Understanding Customer Choices in E-Financial Services

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Now that the dust of the dot-com fallout has settled, e-commerce topics are again making the cover of business journals. *The Economist* states that e-commerce is coming of age and is being embraced by consumers who are beginning to spend as much time on the Internet as they do watching television.[1] *Business Week* appropriately titled a story "E-Biz Strikes Again!" and identified several industries where web-centered firms are becoming stiff competitors to non-Internet-based companies.[2] In addition, the use of various types of e-services (such as financial, travel, music, auctions, and gambling) is increasing at a considerable rate.[3] While the sales trend is positive, Rust et al. report that over six billion in potential web sales were lost during 1999 because of inadequate e-service offerings.[4] To decrease the number of potential glitches, both business consultants and researchers have been studying critical factors that enable e-service success. Past research has suggested that e-services will succeed if:

- more factual product or service information is provided and brand equities are leveraged within particular customer groups;[5]
- shopping convenience, product value, and customer relations are emphasized;[6]
- web-based ease of use features are emphasized;[7] and
- customer needs such as a better purchasing experience, greater online control tools, and better personalization options are understood.[8]

Scholars have argued that e-services (as compared to offline-only services) have the ability to serve customers more effectively and efficiently, and at a lower marginal cost, while simultaneously offering real-time information.[9] Furthermore, by using monitoring software and customer relationship management techniques, e-service firms can track, analyze, and cater to specific customer needs.[10] While there might be many benefits of web-based tools and technologies, there are also additional costs associated with developing and delivering e-services. Firms face the daunting task of having to create new e-services at a high cost while simultaneously cannibalizing offline sales that are supported by traditional services. Lower marginal costs also have the potential of decreasing profit margins in competitive industries because lower costs typically have to be passed on to customers in order to remain competitive. A strategy based on lower price per transaction alone therefore can increase market-share, but the success may be unsustainable and most likely will lead to cost-based competition that may reduce net revenue and profits in the long run. For example, a number of dot-com companies that followed a pure low-cost strategy were unable to generate required revenue or profits and folded at even earlier stages than the rest of their dot-com compatriots. In that sense, an online business has to offer an attractive overall product and service package to the customer in order to derive a sustainable market advantage. Given that firms have limited capital and other resources, managers need to understand the relative benefits of various online and traditional (non-web-based) features of their e-service offerings for the targeted set of customer segments. This must lead to focused efforts to develop features which enhance customer value and which do not waste capital and other resources that customers either do not want or do not care about.[11] Managers also need to understand customer price sensitivities and offer a targeted mix of online and traditional features to overcome the "price barriers" for making a favorable choice.

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An emerging solution to this dilemma is to search for the "best of breed" features from traditional services and combine with "pure" online-only features to create a new e-service offering. There are some firms—such as Amazon, EBay, Charles Schwab, Southwest Airlines, IBM, and Merck-Medco—that have successfully combined traditional services with online features to create formidable new e-services. For example, Charles Schwab provides customers with the ability to access timely and in-depth company financial information through schwab.com, but also simultaneously provides offline access to traditional services such as brokers and financial advisors. Furthermore, Charles Schwab also maintains brick-and-mortar facilities in various locations to allow customers to access the company offline.

Despite extensive focus on e-services by scholars, many questions related to understanding the market drivers of customer choices in e-services remain unexplored.[12] Therefore, building on past research and recognizing the need to systematically assess the relative importance of various choice drivers, we developed a framework for developing effective e-financial service offerings and conducted an empirical study of customers in the United States. Our single industry-focus is in keeping with similar industry-specific research in e-services.[13]

Research Methodology

In order to understand customer preferences for an e-financial service, we need to consider the relative benefits that customers attach to various features of the service that are available to them at the time of purchase.[14] When faced with a choice task, customers are likely to use features that they are already familiar with and are also willing to consider new features in their choices as long as they are made available and understandable to them.[15] The propensity to use either one or both sets of features is a function of the users search costs and benefits associated with processing the information associated with the features.[16] Therefore, to understand choice drivers for e-financial services, we need to assess how customers make trade-offs between prior feature knowledge acquired through purchasing off-line (i.e., price per transaction, and other traditional off-line features) and new features (i.e., online-only features).

Recent studies have demonstrated that the discrete choice framework is very effective in modeling the choice behavior of customers when exploring service designs.[17] For example, based on discrete choice data collected at a large international airport, Pullman et al. developed a framework matching the needs of multiple market segments with service offerings.[18] Easton and Pullman developed a mathematical modeling formulation of the sellers' utility problem within the context of new service design using discrete choice data.[19] Verma et al. presented a non-linear optimization model linking customer preferences obtained from discrete choice analysis (DCA), production cost, and operating difficulty.[20]

Several papers have reviewed the DCA literature and have provided guidelines for designing and conducting DCA studies for the entire spectrum of service industries.[21] Discrete choice experiments involve the careful design of multiple experimental service profiles and choice sets (combinations of service profiles). In these experiments multiple alternatives are offered to decision makers and they are asked to evaluate the options and choose one (or none). Each subject in a DCA experiment typically receives several choice sets to evaluate (e.g., 8 to 32 sets). The design of the experiment is under the control of the researcher, and consequently, the decision makers' choices (dependent variable) are a function of the attributes of each alternative, the personal characteristics of the respondents, and the unobserved effects captured by the random component.[22]

DCA applications based on choice experiments typically involve the following steps: *identification* of determinant attributes (market driver); *specification* of attribute levels (market driver extensions); *experimental design*; *visual presentation* of choice alternatives to respondents; and *estimation* of the choice model. Although the design of choice experiments and estimation of econometric models requires sophisticated training and skills, implementing the estimated model(s) in spreadsheet-based decision support systems is fairly easy. Hence, DCA is very useful for practicing managers and is used here to explore customer preferences for e-financial services.

Research Design

The first stage in the design of our DCA study involved identification of relevant e-financial service attributes and their levels. As recommended by Verma, Thompson, and Louviere, we collected in-depth qualitative data from high-level executives in the e-financial service industry and requested them to suggest online service attributes and levels that reflected our conceptual variables.[23] Based on the executives' responses, a review of existing service offerings, an assessment of possible new features, and a review of academic and practitioner literature, we selected market drivers and their extensions and also designed a framework that covered all the core market driver issues in an easily to understandable language. This framework was then presented to two other industry executives and also to the initial four executives, all of whom refined the original list of attributes and levels. Finally, we showed the resultant list of attributes to two business school professors, both of whom were blind to the purpose of the study and asked them to verify our classification. The inter-rater reliability was very close to 100% and subsequent discussions resolved any differences. Such a procedure for selecting determinant attributes and levels within DCA is necessary to avoid missing potentially important attributes and also to restrict the experimental factors from expanding to a large number.[24]

Table 1 lists the final set of attributes, their levels, and their classification mapped on to various conceptual variables of interest. (Note that we have listed the attributes and their levels in general terms because of the confidentiality agreement we had to sign with the organization that sponsored the data collection efforts. This practice is quite common in empirical research involving high data collection costs.)

