School of Economics and Finance

Consumer Preferences for Mobile Phone Service in the U.S.: An Application of Efficient Design on Conjoint Analysis

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Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgment has been made. This thesis contains no material, which has been accepted for the award of any other degree or diploma in any university.

Signature: ………………………………………….

Date: ………………………...

To Bim and Vanessa – the loves of my life

Abstract

The wide commercial success of certain mobile phones, such as Apple's iPhone and RIM's Blackberry, was the motivation behind this study to examine empirically what drives the demand for mobile service bundles. If casual observation is an accurate indicator, consumers make their mobile purchasing decisions based solely on the type of mobile phone that mobile service providers are offering at the time as part of a bundle of services. This, in turn, raises the question of whether service bundle components, other than the mobile phone, matter to consumers. In light of increased competition and saturation in the U.S. mobile sector, gaining a deeper understanding of consumer choice is critical not only for the development of effective market strategies but also for policymaking. As governmental agencies take a closer look at competition and the need or lack thereof of regulation in the mobile sector, it is crucial to understand how consumers purchase mobile service as this may very well form the basis of new regulations and public policies. Surprisingly, although there is a large literature addressing various aspects of mobile demand, no prior study has examined this topic from a mobile service bundle perspective.

The present study uses data from an online stated-preference survey with a conjoint analysis component. The design for the conjoint analyses incorporates efficient survey design, which promises most accurate parameter estimates. It is the first application of efficient survey design theory to telecommunication services. It is also one of the first practical applications of this innovative concept. In these trade-off exercises, 503 survey respondents ranked three mobile service plan alternatives, each described via 10 service attributes. Survey respondents completed six such exercises. A thorough quality review of the survey results revealed 14 invalid survey responses and survey respondent fatigue in the last two choice situations. After eliminating the 14 invalid responses, the resulting data were fit to several versions of the multinomial exploded logit model. Using likelihood ratio indices and hypotheses tests, such as the likelihood-ratio test, the Wald test, and the Hausman test, to determine the best model for this study, the final model selected was a multinomial mixed exploded logit model with 10 lognormal distributed and two fixed parameters. This model provides direct insight into the demand determinants for mobile service bundles. It reveals demand elasticities and calculates the consumers' maximum willingness to pay for specific bundle components.

The fitted model reveals several interesting econometric, competitive, and public policy findings. First, applying D-efficient survey design requires a priori information on the final model's specification and the signs and sizes of its coefficients. Data from a pilot survey fitted to a multinomial logit model generate the necessary a priori proxies. The design matrix is D-optimized relative to this a priori model. Any deviation from the pilot model's specifications and its coefficient priors jeopardizes the optimality of the design matrix. A test was derived to measure whether the optimized design matrix retained its optimality when evaluated under the final model instead of the pilot model. In the present study, the final model specifications and coefficients deviate sufficiently from the a priori proxy to render the optimized design matrix no more or less efficient than a design matrix randomly created. Hence, no benefits from D-optimization carried through to the final model. With perfect foresight, however, D-optimality could have decreased the design matrix's D-error by 83%, thereby significantly increasing the model's accuracy. This practical application of D-efficient survey design illustrates that further research in efficient design needs to address how the benefits from D-optimization can be retained.

In terms of competition, the fitted model explores several competitive strategies, simulating market share gains and losses from changes in attribute levels and calculating demand elasticities for specific bundle components. This analysis reveals that only certain pricing strategies are effective. It also demonstrates that a combinatorial strategy might be most effective. Specifically, decreasing mobile phone prices, increasing term lengths, and increasing the monthly recurring charge increases subscriber revenue in addition to gaining market share.

In terms of public policy, the study finds that regulators must examine market behavior and alleged market failures in terms of service bundles. Considering individual bundle attributes on a standalone basis, which is currently the common practice, yields incorrect results. Finally, the fitted model highlights the importance of making additional radio spectrum available to mobile service providers.

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Christian Dippon

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Introduction and Overview

In the United States, mobile service providers introduced first generation (1G) mobile phone services in the 1980s. High prices, limited network coverage, relatively poor quality of service, and large and heavy mobile phones limited the initial adoption of mobile telephony, which remained a luxury throughout the 1980s and well into the 1990s. In November 1992, *The New York Times* reported, "Cellular phone users are finding that the price of making wireless phone calls has remained high—in some cases, as much as 80 times the price of a conventional call" (as cited in Parker & Röller, 1997, p. 304). The literature on mobile market development seems to confirm that when first introduced mobile telephony was more a status symbol than a commodity (see, e.g., Katz & Sugiyama, 2005; Lemish & Cohen, 2005; Ozcan & Kocak, 2003; Turel, Serenko, & Bontis, 2007).

The introduction of digital mobile telephony,[1] or second generation (2G), fundamentally altered the demand, supply, and overall perception of mobile phone service. This change led to substantial growth in terms of subscribership, usage, and revenue. From a global perspective, the International Telecommunication Union (ITU) reported 4.6 billion mobile cellular subscriptions at the end of 2009 and expected this to reach 5 billion in 2010, whereas the world population in April 2010 was 6.8 billion (ITU, 2010). Specific to the United States, there were 33.8 million subscribers in December 1995 compared to 286.6 million in December 2009 (CTIA, 2010). In many countries, the mobile market is growing at rates comparable to or even higher than in the United States and, at times, has exceeded the 100% penetration level because individual subscribers have more than one subscription to accommodate their multiple mobile devices. For instance, as of March 2010, 72 of 170 countries had mobile penetration rates in excess of 100% (TeleGeography, 2011).

Steep declines in prices paid by subscribers for mobile service plans were responsible, in part, for the rapid growth of the mobile services sector. Facilitating the steep decline in mobile prices has been: (a) dramatic reductions in the costs that mobile service providers incur to provide services, (b) competition among mobile service providers, (c) intermodal competition with alternatives like fixed-line and

[1] Analog and digital cell phones both use the same radio spectrum but in a different way. Digital phones compress voice into a binary format (i.e., ones and zeroes), thus making it possible to send between three to 10 calls using the same space as one analog call.

Internet-based communications providers, (d) procompetitive regulatory change, and (e) rapidly increasing consumer acceptance of the mobility, coverage, and flexibility offered by mobile telephony. In contrast, because of the inroads from mobile and other emerging technologies, fixed-line demand and revenue have been declining, a trend that is likely to continue.

Despite the tremendous growth of mobile telephone services, there is limited knowledge about how consumers select mobile phone service bundles. For instance, although it is a common practice in the United States to offer new subscribers a term contract with a subsidized mobile phone, it is unclear how sensitive consumers are to such offerings: Do consumers prefer the subsidy to the associated term contract if the subsidy exceeds a certain threshold? Similarly, how do consumers react to a change in the monthly recurring charge (MRC)?[2] If a mobile service provider changes the price components of its service plan bundle, how much market share does it stand to lose or gain? It is also unclear how consumers view mobile data services relative to mobile voice services. Could a mobile service provider decrease SMS rates and compensate for this decrease with a decrease in the monthly voice allowance?

