	1.36	ns
Advanced products	3.07	ns	0.81	0.59	ns	ns
Information Source						
Broadcast	ns	2.70	ns	ns	-3.53	1.10
Print	1.95	ns	-6.01	1.49	ns	ns
Internet	-1.15	ns	3.15	ns	2.05	-4.02
Segment Size	26.4%	24.8%	14.1%	12.9%	12.5%	9.3%

Table 4. Model Fit

In-Sample Estimation Fit	Segment Solution	**LL**	**BIC**	**CAIC**
Latent clustering without barriers	4	-2659.82	5923.89	6003.90
Latent clustering with barriers	5	-2308.65	5115.72	5182.87
Mixture regression without barriers	5	-2431.79	5316.33	5404.01
Mixture regression with barriers	6	-2103.54	4833.96	4906.17

Out-of-Sample Predictive Fit		**Hit Ratio**
Latent Clustering without barriers	4	67%
Latent Clustering with barriers	5	72%
Mixture regression without barriers	5	69%
Mixture regression with barriers	6	84%

Figure 1. Illustration of Heterogeneity in Barriers



Barrier 1: too dependent on one company
Barrier 2: no company has all the best
Barrier 3: no need to consolidate
Barrier 4: too risky to tie all assets
Barrier 5: one company can not serve my need

APPENDIX
Mixture Regression with Concomitant Variables

We initially classify a customer into one of the latent classes based on demographic and behavioral characteristics, (e.g., demographics, ownership of financial products, and information source). It is assumed that the prior probability that customer *i* comes from latent class *s* is a function of these concomitant variables, Z_{il} (Kamakura, Wedel, and Agrawal 1994) as

(1) $$\pi_{s|Z} = \frac{\exp(\sum_{l} \theta_{ls} Z_{il})}{\sum_{s=1}^{S} \exp(\sum_{l} \theta_{ls} Z_{il})}$$

where θ_{ls} is a parameter that shows the impact of the *l*-th customer characteristic on the prior probability for latent class *s*.

Given that subject *i* comes from class *s*, the conditional distribution function of intent-to-adopt, y_i, is represented by the general form $f_{i|s}(y_i \mid \beta_s)$ where β_s denotes the vector of parameters for predictors in class *s*. The predictors include three barriers to adoption (no need, perceived risk, and inadequate products) plus attitude towards technology. In this case, we assume the observations are independent normally distributed, and β_s contains the means and variances of the normal distribution for each segment. Then the conditional distribution is

(2) $$f_{i|s}(y_i \mid \beta_s) \sim N(X_i \beta_s, \sigma_s^2)$$

The likelihood function is given as

(3) $$L = \prod_{i=1}^{N} L_{i|s} = \prod_{i=1}^{N} \sum_{s=1}^{S} \pi_{s|Z} \cdot f_{i|s}(y_i \mid \beta_s)$$

Estimates of the parameters of the model in (3) are obtained via maximum likelihood. Once estimates of the parameters are obtained, the posterior probability, λ_{is}, that consumer *i* belongs to latent class *s* can be calculated as

(4) $$\lambda_{is} = \frac{\pi_{s|Z} \cdot f_{i|s}(y_i \mid \beta_s)}{\sum_{s=1}^{S} \pi_{s|Z} \cdot f_{i|s}(y_i \mid \beta_s)}.$$

In determining the number of components in the mixture (Bozdogan 1987), we use the consistent Akaike information criterion (CAIC) and Bayesian information criterion (BIC).

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