In all, the attributes of e-financial services selected for the experimental DCA can be classified in four broad categories: Price Per Transaction, Traditional Services, Online Services, Brick-and-Mortar Retail Backup, and Marketing Promotions. *Price Per Transaction* was varied at four levels representing the lowest to the highest levels observed within the marketplace. Within the *Traditional Services* construct, each represented by two levels (no and yes), three variables were selected (availability of in-depth research and analysis at no additional cost; option of account management by a professional staff for an additional fee; and access to unique financial products earlier than the open market introduction). The *Online-Only Services* construct was represented by three variables that can only be offered via the online medium (availability of real-time product information Anytime, Anywhere; availability of real-time customized account status; access to advanced online analysis tools for better decision making). The *Access to Brick-and-Mortar* construct was manipulated by including an attribute that allowed accessibility to local branch sales offices. *Marketing Promotions* were manipulated by two attributes (ability to register online and transact immedi-

TABLE 1. List of Constructs, Attributes, and Levels

Constructs	Attributes	Levels
Price	Price per Transaction	Level 1: Low Level 2: Medium Level 3: Medium High Level 4: High
Traditional Services	Availability of In-Depth Research and Analysis at No Additional Cost	Level 1: No Level 2: Yes
	Option of Account Management by a Professional Staff for an Additional Fee	Level 1: No Level 2: Yes
	Access to Unique New Products Earlier than the Open Market	Level 1: No Level 2: Yes
Online-Only Services	Availability of Real-Time Product Information Anytime, Anywhere	Level 1: No Level 2: Yes
	Availability of Real-Time Customized Account Status	Level 1: No Level 2: Yes
	Access to Advanced Analysis Tools for Better Decision Making	Level 1: No Level 2: Yes
Brick-and-Mortar Backup	Access to Local Branches	Level 1: No Level 2: Yes
Marketing Promotions	Ability to Apply and Start Using the Account Online Within Minutes	Level 1: No Level 2: Yes
	Special Offer for New Customers	Level 1: 25 Free Transactions Level 2: $100 Credit

The descriptions of the attributes are disguised from the actual empirical study because the author(s) had to sign a confidentiality agreement with a sponsoring organization. However, the general nature of the attributes as presented above accurately describes the nature of the study.

ately; and a special offer for new customers varied at two levels: 25 free transactions in a given time period or $100 credit to open an account).

Next, we used a fractional factorial design that simultaneously created both the e-financial service profiles as well as the choice sets into which to place them.[25] We created 16 orthogonal fractional factorial profiles that allowed us to reliably estimate all the main effects of the attributes included. To enhance the realism of the task, a full-profile approach was used in presenting the choice sets, i.e., each profile shown to the respondents simultaneously described some combination of all the attributes.[26] In order to generate the discrete choice sets, we used a "foldover" design approach suggested by Louviere.[27] A foldover design contains the opposite levels of every attribute for a given profile and therefore presents two completely orthogonal profiles to respondents in each choice set. This experimental design procedure has been used and recommended by other DCA studies focused on service applications.[28]

We pre-tested the e-financial services choice task with 50 randomly selected customers to ensure ease and comprehension of the task, as well as to ensure reliable data collection methods. Average task completion time was approximately 10 minutes and respondents did not indicate difficulty in task

TABLE 2. A Sample E-Financial Service Choice Set

Attribute (Market Drivers)	Service A	Service B
Price per Transaction (presented in actual $ amount to respondents)	High	Medium
Availability of In-Depth Research and Analysis at No Additional Cost	No	Yes
Option of Account Management by a Professional Staff for Additional Fee	Yes	No
Access to Unique New Products Earlier than the Open Market	Yes	No
Availability of Real-Time Product Information Anytime, Anywhere	No	Yes
Availability of Real-Time Customized Account Status	No	Yes
Access to Advanced Analysis Tools for Better Decision Making	No	Yes
Access to Local Branches	Yes	No
Ability to Apply and Start Using the Account Online Within Minutes	No	Yes
Special Offer for New Customers	$100 credit	25 Free Transactions
I will choose to use this e-financial service →	Service A	Service B
	Neither	

comprehension. A sample choice set is presented in Table 2. In addition to the e-service choice tasks, the survey instrument included general demographic questions (e.g., age, gender, education, and marital status). We also asked the respondents to state the number of times they used any e-financial service for purchase transactions during the preceding year. The purchase frequency can be used as a measure of product familiarity as described by Alba and Hutchinson.[29] In addition, we also asked the customers to rate their individual involvement in the purchasing decision on a 6-point scale. The purpose of including this question was to only select the respondents with a high degree of involvement with the e-financial service. Only those respondents that indicated a high degree of involvement with the purchase decision, i.e., answered 4 or higher on a 6-point scale, were included in our analysis. By including only involved customers in our study, we simulated a reasonable decision made by firms to initially target involved and motivated customers when introducing a new e-service.

Data Collection

Those who made up the panel of respondents were active customers in the e-financial services industry and were a demographically balanced group obtained through a well-known marketing research firm. Customer panels are an appropriate sampling frame and have a rich history of business applications.[30] Also, given the lack of choice of sampling frames in studying online behavior, our decision to use a purchased list for our customer panel is consistent with the current state-of-the-art in the field.[31]

During the data collection phase, each respondent received an e-mail from the research team with an invitation to join the research project. In addition to reimbursement from the marketing research firm for panel participation, each respondent's name was entered in a raffle for winning attractive prizes. After logging into a secure web site, each respondent was given a unique identification code and then was able to read a common core concept of e-financial service as used in this study. The respondent was also informed that some aspects of the e-financial service space would be held constant across all choice sets for all respondents (e.g., the physical design of a brick-and-mortar retail backup outlet). The features that were held constant included web site reliability, on-site support, privacy, security, breadth of product assortment, information quality, and web site usability. After reading the core concept, each respondent was asked to respond to 16 experimentally generated e-service choice sets similar to the one shown in Table 2. The respondents were asked to choose one of the two presented e-service concepts, or indicate that they refused to choose either. Similar to the pre-test, average task completion time was approximately 10 minutes.

Of the 10,000 potential respondents, less than 2% chose not to participate in the study. Thus, gross non-response bias is not a factor in our study. As discussed, we also screened respondents based on their response to a purchase involvement question (the extent to which they were involved in the purchase decision). After screening for involvement, our sample size was 2209, leading to a qualified response rate of 22%. The characteristics of the sample are in conformance with published studies on online behavior that demonstrate similar sample statistics.[32]

The final sample contained around 29% respondents ranging from 18 to 34 years, 53% were from 35 to 54 years, and the remaining were 55 years or older. They were 66% male and 57% married. Around 41% of the respondents either had a high school degree or at least some college, and 41% respondents had a post-graduate degree. There was quite a bit of variability in terms of annual household income and financial assets invested—around 10% respondents earned over $150,000; 36% respondents earned between $100,000 and $150,000; 22% respondents earned between $50,000 and $100,000, and around 18% respondents earned less than $50,000. The amount of assets invested in financial markets varied from less than $30,000 to over $250,000, with a wide range of variability.

Analysis

The primary analytic approach associated with DCA is the estimation of the multinomial logit (MNL) models based on a maximum likelihood estimation technique.[33] We first developed the aggregate MNL model followed by segment level MNL models based on the three specific characteristics described by hypotheses 2a, 2b, and 2c. In addition, we conducted a chi-square test developed by Swait and Louviere to assess the statistical similarities and differences across the various estimated MNL models.[34] Statistical details about MNL model estimation is described in extensive detail by Ben-Akiva and Lerman and by

Louviere, Hensher, and Swait.[35] A more applied description of DCA and MNL model estimation is provided in Verma, Thompson, and Louviere; Verma, Plaschka, and Louviere; and Verma and Plaschka.[36]

Louviere, Hensher, and Swait along with Ben-Akiva and Lerman recommend that when estimating MNL models, experimental variables can be "effects-coded" to accurately estimate the relative impact on respondents' choices.[37] So for each of the variables listed in Table 1, the first level (no or not available) was coded –1 and the second level (yes or available) was coded as +1. Since price was varied at four levels, it contains three degrees of freedom and 3 variables were necessary. The highest level (or most undesirable price) was coded as –1. Each of the other three price variables was coded +1 once. Thus the estimated parameters for the three price variables show the relative impact of changing price from the highest to one of the lower levels.