The objective of this study is to identify the demand drivers of mobile demand when service elements are bundled and to estimate demand elasticities and the consumers' maximum willingness to pay for specific bundle components. In particular, it considers consumers' choice behavior in an experiment where mobile service plans are comprised of service bundle elements. No prior study has analyzed mobile demand when offered as a service bundle. Attributes associated with each separate element of the plan jointly form the mobile service plan's attributes.

Mobile service plans are complex because they are composed of multipart prices that typically consist of: (a) a one-time upfront fee that includes the price of the mobile phone and a registration fee; (b) a monthly charge that entitles the subscriber to a certain amount of voice minutes; (c) monthly charge options for items like data, SMS, and MMS, as well as family plans; and (d) a usage sensitive portion that comes into play only if the subscriber exceeds the allotment contained in the monthly plan. The monthly charge consists of the charge for voice minutes and charges for any plan options in addition to any overage charges incurred in that particular month. Many plans also require a commitment of a minimum term

[2] The MRC is the monthly price for the mobile service plan.

length—typically 24 months. Service providers frequently charge subscribers who wish to terminate their term contracts an early termination fee (ETF).

This study hypothesizes that consumers consider multiple mobile service plan attributes when selecting a plan. The modeling of this selection process is challenging because it involves the modeling of a nonlinear pricing structure. The relevant literature has ignored these complexities and focused on individual services or service pairs when studying mobile demand. As such, the present study is a first of its kind.

This study also offers an innovative approach to qualitative choice analysis by applying efficient design methodology to conjoint analysis. It is the first application of efficient survey design to telecommunications services and one of the first practical applications of this method. Conjoint analysis asks decision makers to trade-off mobile plan attributes thereby revealing how they make their decisions. It forms part of the consumer survey. The study develops a test that assesses the practical value of efficient design relative to more traditional conjoint design methods.

The results of this study put forth some important implications for mobile service providers, policy makers, and regulators. For the service providers, it reveals which plan attributes are important to subscribers and which attributes subscribers commonly ignore. More important, the resulting demand elasticities demonstrate the market shares that service providers potentially could gain by introducing mobile service plans with certain desirable combinations or the effect that the change of one plan attribute could have on the attractiveness of the overall plan to subscribers. For regulators and competition authorities, the study identifies the interaction of specific demand determinants that are currently subject to policy debates. These factors include the imposition of term contracts, the demand elasticities of voice and SMS services, the impact of mobile broadband on mobile demand, and the competitive effects of flat-fee pricing.

The study begins with a review of the relevant literature, examining three different yet related streams: fixed-to-mobile substitution, mobile diffusion, and mobile demand determinants. Next is a discussion on the development of the theoretical model for measuring mobile demand followed by a discussion on the derivation of the efficient design survey. Finally, the model results are presented along with a discussion of the practical, strategic, and policy implications derived from this study.

Literature Review of Consumer Demand for Mobile Services

The interest in mobile telephony increased post-2000 with the introduction of free long distance and decreasing mobile phone service prices. It was during this time that mobile subscribers started to outnumber fixed-line subscribers. A review of the literature on mobile demand reveals three time appropriate epochs.

In the first epoch, research focused on the substitution effects of mobile phone service and attempted to determine if mobile telephony was eroding the demand for plain-old-telephone-service (POTS) and other services. One of the first studies in this field was Hausman and Ruud (1987) who used rank-ordered data to examine the trade-off effects between cellular radio (car phones) and mobile phones. In later years, analysts in many different countries studied the impact of fixed-to-mobile substitution (FMS). Parker and Röller (1997) performed one of the first FMS studies, finding indirect evidence of FMS in the United States. In contrast, in 2001, Barros and Cadima found no significant impact of FMS in Portugal. However, after some time had passed, the results began to show a definite trend toward FMS. Rodini, Ward, and Woroch (2003) and later Ward and Woroch (2004) arrived at a similar conclusion as Parker and Röller for the United States. Sung, Kim, and Lee (2000), Sung and Lee (2002), and Ahn, Lee, and Kim (2004) found evidence of FMS in Korea, whereas Madden and Coble-Neal's (2004) study showed the first evidence of FMS in Australia. In Eastern Europe and the former Soviet states, Vagliasindi, Guney, and Taubman (2006) examined competition between fixed and mobile technologies and found some evidence of FMS. Vogelsang (2010) offers a comprehensive literature review focusing mostly on this first epoch of the mobile demand literature. He concluded that emerging mobile networks tended to act as complements to fixed-line networks, whereas mature networks were substitutes. Table A1 in Appendix A provides an overview of this epoch of the mobile demand literature.

In the second epoch, researchers concentrated on mobile subscriber growth, specifically on how and why mobile telephony would diffuse on a national level. The mobile diffusion literature frequently uses S-curve type models that categorize mobile subscribers based on the timing of adoption into early adopters, early majority, late majority, and laggards (Kauffman & Techatassanasoontorn, 2005). Analysts used various diffusion curves to determine the demand driver of national mobile demand and to forecast a country's saturation point. Gruber and Verboven (2001a, 2001b) were among the first to apply diffusion curves to model mobile diffusion rates. Their study revealed that the technological transition from 1G to 2G in addition to increased competition were the major drivers of mobile penetration. In addition to technological advances as a driver of change, Massini (2002) found that declining phone prices and lower MRCs had a significant impact on mobile diffusion. Banerjee and Ros (2004) added teledensity to the list of national demand drivers with lower teledensity exhibiting higher mobile penetration. Vagliasindi et al. (2006) and Vogelsang (2010) confirmed this finding. Koski and Kretschmer (2005) found technology standardization, technological advances, and competition in the fixed-line market to be significant accelerators to 2G adoption. Kauffman and Techatassanasoontorn (2005) found that technology standards, retail price levels, and analog diffusion as opposed to competition were the drivers of mobile diffusion, which was counter to the previous literature. However, Rouvinen (2006) found that standardization as well as market competition did act as accelerators to mobile diffusion. Analyzing the effect of technology, Dippon (2010) examined the diffusion of 3G mobile technologies. His study revealed that the key driver of 3G demand was time. The results of his study also showed a positive correlation between population density and 3G adoption, although there was negative correlation for mobile penetration. Dippon found negative correlation between 3G diffusion and penetration. Table A2 in Appendix A provides a summary overview of this epoch of the mobile demand literature.