Aggregate Results

The estimated online financial brokerage services choice model for all respondents (aggregate model) is summarized in Table 3. It shows parameters (part-worth utilities) for each variable included in the experimental design along with the intercept. A positive β-value for an attribute means that the probability of selection of an online financial brokerage service will increase if this particular attribute in changed from –1 to +1 level. As suggested by Louviere, Hensher, and Swait, we have calculated the relative utilities of both levels of each online brokerage feature and for all four levels of price.[38] For each attribute, the relative utility for the lowest level is simply –1 * β-value. Since price is represented by three variables, the relative utility of the fourth level will be the negative of the sum of the other three β-values. The relative utilities presented in Table 3 clearly show that the probability of choice of an online brokerage service increases when the availability of variables is changed from "no" to "yes" or if price is reduced. The table also shows McFadden ρ^2 and Adjusted ρ^2 (similar to R^2 in ordinary least square regression), which are aggregate measures of statistical fit of MNL models. Unless specified within the tables, all estimated parameters are statistically significant at the 5% level.

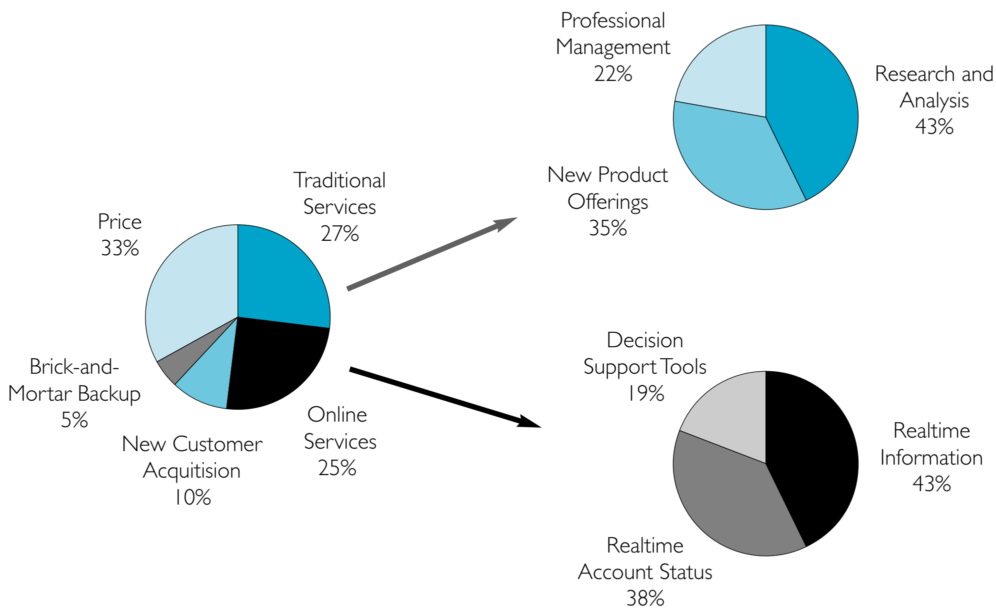
To illustrate the relative impact of each attribute and corresponding theoretical constructs, we calculated the main effects of each attribute. For each two-level attribute, the main effect is calculated as equal to the beta-value; for the four-level attribute (price), the main effect is equal to sum of the three beta-values.[39] The estimated main effects are shown in Table 3 and their relative values are plotted in Figure 1 (In addition to showing the relative main effect of each construct, Figure 1 also shows the relative weights for each of the three attributes included within the Online Services and Traditional Services constructs). We have shown the estimates at the attribute level and also at the construct level. The main effect of price is highest, but main effects of both online-only and traditional services are almost equal and quite close to the effect of price. This means that some combination of the two types of services might

TABLE 3. Estimated E-Financial Services Choice Model for All Respondents

Constructs	Variables	MNL Model		Main Effects of Each Variable	Main Effects of Each Construct
Price	Price1 (Low)	0.7277		0.6435	**0.6435**
	Price2 (Medium)	0.2827			
	Price3 (High)	–0.3669			
	Price4 (Very High)		*–0.6435*		
Traditional Services	Research and Analysis (Yes)	0.2271		0.2271	**0.5338**
	Research and Analysis (No)		*–0.2271*		
	Professional Management (Yes)	0.1180		0.1180	
	Professional Management (No)		*–0.1180*		
	New Product Offerings (Yes)	0.1887		0.1887	
	New Product Offerings (No)		*–0.1887*		
Online-Only Services	Realtime Information (Yes)	0.2189		0.2189	**0.5049**
	Realtime Information (No)		*–0.2189*		
	Decision Support Tools (Yes)	0.0950		0.0950	
	Decision Support Tools (No)		*–0.0950*		
Brick-and-Mortar Backup	Local Branches (Yes)	0.0961		0.0961	**0.0961**
	Local Branches (No)		*–0.0961*		
Promotions for New Customer Acquisition	Apply and Trade Instantaneously (Yes)	0.1639		0.1639	**0.2023**
	Apply and Trade Instantaneously (No)		*–0.1639*		
	Marketing Promotion (Yes)	0.0383		0.0383	
	Marketing Promotion (No)		*–0.0383*		
	Intercept	–0.6019			
	McFadden's Rho Square		0.9644		
	Rho-Square—Adjusted		0.9614		

be sufficient to overcome any price barriers. It is very interesting to note that the effect of brick-and-mortar backup facilities is one of the lowest among all the attributes considered. Among the top-five most important attributes, two are within the online-only construct (Real-Time Information; Real-Time Account Status), two are within the traditional services construct (New Product Offerings; Research and Analysis), and one is within the new customer acquisition (Apply and Trade Instantaneously) construct. These results show the multi-dimensionality in the choices of online financial brokerage services. It is not sufficient to offer price incentives and/or only online services. Such efforts need to be supplemented by other features (e.g., traditional services) to effectively attract customers.

FIGURE 1. Relative Main Effects of E-Financial Services Attributes



Intercepts in MNL models measure the impact of all unobserved attributes and they therefore provide an assessment of switching inertia. A positive value of the intercept means that the respondents choose one of the two online financial brokerage services more often than choosing "neither." Similarly, a negative intercept means that "neither" was chosen more often than the two other alternatives. Therefore, the intercept is an appropriate measure of "inertia" in the choice of an online financial brokerage service. In Table 3, we notice that the intercept for the aggregate MNL model is –0.6019. In other words, the respondents choose "neither" more often than the two alternatives of online financial brokerage services offered to them.

Segmentation Results

We used two different sets of segmentation approaches: three segmentation criteria based on demographics; and three different segmentation criteria based on actual usage of e-financial services. Within the demographics-based segmentation approaches, we developed models based on gender, education, and age. Within the usage of e-financial services segmentation, we developed models based on usage frequency, amount of assets invested, and type of brokerage service used.

When segmenting customers based on usage frequency, we used the criteria established by the majority of the online financial services companies. The four segments based on usage frequency include offline users and low-, medium-, and high-frequency users. The offline customers are those who do not yet use the online medium for financial brokerage services. Similarly, we segmented customers into four groups based on financial industry norms: low, medium, high, and very high assets, based on the amount of assets they had invested in the financial brokerage industry. The third criterion for segmentation was the type of financial brokerage accounts the customers currently used. Based on their self-reported information, we segmented customers into four groups: two segments for customers of the two largest traditional full-service financial brokerage companies (one high-end full service firm and one relatively lower-end full service firm); one segment for a traditional discount brokerage company; and one segment for customers of an online-only brokerage company.