The third epoch examines the individual demand components or the relationship between a pair of such components (e.g., voice and SMS). As many countries have reached or are reaching mobile saturation, research focuses less on mobile adoption and more on gaining an understanding of how consumers make their related purchase decisions. Fierce competition in the mobile sectors of many nations seems to be the main driver behind this research as subscriber growth is now limited to competitive gains. This switch from "organic" growth to "competitive" growth requires a deep understanding of the factors that drive mobile demand. Among these factors are retail prices and various service attributes, including mobile phone subsidies, MRCs, SMS fees, roaming charges, and other aspects of this multifaceted demand model. Relative to the FMS and the mobile diffusion literature, this strand is broader in terms of topics analyzed. Studies in this part of the mobile literature focus predominately on customer preferences and cover areas such as subscriber retention, switching and switching barriers, and various own-price and cross-price elasticities. The distinguishing feature in this epoch is that bundle components are treated as if they can be purchased individually or in pairs. This, however, is not how mobile providers offer their services. Mobile services are typically provided in bundles, or plans, at some fixed monthly recurring charge. Beyond this price, certain components of the plans are usage sensitive, often after some monthly threshold or allowance. Accordingly, the intent of this third literature review is to identify the determinants, or independent variables that studies of bundled service provision should consider. Given the direct relevancy of this epoch, a comprehensive review of the existing literature follows.

Hausman (1999) offered some of the first work in this stream of the literature, although the motivation for his studies differs from that of others that followed. Specifically, in 1999, Hausman examined the impact that the omission of mobile telephones from the U.S. consumer price index (CPI) had on the index. Relying on the prices of mobile service plans in the top 30 metropolitan statistical areas (MSAs) in the United States,[3] Hausman modeled mobile demand as a function of a time series of prices and average annual household income per MSA. Based on this model, he found a demand elasticity of −0.51, which shows that changes in price have a relatively small effect on the quantity demanded.

In contrast to Hausman's (1999) study, subsequent mobile demand studies were primarily motivated by an alleged market failure (and proposal to regulate the relevant market) and to obtain competitive insights. For instance, Dewenter and Haucap (2008) noted that national regulatory agencies (NRAs) in Europe started questioning whether mobile sectors were effectively competitive. Thus, Dewenter and Haucap examined the market's and the service providers' demand elasticity. Revenue and quantity (minutes-of-use) information from three Austrian service providers (which accounted for about 90% of the mobile market) from 1998 through 2002 provided the source data for this study. Dewenter and Haucap distinguished

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[3] "*Metropolitan Statistical Area*—"A Core Based Statistical Area associated with at least one urbanized area that has a population of at least 50,000. The Metropolitan Statistical Area comprises the central county or counties containing the core, plus adjacent outlying counties having a high degree of social and economic integration with the central county or counties as measured through commuting" (http://www.whitehouse.gov/sites/default/files/omb/assets/fedreg_2010/06282010_metro_standards-Complete.pdf).

between short- and long-run elasticities. A function of price, number of subscribers, and firm dummies modeled mobile demand. For short-term elasticities, the study found them to range between −0.7 and −0.44. Long-term elasticities were between −1.05 and −0.61. Contrasting these results to some of the earlier related economic literature, Dewenter and Haucap concluded that Austrian mobile demand was more elastic than that of other countries. Interestingly, their study also revealed negative network effects as it found that minutes-of-use decreased with the size of a service provider's subscriber base.

Kim, Park, and Jeong (2004) analyzed the impact of customer satisfaction and switching barriers on consumer demand. Finding subscriber retention an essential component of a service provider's competitive strategy, Kim et al. conducted a survey of Korean mobile subscribers. The resulting survey data were analyzed using hypothesis testing on a structural equation model. Subscriber satisfaction, as defined by Kim et al., was comprised of a number of service quality metrics, such as call quality and subscriber support. Switching barriers measured the cost a subscriber incurred by switching from one service provider to another and included time, money, and psychological cost. The hypothesis that higher call quality leads to higher subscriber satisfaction was accepted. Similarly, the hypothesis that higher subscriber satisfaction leads to higher subscriber loyalty (and thus lower churn rates) also was accepted.[4] Kim et al. concluded that relatively higher call quality, subscriber service, and the number of value-added services positively contributed to mobile demand. Conversely, higher switching costs were negatively associated with mobile demand.

Ishii (2004) used consumer usage surveys to assess the demand determinants for a specific mobile bundle component—mobile phone Internet use. His focus was on the social and cultural factors that shape mobile Internet use in Japan. Rather than modeling a demand function, Ishii relied on descriptive survey response statistics to assess mobile Internet demand, differences in mobile Internet and personal computer (PC) Internet use, and factors affecting mobile phone Internet use in Japan. Ishii found that relative to PC Internet access mobile phone Internet adoption was relatively low because many subscribers did not enable this function on their mobile phones. Among the mobile phone Internet users, the average time spent on the

[4] The word "churn" means that a subscriber changes mobile service provider.

Internet was approximately one-third of the time spent by PC Internet users. In contrast to Wareham, Levy, and Shi (2004), Ishii found that age was an important determinant of mobile phone Internet demand. Contrary to media statements, Ishii found that commuting time was not. His study also revealed that mobile phone usage differs from PC usage in terms of content accessed.

Iimi (2005) studied mobile demand determinants, product differentiation, network effects, and demand elasticities in the Japanese market for mobile telephone services. Similar to the present study, Iimi's objective was to examine empirically the demand structure of mobile phone service. Iimi used a discrete consumer choice (logit) model and fitted data derived from a revealed-preferences survey conducted by the Ministry of Post and Telecommunications. Relevant to the present study, Iimi found that an ideal data source for this type of study consisted of contract-based information that included information on the contract and billing structure offered by each service provider. Iimi modeled mobile demand as a function of the MRC, a set of observable product characteristics, and network size (to measure the network effects). Iimi concluded that network effects no longer determined mobile demand. In contrast, product differentiation (measured as the number of advanced value-added features) was a significant demand determinant. Iimi measured the price elasticity at between −2.43 and −1.30, attributing the high elasticity to intense competition during the process of privatization and liberalization.

Ahn, Han, and Lee (2006) assessed mobile demand determinants in the mobile sector in Korea through a study of mobile churn determinants. Random samples of subscriber accounts that churned from a leading Korean mobile service provider provided the data for this study. Ahn et al. supplemented these data with customer dissatisfaction data collected by the service provider. Ahn et al. fitted these data to a logistic regression model. Dropped call and failure rates, number of complaints, loyalty points, calling plan type, mobile phone capability, mobile phone manufacturer, payment method, and gender served as explanatory variables. The study revealed that mobile demand was positively correlated with call quality and the age of the mobile phone and negative correlated with call volume and participation in a membership loyalty program.

Eshghi, Haughton, and Topi (2007) also approached mobile demand from the perspective of subscriber loyalty by analyzing U.S. subscribers' propensity to switch mobile service providers. Using data from a subscriber satisfaction survey, Eshghi et al. used correlation and causation analysis to assess the impact that subscriber satisfaction had on mobile demand. The propensity to churn was modeled as a function of age, education, income, years connected to the Internet, number of cell phones, propensity to add cell phones, total mobile spending, propensity to replace fixed-line phone service with mobile service only, and customer satisfaction. The study found a negative correlation between customer satisfaction and the propensity to switch service providers and a positive correlation between "wireless orientation" (i.e., propensity to add cell phones and propensity to replace fixed-line service with mobile service only) and the propensity to switch. Interestingly, age, income, and education had only an indirect effect on the propensity to switch in that they influenced variables that directly or indirectly influenced the propensity to switch. The study also examined the effectiveness of switching barriers and found them to be ineffective relative to the quality of service. Eshghi et al. concluded that a service provider's competitive strategy should focus on improving its quality of service instead of erecting barriers to prevent switching service providers.