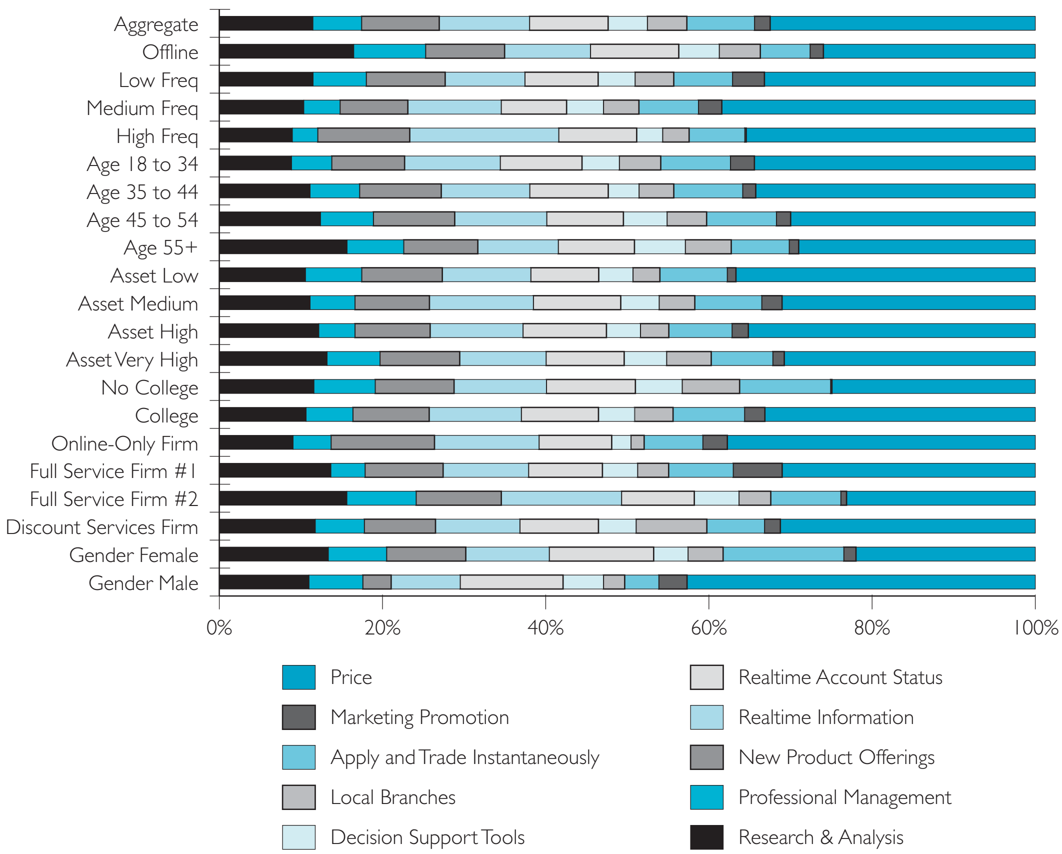
To test the similarities and differences between the estimated MNL models for various segments we ran a chi-square test developed by Swait and Louviere.[40] This procedure first "scales" the random variance of the two models being compared and then tests if the estimated MNL models are statistically equivalent. As suggested by Swait and Louviere, within each segmentation approach, one of the MNL models was fixed as the "baseline" and the other models were compared to it. All comparisons within each of the six segmentation approaches showed that the segment-level MNL models are statistically different from each other at the 5% level.

Relative main effects of all attributes for the aggregate and segment level models are presented in Figure 2. Each horizontal bar in Figure 2 is scaled to 100% so that the reader can easily compare the relative weights of e-financial attributes across various segments. It can be clearly seen that relative main effects of attributes are quite different across segments. For example, Figure 2 clearly demonstrates that the relative weight for price varies considerably across segments. Segments based on medium-usage rate, low invested assets, customers of an online-only financial service company, and male customers appear to be the most price-sensitive (they have relatively higher utilities for price). Similarly, the relative impact of research and analysis varies considerably across the segments.

To explore customers' reluctance to switch (inertia) in e-financial services further, we compared the intercepts for the MNL models estimated by each of the six segmentation approaches. Figure 3 summarizes the results and shows that inertia reduces as e-financial services usage frequency increases. The inertia increases as the amount of assets invested in the financial market increases. In addition, the users of "full service" financial services firms are less likely to switch compared to the uses of "discount" or "low-cost" online-only e-financial services firms. Figure 3 also shows differences in inertia for the three demographics-based criteria: inertia increases with age; females have higher inertia than males; and more educated customers have lower inertia than less-educated customers.

Figures 4 and 5 show price sensitivities for each of the six segmentation schemes. Price sensitivities increase with usage frequency and the customers of

FIGURE 2. Relative Main Effects of Attributes in Various Segments

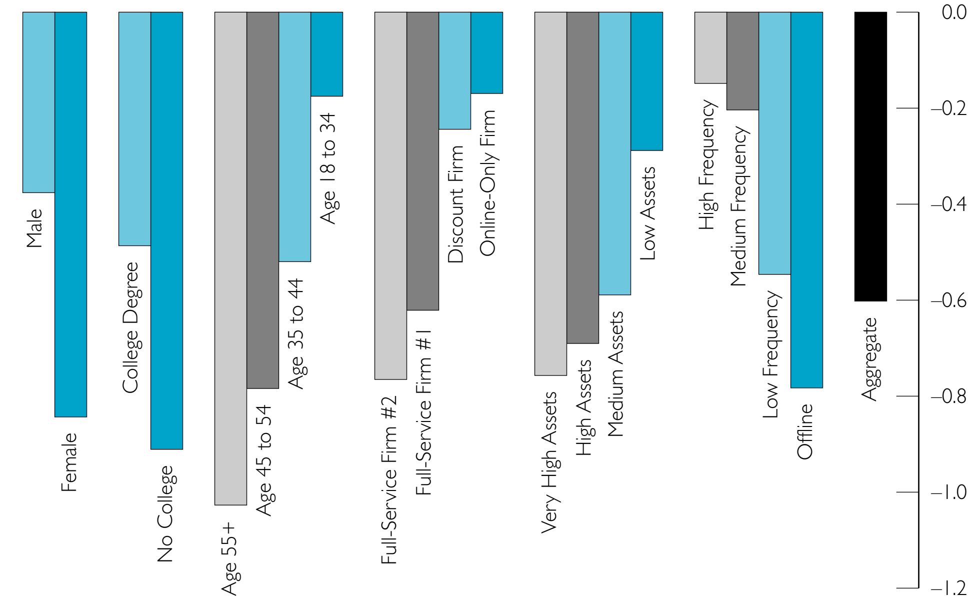


full-service financial services firms are less price-sensitive than those of online-only and discount services firms. On the other hand, the amount of invested assets does not seem affect price sensitivity. Within the demographics-based segments, price sensitivity is higher for younger customers, males, and less-educated customers.

Figure 6 shows how the relative utility of the three online-only services (Real-Time Information, Real-Time Account Status, DSS Tools) varies for various market segments. The importance of real-time information increases with usage frequency, increases for discount services firm, and increases for female customers. The relative importance of real-time account status and DSS tools stay relatively constant for all segments.