Noting that both fixed and mobile telecommunications markets around the world had been privatized and largely liberalized, Garbacz and Thompson (2007) researched the factors that determine the demand for fixed and mobile services in developing nations. Using an ordinary least squares (OLS) model with fixed effects, Garbacz and Thompson modeled mobile demand as a function of a privatization dummy, several variables measuring market regulation and competition, total revenue per subscriber, teledensity, gross domestic product (GDP), pricing variables, population density, and educational level. The study revealed that mobile demand was determined by the price for fixed residential service, the price for mobile service, the activation charge for mobile service, income (GDP), and education. They found that own-price elasticity ranged between −1.27 and −0.20.

Tallberg, Hammainen, Toyli, Kamppari, and Kivi (2007) investigated the impact of mobile phone bundling on mobile data usage in Finland. As such, the study examined whether the demand for the data components of a service bundle was a function of mobile phone bundles. Regulation in Finland at the time prohibited the bundling of mobile phones and mobile services. The objective of Tallberg et al.'s study was to examine whether allowing the bundling of mobile phones and data services would positively affect the demand for mobile data services. The data consisted of interviews with industry experts, the results of which were analyzed using descriptive statistics. Mobile service providers found bundling to be a critical determinant of mobile demand, an opinion confirmed by mobile subscribers. Regulators and mobile equipment manufacturers, however, did not find bundling desirable, but they agreed that short-term contracts and a focus on only advanced service bundles could improve their view on bundling.

Grzybowski and Pereira (2008) investigated possible interdependencies between two mobile bundle components. Specifically, they analyzed complementarities between mobile voice calls and SMS in Portugal. Using consumer-level data from April 2003 and March 2004, Grzybowski and Pereira employed a tobit model with individual random effects.[5] Counter to the present study, Grzybowski and Pereira assumed that mobile voice was a separate service from SMS and not offered in the same bundle. They modeled the demand for mobile voice services as a function of the price for voice calling, the price for SMS, age, and gender. Similarly, the prices for SMS and voice calling as well as age and gender determined the demand for SMS. The fitted model revealed that the prices of SMS and voice calling as well as age and gender were statistically significant determinants of SMS demand. For mobile voice demand, however, age and gender were statistically insignificant. The own-price elasticity of voice calling was −0.38, whereas the same measure for SMS was −0.28. They also found that mobile voice calls and SMS were complements with a cross-price elasticity of −0.06 (voice to SMS) and −0.28 (SMS to voice).

Finding that retaining existing subscribers was cheaper than acquiring new subscribers, Seo, Ranganathan, and Babad (2008) studied mobile demand from the perspective of subscriber retention. Specifically, Seo et al. examined how switching costs, subscriber satisfaction, gender, and age affected a subscriber's propensity to churn. In their study, switching costs consisted of plan complexity, mobile phone sophistication, and length of time with the current service provider. Seo et al. also used the latter variable to assess customer satisfaction in addition to obtaining the

[5] A tobit model estimates linear relationships between variables when there is either left or right censoring (or below and above censoring) in the dependent variable. When cases with a value at or above some threshold all take on the value of that threshold censoring from above occurs; therefore, the true value may be equal to the threshold or higher. With censoring from below, censoring affects values that fall at or below some threshold. The tobit model is also called a censored regression model.

statistics for dropped calls.[6] Seo et al. used a binary logistic regression model. This model found a negative correlation between customer retention and the length of association, mobile phone sophistication, and service plan complexity. The fitted model revealed a positive correlation between the dependent variable and the dropped call ratio. Age and gender were not part of the fitted model, although Seo et al. concluded that different age and gender groups displayed different retention behavior.

Tripathi and Siddiqui (2009) conducted an empirical investigation of subscriber preferences for mobile service attributes. Based on a conjoint analysis, Tripathi and Siddiqui examined how mobile subscribers in India made their purchase decisions and whether these decision factors differed among different demographic groups. Unlike some of the earlier literature, which largely focused on subscriber retention, the focus of this study was to obtain empirical insight on both retention and acquisition. Tripathi and Siddiqui conducted an opinion survey, which included a conjoint analysis, using personal interviews through shopping mall intercepts. The conjoint exercise asked respondents to rank 18 different mobile service packages based on a variety of features such as call quality (e.g., dropped call rate, coverage, congestion), features of mobile service tariffs (e.g., call rates, variety of the tariff plans), customer service (e.g., resolution of queries, complaint handling), value-added services (e.g., ringtones, caller tunes, services like news updates), variety of the plans (e.g., postpaid, lifetime, prepaid), and the technology of the service provider. The survey also collected sociodemographic information including age, gender, monthly income, education, profession, and the type of current service account (i.e., government or private). Tripathi and Siddiqui fitted the resulting data using an OLS thus revealing that mobile demand in India was mainly a function of service quality, customer service, and price. Value-added services, such as ringtones and news flashes, were not significant. Similarly, Indian subscribers were indifferent about the technology used by the service provider.

Kim, Telang, Vogt, and Krishnan (2010) analyzed the interaction between mobile voice and SMS by measuring the services' cross-price elasticities. Finding that the multifaceted pricing structure and myriad of plan choices posed a significant econometric challenge, Kim et al. constructed a two-stage choice model. In the first

[6] A dropped call is a call that is terminated before the end of the call due to technical difficulties (including dead zones).

(discrete) stage, subscribers selected a mobile plan based on their past consumption behavior. In the second (continuous) stage, they chose quantities for mobile voice and SMS based on the fixed fees to enroll in the mobile plan, the marginal mobile voice price, past mobile voice consumption, the monthly voice allowance, SMS pricing, and the subscriber's income. The model was fitted using revealed-preference data from a mobile service provider in Asia. The study showed that mobile voice and SMS were weak substitutes with a cross-price elasticity of −0.8 (voice to SMS). The own-price elasticity of mobile voice was −0.1. Kim et al. also found differences in subscriber preferences based on age. Younger users showed lower mobile voice elasticity relative to older users.

In contrast to the first two mobile demand literature epochs, the literature on mobile demand determinants is clearly a work in progress. With the exception of Hausman (1999), who focused on economic performance metrics, most of the work on mobile demand determinants appeared in the last six to seven years. The literature focuses primarily on gaining an understanding of the drivers of mobile demand and mobile churn. As summarized in Table 1, most of the empirical models assessing mobile demand determinants include provider-specific variables, in particular price variables. The exceptions are Ishii (2004) and Tallberg et al. (2007) who focused on the aggregate mobile market instead of individual service providers.

There appears to be no consensus as to which respondent-specific variables should be included in a demand model, if any at all. Dewenter and Haucap (2008), Kim et al. (2004), Iimi (2005), and Tallberg et al. (2007) elected to include no such variables. Eshgi et al. (2007) found them to be statistically insignificant, whereas Grzybowski and Pereira (2008) confirmed their significance for SMS demand but rejected it for voice demand. Others, such as Ishii (2004), Tripathi and Siddiqui (2009), and Kim et al. (2010) did not test for the significance of the sociodemographic variables included in their models, but they displayed their results based on age and gender. Hausman (1999) found income a significant variable to explain aggregate mobile demand. Similarly, Garbacz and Thompson (2007) found income and education to be drivers of national mobile demand. Ahn et al. (2006) found gender to be statistically significant in explaining customer churn. Finally, market-specific variables were included only in multinational studies (e.g., Garbacz and Thompson, 2007).

Based on this latest epoch in the mobile demand literature, mobile demand seems to be a function of price and service attributes and possibly a set of socio-demographic variables. Age and gender appear the most frequently used socio-demographic variables (e.g., Ishii, 2004; Ahn et al., 2006; Eshghi et al., 2007; Grzybowski & Pereira, 2008; Seo et al., 2008; Tripathi & Siddiqui, 2009). Income also frequently appears (e.g., Hausman, 1999; Eshghi et al., 2007; Garbacz & Thompson, 2007; Tripathi & Siddiqui, 2009; Kim et al., 2010). Income, however, is primarily used in studies that examined aggregate demand (e.g., Hausman, 1999) and in cross-country studies (e.g., Garbacz & Thompson, 2007; Kim et al., 2010). Furthermore, Eshghi et al. (2007) and Tripathi & Siddiqui (2009) found income to have only an indirect impact.

Elasticity of demand estimates for mobile voice services varied from −2.43 (for Korea) to −0.1 (for an Asian country) with an average of −0.71. Cross-price elasticities for voice to SMS ranged between −0.08 and −0.06; SMS to voice was −0.28. Sufficient alternative observations for the elasticity estimates do not exist to form an opinion about trends or country differences. For the United States, Hausman (1999) appears to be the only study that measured mobile demand elasticity (i.e., −0.51).

The review of the mobile demand literature reveals a number of areas where further research can significantly add to the current knowledge of how consumers select mobile phone services. As found by Kim et al. (2010), most of the existing literature focused on mobile voice demand only, leaving out other mobile service bundle components.[7] Kim et al. added the SMS components to voice, thereby further expanding the literature. They also noted that the multifaceted pricing structure posed significant econometric challenges. The present study sets out to address some of these unexplored frontiers in assessing mobile demand. Specifically, it examines whether the pricing variables and the socio-demographic variables identified above flow through in a bundled service context.

[7] Interestingly, in the field of fixed telecommunications, researchers have acknowledged that subscribers purchase services in bundles and have set out to explore its economic consequences (see, e.g., Pereira, Ribeiro, and Vareda (2011).

Table 1

Relevant Mobile Demand Literature

Author	Year	Dependent variable	Independent variables: Provider specific	Respondent specific	Market specific
Hausman	1999	mobile demand	subscribers (time-series)	household income	(none)
Dewenter & Haucap	2008	mobile demand	price, subscribers, firm dummies	(none)	(none)
Kim, Park & Jeong	2004	mobile customer churn	service quality, switching barriers	(none)	(none)
Ishii	2004	mobile Internet demand	(none)	age, gender, education, current consumption patterns	(none)
Iimi	2005	mobile demand	mrc, service attributes, subscribers	(none)	(none)
Ahn, Han & Lee	2006	mobile customer churn	dropped calls, failure rates, customer complaints, loyalty points, mobile phone capability, plan type, mobile phone manufacturer, payment method	gender	(none)
Eshghi, Haughton & Topi	2007	propensity of mobile customer churn	customer satisfaction	age, education, income, years connected to Internet, number of mobile phones, propensity to add mobile phones, mobile spending, propensity to drop fixed-line	(none)
Garbacz & Thompson	2007	mobile demand	total revenue per subscriber, service prices	income, education	privatization dummy; market regulation, competition, teledensity, population density
Tallberg, Hammainen, Toyli, Kamppari & Kivi	2007	mobile data demand	(none)	(none)	market regulation
Grzybowski & Pereira	2008	mobile voice demand, mobile SMS demand	mobile voice prices, SMS prices	age, gender	(none)
Seo, Ranganathan & Babad	2008	mobile customer churn	switching cost, subscriber satisfaction	age, gender	(none)
Tripathi & Siddiqui	2009	mobile demand	call quality, mobile voice prices, value added services, plan variety, technology	age, gender, income, education, profession, type of account	(none)
Kim, Telang, Vogt & Krishnan	2010	mobile voice demand, mobile SMS demand	fixed fee to enroll in plan, marginal mobile voice price, monthly voice allowance, SMS pricing	mobile voice consumption, income	(none)

Theoretical Model

Measuring Mobile Service Plan Demand

Success stories, such as Apple's iPhone or RIM's Blackberry, lead the casual observer to believe that consumers select mobile phone plans based on the attractiveness and functionality of the mobile phone with little regard for monthly prices, minutes and data allowances, and contract lengths. For instance, U.S. consumers filed several class action lawsuits against Apple's iPhone exclusive provider contract with mobile service provider AT&T that expired in January 2011. These lawsuits also received the attention of the U.S. Congress. At the center of the debate was whether AT&T had an unfair competitive advantage due to its exclusive offering of the iPhone.

If one were to believe that the exclusive offering of a mobile phone provides a competitive advantage, consumers predominantly, or even exclusively, would choose a mobile service provider based on the attractiveness and functionality of its mobile phones. However, mobile phones generally are not sold separately but as part of a bundle of mobile services. Typically, a mobile service bundle includes, among other things, airtime allowances, overage charges, data download and upload speeds, data options, and SMS and MMS options. Contrasted against the apparent importance of the mobile phone, this raises the question of whether the components of the bundle, other than the mobile phone, actually play a role in a consumer's purchase decision. If they do, then to what extent does the mobile phone alone shape the demand for the overall service bundle? Are consumers willing to trade a less desirable mobile phone for a better service plan or are they willing to subscribe to a lesser plan in order to obtain a better mobile phone?

Shedding light on these questions is critical for mobile service providers for several reasons. First, data from September 2010 indicates that 94.1% of the U.S. population had mobile phone service. This includes all U.S. citizens regardless of age. For mobile service providers, this high level of saturation means that subscriber growth mainly comes from subscribers switching from competitors and not from new subscribers entering the market. Second, as of January 2011, the Apple iPhone was not only available on the AT&T network but also on rival Verizon Wireless' network. This essentially marked the end of exclusive mobile phone contracts, although the iPhone is still not available on other networks, such as Sprint, T-Mobile, and MetroPCS. This potentially further intensifies mobile competition if in fact mobile phone offerings are correlated with market share. Hence, understanding and measuring the demand for mobile service bundles and the underlying components of mobile demand is of critical strategic importance for mobile service providers. The specific elasticities provide service providers with an analytical tool to assess the competitive effects of a change in the structure of currently offered mobile bundles.