The relative importance of traditional services (Research and Analysis, Professional Management, New Product Offerings) is presented in Figure 7. The importance of research and analysis reduces with an increase in usage frequency; increases slightly with an increase in assets; increases for full-service

FIGURE 3. Switching Inertia



firms compared to discount firms; increases for older customers; is higher for female customers; and is not affected by customers' education level. Importance of new product offerings is significantly higher for female customers compared to male customers; significantly higher for online financial services firm compared to other companies; and almost similar for all other segments. The importance of professional management reduces with an increase in usage frequency; increases for older customers; and for all other segments a somewhat non-linear trend is observed.

Figure 8 shows the relative impact of marketing promotions and brick-and-mortar back-up facilities. Generally speaking, the importance of local branches and marketing promotions is quite low for most of the segments. "Apply and trade instantaneously" is desired much more than then the other two features, especially for female customers.

Discussion and Conclusions

Our study set out to explore the choices that customers make when evaluating online financial services offering. The results provide several key managerial insights for competing in this market.

- *Switching Inertia*—Each segment has a significant switching barrier, i.e., customers in all segments need to be offered some substantial value to persuade them to consider a new alternative. On the other hand, it is

FIGURE 4. Price Sensitivities for Usage-Based Segmentation Schemes

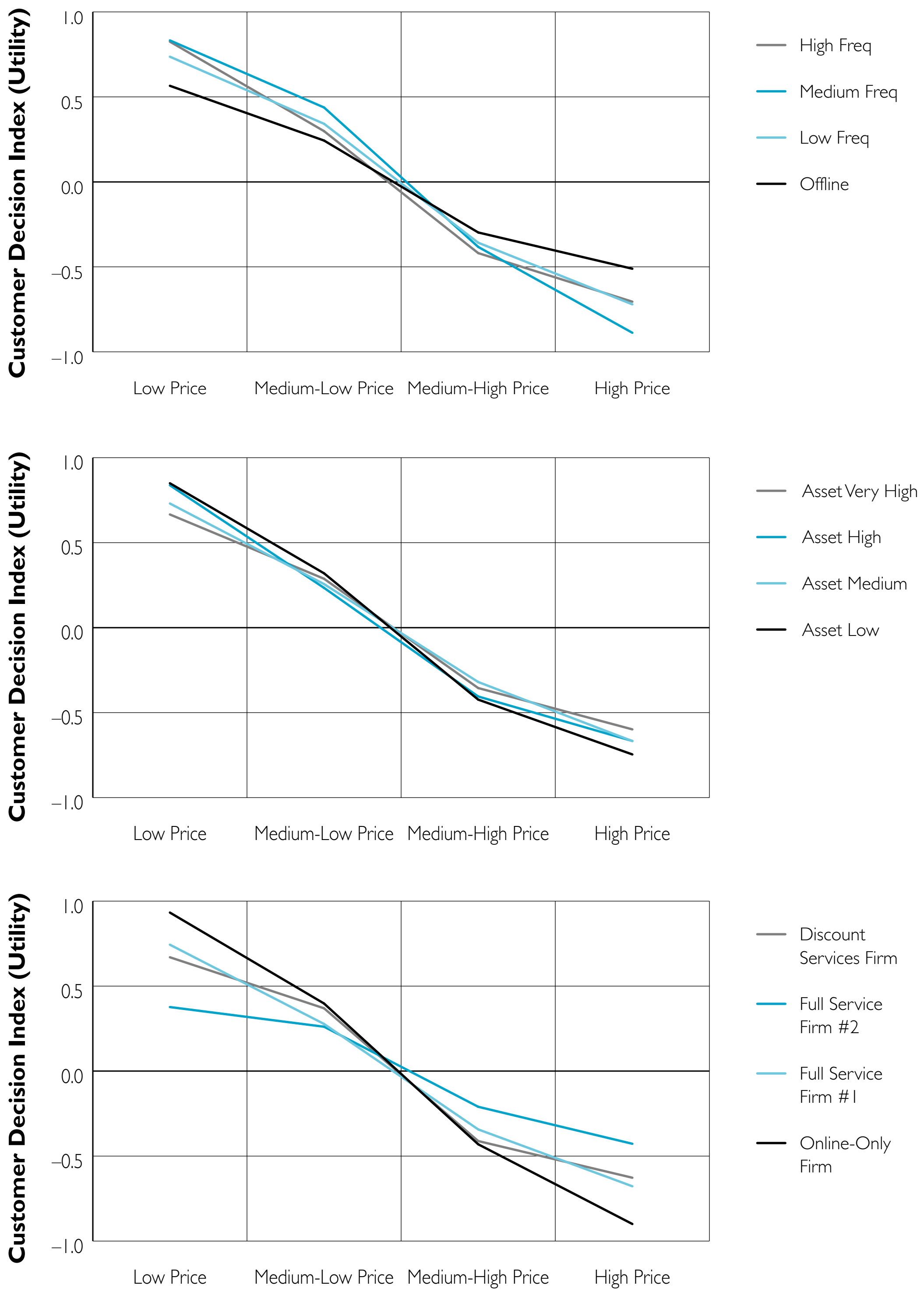


FIGURE 5. Price Sensitivities Based on Demographics-Based Segmentation Schemes