Understanding consumer preferences for mobile phone service is also important to policy makers. For instance, legal actions in U.S. federal courts (see, e.g., *Ayyad et al. v. Sprint Spectrum et al.*, 2008) and various complaints heard by the FCC (2009, 2010a) have questioned the competitive impact of term contracts. Most U.S. service providers offer postpaid services as part of a two-year contract with a liquidated damages clause that calls for the payment of an ETF should the subscriber terminate the contract prior to its expiration. Service providers justify term contracts stating that they are a recovery tool for subscriber acquisition fees and mobile phone discounts that subscribers receive at the beginning of a contract. However, consumer advocacy groups (e.g., Mierzwinski, Smith, & Cummings, 2005) argue that it increases switching barriers and thus reduces competition and consumer welfare. A study on consumer preferences for mobile service bundles can directly assess the impact that term contracts have on consumer demand. Specifically, measuring the correlation of the length of the term contracts and mobile phone prices sheds light on whether consumers prefer the upfront mobile phone discount in conjunction with a term contract or whether they prefer to pay for the mobile phone and not have a contract.

Similarly, measuring the demand for mobile service plans and inferring consumer preferences can also resolve the U.S. Congress' investigation of SMS charges. On September 9, 2008, U.S. Senator Herb Kohl (D-WI), Chairman of the Senate Antitrust Subcommittee, sent a letter to the CEOs of Verizon Wireless, AT&T Mobility, Sprint Nextel, and T-Mobile (the four largest U.S. mobile carriers) demanding an explanation of recent price increases for text messaging (see Kohl, 2008). Text messaging is a broad term that means sending messages from one device to another using a wireless technology. This includes services such as SMS, email, instant messaging, Internet access, voice SMS (where the text is converted to voice), text-to-fixed-line SMS (where the text is also converted to voice), and the sending of content (e.g., pictures and video messaging). Senator Kohl questioned only the price of SMS, which is just one form of text messaging. This distinction is crucial as there is a significant difference in the use of SMS and other forms of messaging such as emails, Internet access, and voice SMS. Senator Kohl's letter asks the service providers to "justify" what "some industry experts contend" are price increases that "do not appear to be justified by any increases in the costs associated with text messaging services." Specifically, Senator Kohl asked for:

- An explanation of why text-messaging rates have dramatically increased in recent years.
- Cost, technical, or other factors "that justify a 100% increase in the cost of text messaging from 2005 to 2008."
- Data on the utilization of text messaging during this period.
- Comparison of prices charged today as opposed to 2005 for text messaging as compared to other services offered by the service providers, such as:
  - Prices per minute for voice calling
  - Prices for sending emails
  - Prices for data services such as Internet access over mobile devices
  - Information on whether the pricing structure for text messaging differs in any significant respect from the pricing of competitors

Only days after the release of Senator Kohl's letter, various jurisdictions began to receive consumer class action lawsuits. For instance, the U.S. District Court, Northern District of Ohio, Western Division received a class action complaint alleging an "illegal scheme of price-fixing conspiracy." The Northern District of Illinois, Eastern Division received a similar suit. There have been 20 related consumer class action lawsuits filed, all of which were consolidated in the Illinois Federal Court. A deeper understanding of how U.S. subscribers purchase mobile phone service can assess whether SMS charges are a statistically significant determinant of demand. Such an analysis must examine the price elasticity and the relationship between SMS charges and other price and non-price attributes of a service bundle.

The saturated market faced by mobile service providers, the increasing availability of mobile phones, and the various regulatory and legal challenges involving mobile service offerings all require a detailed understanding of subscriber preferences in a bundled setting. Although there is a growing body of economic literature on mobile telephony, the focus of these studies is on isolated aspects of mobile demand and not on mobile demand when offered as a service bundle. The latter type of study, however, is necessary to resolve the strategic, regulatory, and legal challenges that the mobile industry is raising. Vogelsang (2010) corroborates this assessment of the literature. He found that the current literature lacked studies that considered all price and non-price factors of mobile demand. Specifically, he found that four prices (mobile phone price, installation/setup fee, MRCs, and per-minute calling charge) must be part of the consideration to avoid an omitted variable bias. He also found that studies must take into consideration non-price attributes, such as speed, functionality, presence/absence of a camera, and so on. Similarly, Kim et al. (2010) concluded that researchers know very little about how mobile subscribers make their purchase decisions and that the existing literature focused on mobile voice only.

The present study attempts to address the requirements set forth by Vogelsang (2010), addresses the concerns raised by Kim et al. (2010), and fills an apparent gap in the literature. Specifically, it expands the literature in several respects. First, it seeks to update the demand elasticity estimates for the United States determined by Hausman (1999).[8] Second, it expands on Kim et al.'s study by considering all mobile service plan components, including voice, SMS/MMS, other data options, the mobile phone, and the term contract. It examines consumer demand in a postpaid-service bundle scenario where mobile phone features and prices are bundled with other service attributes such as the allowed monthly voice minutes and the price of excess data usage. Third, given the econometric challenges provided by this multidimensional pricing decision, the study employs advanced and flexible econometric tools, the mixed exploded logit model in particular. It expands on these tools by introducing a recent addition to the survey design literature called efficient design. Fourth, although most of the existing literature relies on aggregate demand data, no recent studies employ stated-preference surveys.

This study includes price and other service attributes as independent variables. Given there are conflicting results in the literature on the significance of sociodemographic variables, the present study tests for them to avoid an omitted variable bias. The data from the consumer survey are analyzed using descriptive statistics and a discrete choice model. The descriptive statistics are used to compare the survey results to U.S. benchmarks. The choice model estimates the probability of

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[8] The nature of mobile service has dramatically changed since Hausman (1999). Thus, a direct comparison with Hausman's study is not meaningful.

a consumer selecting a plan given a set of attribute levels. The most common form of choice model is the logit model (Train, 1993). Depending on the choices faced by the decision maker, a logit model is either binomial or multinomial. In binomial logit models, the decision maker selects between two choice alternatives. In multinomial logit (MNL) models, the decision maker selects from three or more choice alternatives. For instance, Hausman and Ruud (1987) used a rank ordered logit model to explore mobile choice. An advanced version of the logit model is the mixed exploded logit model. This model introduces variation in the attribute levels through the ranking of choices and the repetition of trade-off exercises, essentially introducing a mixture of logit models (Train, 1993). In addition, rather than assuming fixed parameter estimates, it uses stochastic parameter estimates, thereby allowing for respondent-specific taste variations. The analysis focuses on statistically significant demand determinants and the interaction of the dependent variables (i.e., the probability that a particular mobile plan will be purchased) with the independent variables, such as choice and consumer attributes. Subgroups of the population are examined to determine whether behavioral differences exist among them.

The following sections contain a discussion of the statistical foundation of discrete choice models, the modeling of discrete choice, and the mixed exploded logit model after which the specific model for this study is presented.

Discrete Choice Models

Unlike aggregate models that describe markets as a whole, discrete choice models are disaggregate models in that they examine individual decision making (Train, 1993). Using disaggregate models to draw conclusions about market behavior builds on the fact that demand and supply are simply the aggregate of economically relevant individual decision making. For instance, much of the literature on mobile demand (and particularly the literature on FMS and mobile diffusion) contains studies that start with total mobile subscriber numbers (i.e., aggregate demand), and the researcher performs a type of regression analysis to arrive at the demand drivers of mobile demand. Only the more recent work on mobile demand determinants contains studies that analyzed individual (disaggregate) purchase decisions.

As Train (1993) points out, using standard regression techniques on disaggregate models is not appropriate if the values do not fall within a specified range; that is, they are not continuous. Total mobile subscriber numbers are continuous in time and geography. However, individual purchasing decisions are not. An individual either purchases mobile phone service or not. A dummy variable of zero and one best describes this qualitative (noncontinuous) selection process. Under these circumstances, methods other than regression analyses are used.[9]

One econometric technique for noncontinuous dependent variables is discrete choice analysis. As noted by Train (1993), discrete choice analysis applies to situations in which: (a) the number of choice alternatives is finite, (b) the choice alternatives are mutually exclusive, and (c) the set of alternatives is exhaustive. Choice alternatives are competing options. In the present study, the choice alternatives are the mobile service plans faced by the decision maker. These characteristics describe fairly well individual purchasing decisions for mobile phone services, particularly when examined in a survey where consumers make hypothetical (stated) purchase decisions.

First, the number of mobile service plans in the United States is finite. Although this number may be too large for consumers to compare alternatives in a meaningful way, a consumer survey allows the researcher to limit the number of choice alternatives in an experimental setting. In the present survey, the number of choice alternatives was three. Furthermore, the survey respondents were informed that the alternatives offered in the survey were exhaustive and that they had to select one plan and one plan only as their most preferred plan. Hence, the choices offered in the present study were also mutually exclusive, and the set of alternatives was exhaustive. Based on these considerations, a discrete choice model is well suited for this study. Due to the large number of notations in this section, Table 2 serves as a reference of the notations used in the remainder of this chapter.

[9] It is worthwhile noting that not all disaggregate models have noncontinuous dependent variables and therefore require econometric techniques other than regression analyses. For instance, Tripathi and Siddiqui (2009) conducted a consumer survey of individual purchase decisions. However, rather than asking survey respondents to select a plan (and thereby reject all other plans), the survey asked respondents to rank the desirability of the presented alternatives. Thus, the resulting dependent variable was a continuous variable, and Tripathi and Siddiqui used OLS analysis to assess the demand determinants.

Table 2

Model Notations

Term	Notation	Description
Decision makers	N	Number of decision makers
Decision maker	n	An individual making a decision to select a choice alternative in a choice set
Choice situation	tn	A specific choice situation faced by decision maker (n), t=1, 2, 3, 4, 5, 6
Choice set	Jn	All the choices in a choice situation faced by a decision maker (n)
Choice alternative	jn	A specific choice in a choice set faced by decision maker (n)
Choice attribute	xjn	A specific (observed and unobserved) attribute of a choice alternative (j) faced by decision maker (n)
Observed choice attribute	zjn	A specific observed attribute of a choice alternative (j) faced by decision maker (n)
Decision maker attribute	rn	All (observed and unobserved) attributes of a decision maker
Observed decision maker attributes	Sn	Observed attributes of a decision maker
Observed decision maker attributes	sn	A specific observed attribute of a decision maker
Utility	Ujn	All (observed and unobserved) utility derived by decision maker (n) from consuming alternative (j)
Observed utility	Vjn	Observed utility derived by decision maker (n) from consuming alternative (j)
Choice probability	P_{jn}	Probability of decision maker (n) to selected choice alternative (j)

Discrete choice models are probability models in that they calculate the probability of selecting a choice alternative j from a set of choice alternatives J in a choice situation t. In the present study, the choice model produces the probability of selecting one mobile service plan given a set of three alternative mobile service plans. Two common forms of discrete choice models are logit and probit models, which are fundamentally identical, differing only in the functional form that transforms the observed choices into probabilities (Train, 1993).

In both logit and probit models, a decision maker n faces a choice set J_n. The choice set J_n faced by decision maker n consists of several choice alternatives j_n. In the present study, for example, a decision maker (i.e., the survey respondent) faced a choice of three alternative mobile service plans. A choice alternative j_n differs from another choice alternative i_n in terms of their attributes x_{jn} and x_{in}. Different decision makers might make different choices based on the decision maker's attributes R_n. A researcher only rarely observes all choice attributes and decision maker attributes. Therefore, in order to distinguish all attributes (observed and unobserved) from the attributes that are actually observed in the data, observed choice attributes are notated by z_{jn} and z_{in}, whereas observed decision maker attributes are notated by s_n. Hence, the probability P_{in} for decision maker n to select choice alternative i from a set of choice alternatives J_n is a function of z_{in}, relative to all other observed choice alternative attributes z_{jn} and the observed decision maker attributes s_n. Train (1993) specifies the probability as a parametric function of the following general form:

(1) $$P_{in} = f(z_{in}, z_{jn} \text{ for all } j \text{ in } J_n \text{ and } j \neq i, s_n, \beta),$$

where f is the function that relates the observed data to probabilities, specified by some vector of parameters β.

Econometric Modeling of Discrete Choice

The econometric modeling of discrete choice models finds its roots in utility theory (Train, 1993). The decision maker n faces J_n choices. Consumption of each alternative can provide the decision maker with utility. Neoclassical consumer choice theory postulates, among other things, that consumers are nonsatiable (i.e., more is always better than less) and that they always maximize their utility (see, e.g., Silverberg & Wing, 2000). Thus, the decision maker will select the alternative perceived as yielding the highest utility. In the present study, a decision maker (i.e., a survey respondent) chooses from among three mobile service plans and selects the plan that yields the highest utility for this decision maker. Following the notation in Table 2, the utility of choice i faced by respondent n is written as:

(2) $$U_{in} = f(x_{in}, r_n), \text{ for all } i \text{ in } J_n,$$

where f is a function (Train, 1993). To maximize utility, the survey respondent selects mobile plan i as the preferred plan if and only if:

(3) $$U_{in} > U_{jn} \text{ for all } j \text{ in } J_n, j \neq i.$$

Expressed in words, equation (3) simply states that alterative i is the utility maximizing selection for decision maker n only if its utility is higher than the utility derived from all other alternatives in the choice set. Equation (2) defines the utility for a generic choice alternative. Rewriting equation (2) for choice alternative i and j and substituting these equations into equation (3) yields the following relationship:

(4) n chooses i in J_n if $U(x_{in}, r_n) > U(x_{jn}, r_n)$ for all j in J_n, $j \neq i$.