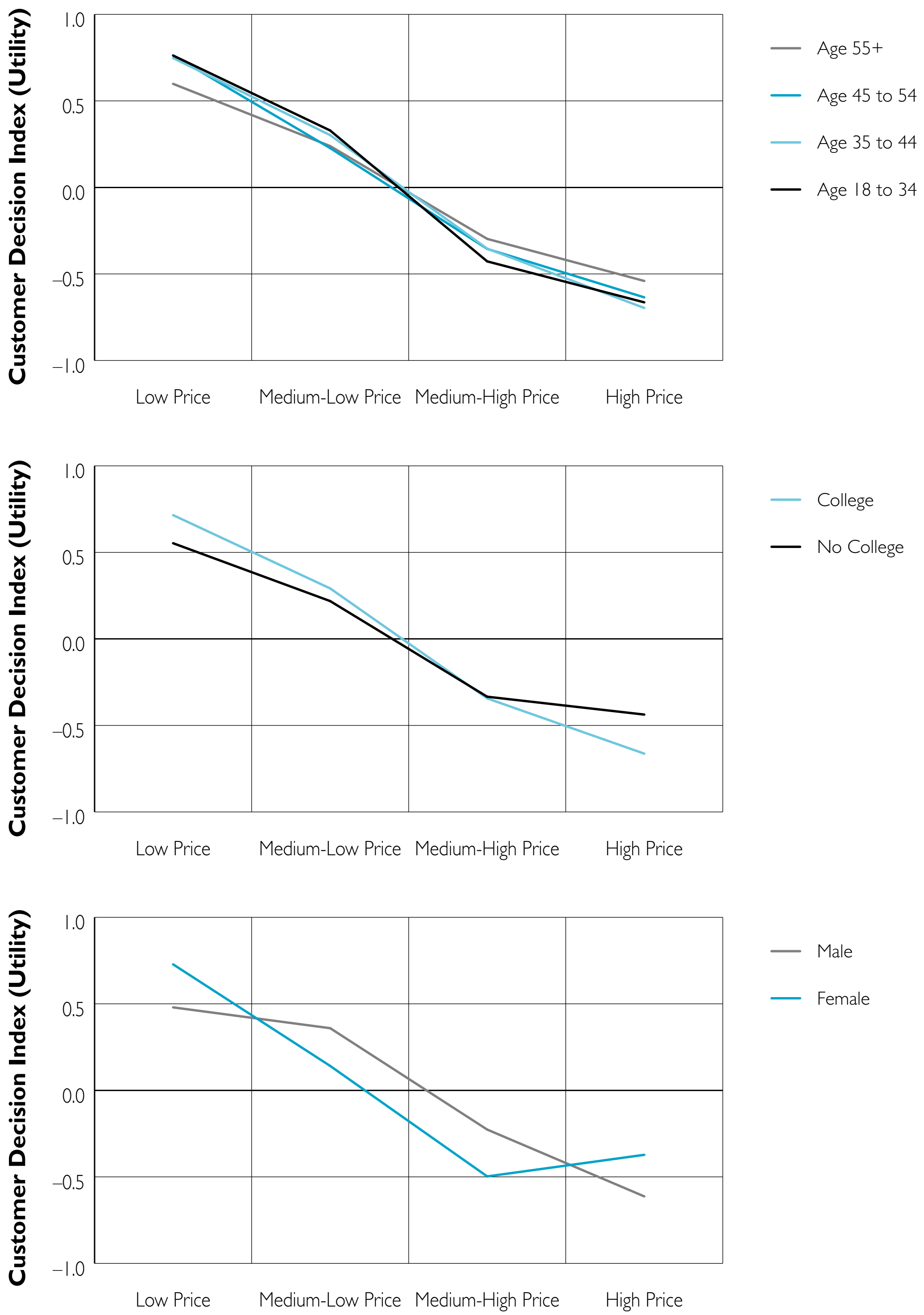


FIGURE 6. Relative Importance of Online-Only Service Features

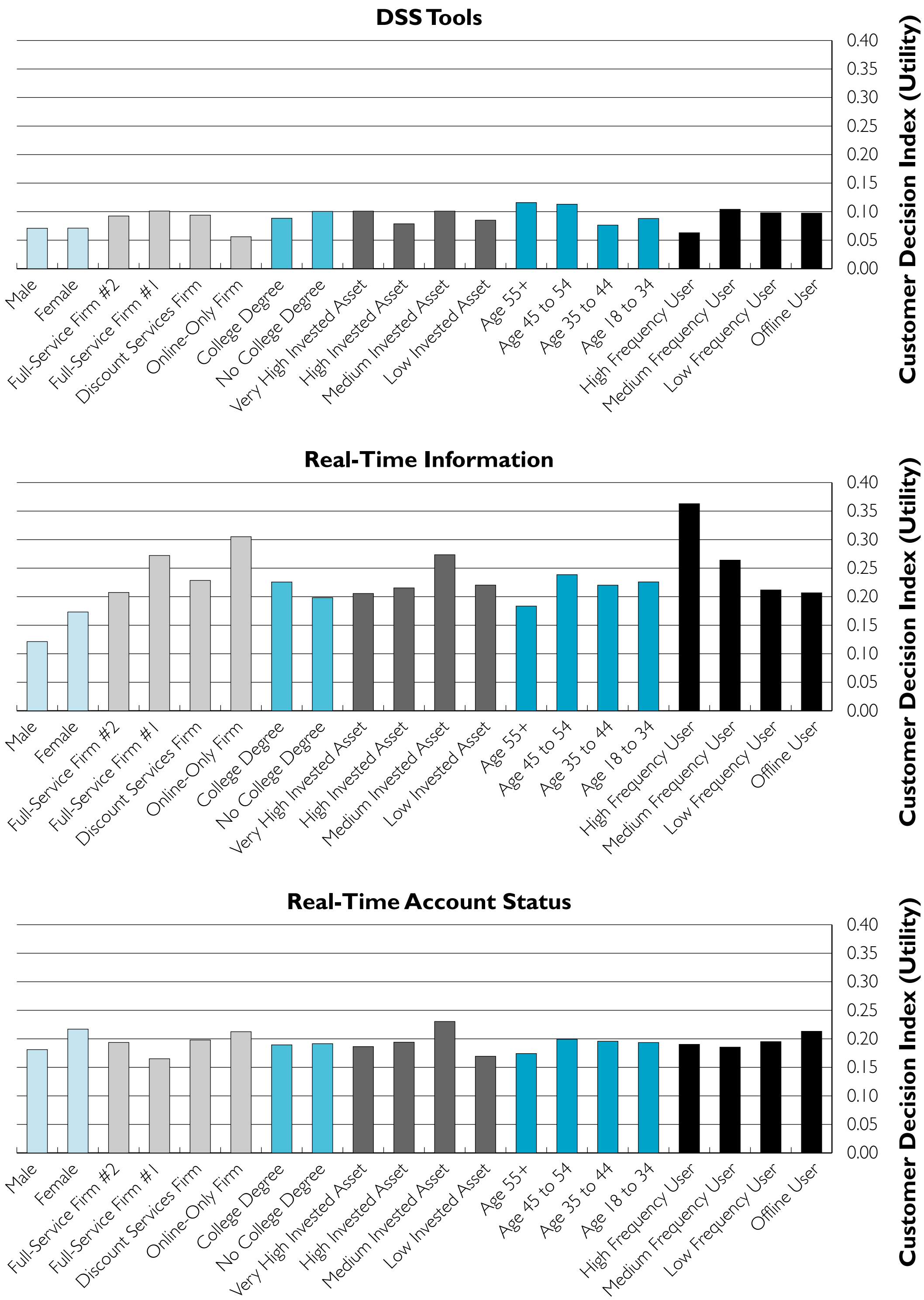


FIGURE 7. Relative Importance of Traditional Service Features

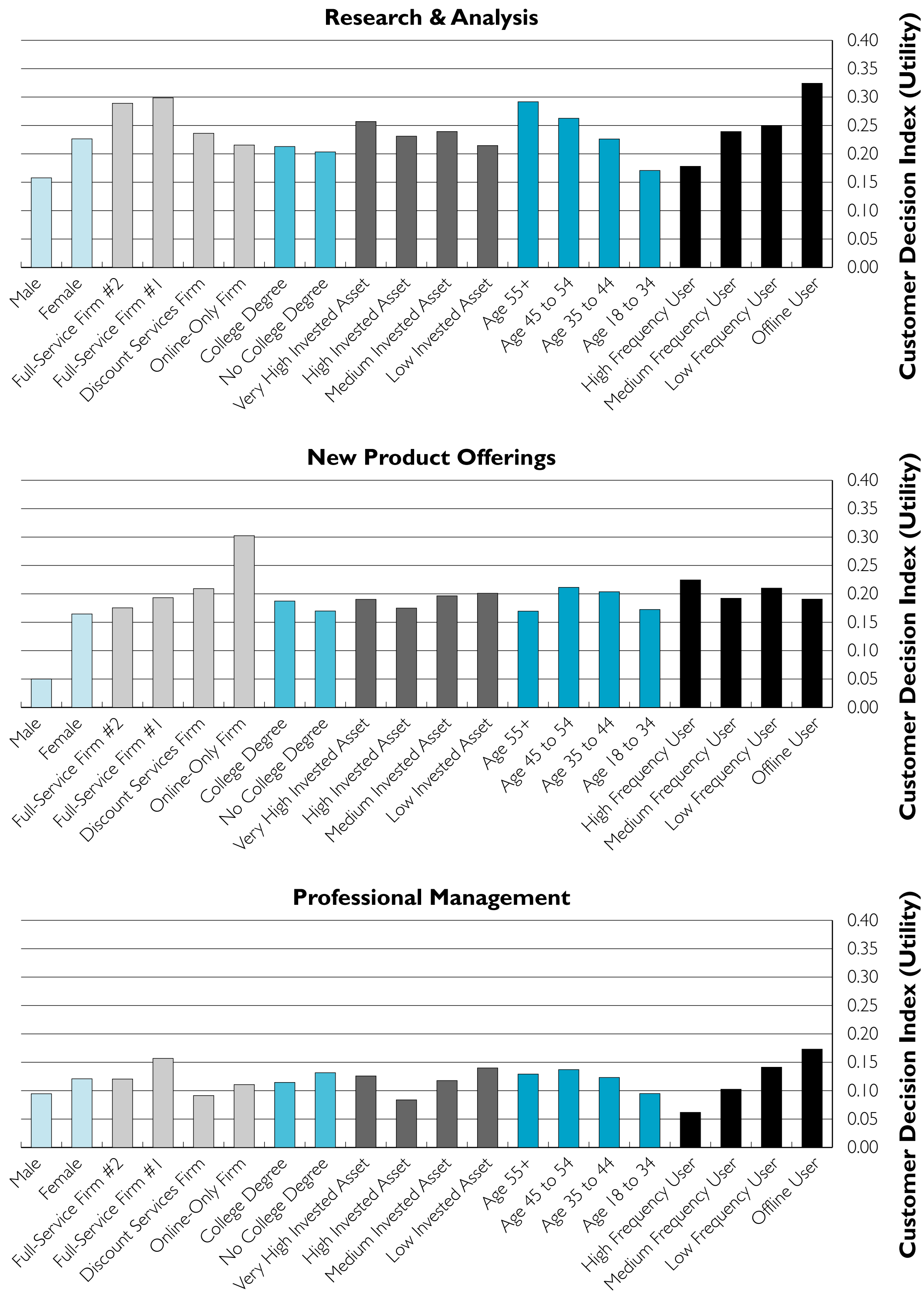
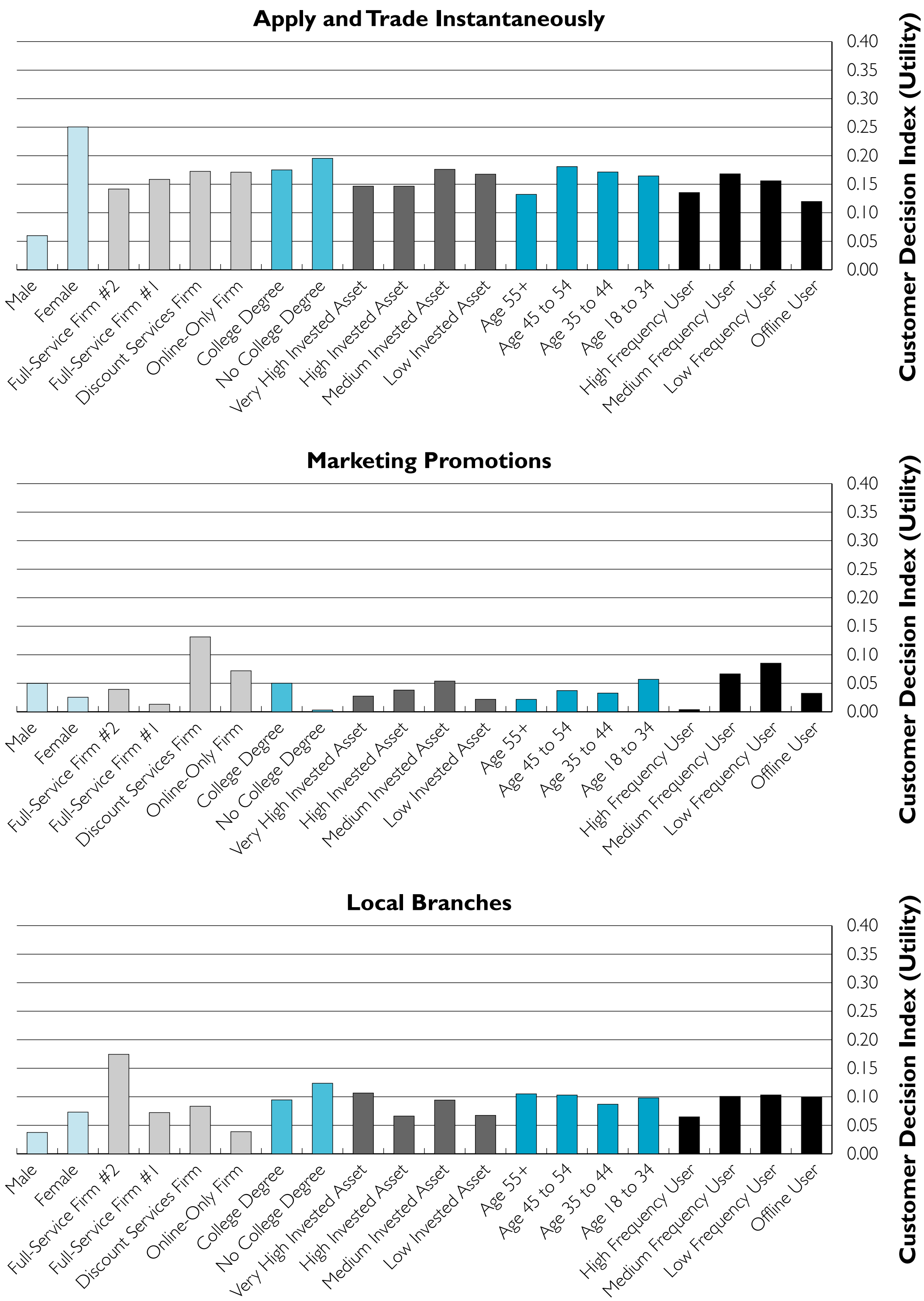


FIGURE 8. Relative Importance of Marketing Promotions and Brick & Mortar Backup Facilities



noteworthy to mention that in the online financial services industry, for any customer segment, a pair-wise combination of price per transaction, availability of traditional features, and availability of online-only features is sufficient to overcome the segment's switching barrier. This result is of vital interest to those firms that wish to enter and compete in the online financial services industry. For example, Charles Schwab has effectively combined traditional and online features, whereas Ameritrade seems to be occupying a position that combines online features and price per transaction.[41] Of course, Charles Schwab must have substantially higher operating costs given the hybrid "brick-and-click" offering. Both of these positions can be only sustained if there is a sufficient customer base attracted to either offering and customers intrinsically adapt this value in their decision process. We also noted the existence of different levels of switching inertia within each segment. This allows managers to target online financial services to the most strategically appropriate customers in order to optimize their ROI/ROE. For example, managers will be better served by targeting customers with higher levels of transaction frequency and lower levels of assets invested who are also customers of traditional discount brokerage firms. This is because these customers have a higher likelihood of adopting new online financial services (low switching barrier) and hence are more appropriate prospects.

- *Traditional Customer Segmentation Approaches and Patterns Currently Used by the Financial Services Industry*—Our results indicate that of the three usage-based segmentation variables, only two (usage frequency; type of financial services firm) deliver a meaningful outcome to managers when developing online financial services. Using transaction (usage) frequency as a segmentation variable allows managers to see that the value of traditional features declines with increasing frequency and that the value of online-only features increases with increasing transaction frequency. Similarly, when managers use "type of brokerage currently used by customers" as a segmentation variable, patterns of preferences differ between online customers and customers using high-end traditional brokerages. Furthermore, this variable is not very useful for understanding the preferences of customers in traditional discount brokerages and low-end full service brokerages. Finally, it is very interesting to find that one of the most commonly used variables for segmentation in the financial services industry—namely, the amount of invested assets—does not have significant discriminating power when explaining customers' value structures for an online financial service. Hence, managers are advised to continue using transaction frequency and type of brokerage used as segmentation variables, and they are further advised to reevaluate using the amount of invested assets for understanding customer preferences for online financial services. Within the three demographics-based segmentation approaches considered, gender and age appear to be significant discriminating factors. Customers' education, on the other hand, does not show significant differences within the segments.

- *Price Per Transaction Matters*—This feature created a very high customer value proposition across all models and segments analyzed. In other words, price per transaction was the single most important feature driving customer choice in all of the segmentation variables that we used. In the online financial services industry, customers are increasingly making service provider decisions based on price per transaction.[42] This confirms previous beliefs that competing on the web in the financial services industry involves price competition; perhaps the worst issue a manager can face in an "almost perfect market." However, this insight needs to be explored further, perhaps in the context of consumer choice theory that links the increase in price information availability on price sensitivity.[43] The online medium does offer the ability to provide increased amounts of pricing information and also allows for ease of price comparisons. On the other hand, information economics theory predicts that lower the search costs for a feature (not only price), the more likely that the feature will be used.[44] Hence, our findings need to be expanded to other industries using hypotheses developed by using an information economics framework in order to understand the various customer value structure maps within the e-commerce space.
- *"Traditional/Classic" Features Still Do Matter*—In all the models that we estimated, online service choice was influenced by the presence of traditional features such as availability of research and analysis, management of a customer account by professionals, and availability of new financial products before the open market. In quite a few segments, availability of multiple traditional features was sufficient to overcome the importance of price per transaction—at almost all levels of pricing—in explaining online service choice. This result strongly supports offerings of pure-offline players by providing only traditional features, which are valued by customers especially because the presence of these features overcomes the importance of price per transaction. Nevertheless, in order to compete in the online services arena, firms have to build from their traditional feature set and, in addition, strengthen their online-only feature offerings. This is also supported by loss aversion theory.[45] Consumers are loath to give up benefits they already have in order to gain uncertain new benefits. Moreover, consumers are more sensitive to losses than they are to gains. In effect, firms will have to offer disproportionately more value in online benefits to persuade consumers to forgo the same amount of offline benefits.
- *Online-Only Features Are Very Important and Can Become Key Drivers*—The availability of real-time information, real-time account status, and online decision tools provides customers in all our segments with value. In some segments, similar to the importance attached to traditional features, the availability of multiple new online-only features is able to overcome the importance of price per transaction, at almost all pricing levels. Clearly being online and being able to transact online adds value for customers in

all segments. This insight can be linked to the "von Restorff effects" that predict that consumers are attracted to new features and that novel information captures attention and enhances recall at the expense of other information.[46] This suggests that new attributes of a service may also benefit from such a bias so long as they are perceived as being "novel." While this seems to contradict the previous effect, both effects occur and their resolution in the online services context is a matter for further empirical analysis.

- *A Combination of Traditional and Online Features*—In order to overcome the importance customers in all segments assign to price per transaction, firms can also provide a judicious combination of traditional and online features. If firms are able to provide this combination, they do not have to necessarily compete on price per transaction. A customer is willing to pay more per transaction for an online service that combines offline value with online benefits. This result is significant for currently offline-only firms that are thinking of going online but are worried about price competition. Similarly, this result is also significant for online-only firms that are thinking of adding an offline financial advising service or professionally managed accounts. This is strongly supported by the literature that demonstrates that increasing information about product quality decreases the importance attached to price.[47] Providing information about the level of features in an online service enables consumers to overcome their preference for only price per transaction.
- *The Design of E-Financial Services*—Our study permits us to infer what features need to be emphasized in order to effectively design e-services. The MNL model calibrated with the actual market shares of competitors can be used to assess many "what-if" scenarios in a decision support system. The information collected in the form of MNL choice models can be used to predict the expected market shares of each competitor within a given market. In other words, the part-worth utilities for each attribute (Table 3) allow one to calculate the utility of each competitor, and hence their expected market shares. When integrated into a customer-relationship-management and customer-specific-transaction database, it becomes an even more powerful part of a manager's tool box.

In order to develop an implementation strategy, the estimated MNL models should be calibrated to actual market conditions. This means that we should assess the relative value of any missing attributes in the estimated MNL models by minimizing the error between the estimated and actual market shares of various competitors.

To calibrate the estimated MNL model to the actual competitive environment, we used published information from Gomez, a highly regarded research firm which conducts large-scale national quarterly customer surveys.[48] They ask the respondents to name their primary providers of various products/services including e-financial services., Gomez assesses the current market share of major competitors in various industries based on responses from customers cross-vali-

TABLE 4. E-Financial Services Implementation Guidelines: An Example

Competitors*	C1	C2	C3	C4	C5	C6	C7	C8
Base Market Share	13.99%	27.98%	17.35%	8.13%	7.05%	2.49%	6.72%	16.27%
Calibrated Market Share (based on purchase frequency based MNL Models optimized be assessing the value of missing attributes)	14.00%	27.99%	17.37%	8.13%	7.17%	2.57%	6.72%	16.13%
Availability of Real-Time Product Information Anytime, Anywhere	1	2	2	1	1	1	2	1
Availability of Real-Time Customized Account Status	2	2	2	1	2	1	1	1
Option of Account Management by a Professional Staff for an Additional Fee	2	1	2	2	2	2	1	1
Availability of In-Depth Research and Analysis at No Additional Cost	1	1	1	1	2	2	1	1
Access to Unique New Products Earlier than the Open Market	2	2	2	2	2	2	1	1
Access to Advanced Analysis Tools for Better Decision Making	2	1	2	1	1	1	1	1
Access to Local Branches	2	1	2	2	2	2	1	1
Ability to Apply and Start Using the Account Online Within Minutes	1	2	1	1	1	1	1	2
Special Offer for New Customers	1	2	1	2	2	2	2	2
Price	4	2	4	1	4	4	1	1
Calibration Factor (combined effects of unobserved attributes such as brand image, equity, and perceived quality)	1.18	0.15	0.45	–0.69	0.05	–0.58	–0.69	0.14

*Actual names of the companies are disguised to protect the confidentially of the organizations.

dated through various other sources (e.g., click stream data). The estimated relative market shares for the largest e-financial services companies are included in Table 4.

Based on published sources and by talking to executives in e-financial services firms we were able to obtain the levels of various attributes for the major competitors. For example, company C1 charges the highest prices but offers: real-time customized account status, account management by a professional staff for an additional fee, access to unique new products earlier than the open market, access to advanced analysis tools for better decision making, and also has branches. On the other hand, C8 offers lowest prices in the marketplace and gives the user an ability to apply online and start using the services instantaneously.

Using MNL model equations[49] along with the actual attribute levels of competitors, we estimated the un-calibrated market shares for each company.[50] Next, we set-up an optimization model in Microsoft Excel Solver minimizing the error between the two estimated market share values (absolute difference between Gomez predicted market share and MNL models predicted market shares) by varying the weights for unobserved attributes for each company. The estimated weights of unobserved attributes for each company along with the calibrated market shares are also included in Table 4.

The calibrated model (Table 4) can be used to assess market impact of any proposed service enhancement and/or strategy decisions. For example, everything else remaining equal, if C8 decides to start offering the availability of real-time product information, then its market share will go up from 16.13 to 13.44 (change the design code from –1 to +1 for real-time product information in market share estimation equation). Similarly, market impact of any simultaneous changes in strategies by multiple competitors can be estimated and evaluated. A number of past studies have shown that, in general, the market share predictions generated from MNL logit models based on discrete choice analysis are relatively accurate.[51]

In conclusion, our study, based on existing consumer choice theory, has provided a series of actionable managerial insights for firms operating in the online financial services industry. The use of theory-based methods before developing and implementing complex and resource-intensive online offerings can help prevent the kinds of losses that occurred during the last Internet boom.

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