Equation (4) implies that the selection of alternative i is a function of the decision maker's attributes and the attributes of alternative i relative to the attributes of all other choice alternatives faced by decision maker n.

This derivation assumes that a researcher can observe all attributes of choice attributes x_{in} and all decision maker attributes r_n. However, this is not realistic as there are choice attributes that the researcher cannot observe. Similarly, it is unlikely that a researcher can capture all the relevant attributes of a decision maker. This is simply a practical observation. Data on some relevant attributes may not be available or may be beyond the scope or feasibility of the study. For instance, one can argue that the social status of a mobile phone is a relevant mobile service plan attribute. However, the social status of a mobile phone (e.g., iPhone 4) can be measured relative only to other mobile phones. This, in turn, requires that the survey respondents be familiar with the mobile phones in the choice set and know the social perception of these mobile phones. Similarly, the decision makers' traveling habits might affect the plan decision. However, this might be beyond the scope of the survey unless the focus is to examine whether the purchasing decisions of the survey respondents differ by traveling habits. To account for this practical limitation, a researcher must separate the utility function specified in equation (2) into an observed component and an unobserved component. Following Train (1993), separating the utility U_{in} into an observed component V_{in} and an unobserved component e_{in} yields:

(5) $U_{in} = U(x_{in}, r_n) = V(z_{in}, s_n) + e_{in}$,

where V is the observed utility derived from choice alternative i faced by decision maker n, z_{in} are the observed choice attributes, and s_n are the observed decision maker attributes. The unobserved component e_{in} contains all the characteristics of the choice alternative i and the decision maker n that the data do not capture.

The observed utility V is a parametric function, specified by a parameter vector β, which relates the observed choice and decision maker attributes to the observed utility. Hence, equation (5) is rewritten as:

(6) $$U_{in} = U(x_{in}, r_n) = V(z_{in}, s_n, \beta) + e_{in}.$$

Substituting equation (6) into the general form of a discrete choice model, as specified in equation (1), yields:

(7) $$P_{in} = \Pr(V_{in} + e_{in} > V_{jn} + e_{jn}, \text{ for all } j \text{ in } J_n,\ j \neq i).$$

Rearranging yields:

(8) $$P_{in} = \Pr(e_{jn} - e_{in} < V_{in} - V_{jn}, \text{ for all } j \text{ in } J_n,\ j \neq i).$$

As pointed out by Train (1993), the right-hand side of equation (8) states that the probability of selecting choice alternative i is equal to the probability that the difference of the unobserved utility components is smaller than the difference of the observed utility. By definition, the observed utility is known (i.e., observed). The unobserved utility component, however, is a random variable. A random variable takes on a continuum of values, each with some probability. It follows a specific probability distribution with a certain mean and standard deviation. In the case of a logit model, the error term is assumed to be distributed independently and identically following the Extreme Value (Weibull) distribution. The difference between two random variables is also a random variable. Specifically, the difference between the two extreme value distributed error terms is a random variable with a logit distribution, thus the name logit model. Figure 1 shows the cumulative logit distribution.

Figure 1. Cumulative Logit Distribution

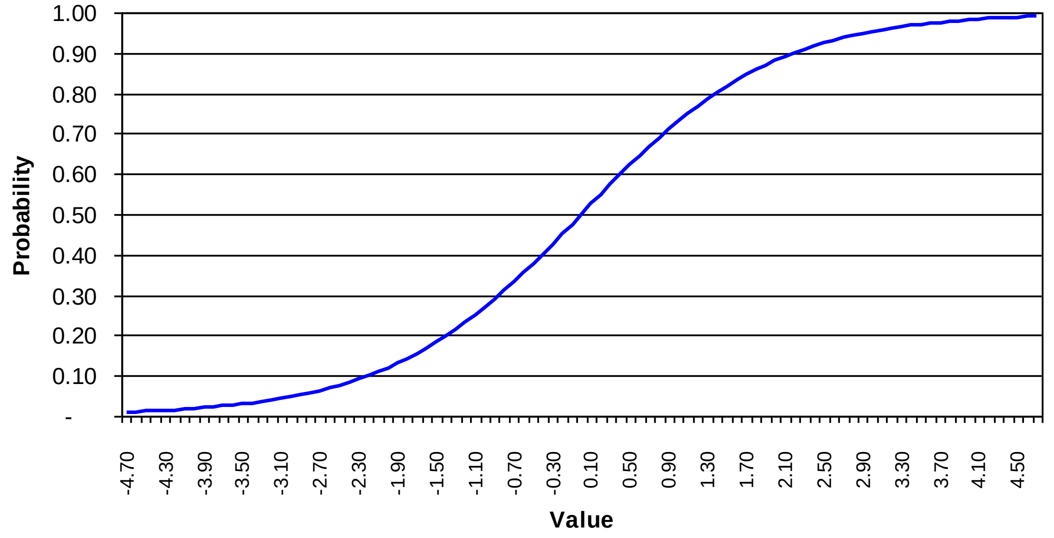

Figure 1. The cumulative distribution function describes the probability that a random variable *X* with a given probability distribution will be found at a value less than or equal to *x*.

Thus, the probability of decision maker n selecting alternative i over alternative j is equal to the cumulative logistic probability that the difference in the unobserved utility component is smaller than the difference in the observed utility component for all choice alternatives in the choice set. For instance, assume that the difference in the observed utility V between alternative i and alternative j equals 2.9. The probability that the difference in error terms is less than 2.9 (when the difference is distributed following a logistic curve) equals 95%. Hence, there is a 95% probability that alternative i is preferred over alternative j. Therefore, for alternative i to be selected over all other alternatives in the choice set J, the actual probability of selecting alternative i is a joint cumulative distribution. Based on this observation, McFadden (1974) derived the following probability of decision maker n to select alternative i:

(9) $$P_{in} = \frac{e^{V_{in}}}{\sum_{j \in J_n} e^{V_{jn}}} = \frac{e^{\beta x_{in}}}{\sum_{j \in J_n} e^{\beta x_{jn}}}, \text{ for all } i \text{ in } J_n.$$

The numerator of this ratio reflects the desirability of alternative i faced by decision maker n, whereas the denominator is the sum of the utility obtained from all choice alternatives. Thus, the ratio forces each choice probability between zero and unity and ensures that all of the choice probabilities add up to unity.

With the logit probability defined, the only remaining issue is how V_{in} is estimated. Equation (6) defines V_{in} a parametric function. Therefore, in order to estimate the observed utility, the parameter vector β needs to be estimated. A basic aspect of choice analysis is that the researcher only observes the selection of the choice with the highest perceived utility. For instance, by having a survey respondent select the most preferred mobile service plan from a choice set of three plans, the researcher can only observe that one plan is preferred over two other plans. The researcher does not observe an actual utility value. Thus, a regression analysis of the representative utility on a number of alternative and respondent-specific attributes is not possible. Instead, one needs to resort to maximum likelihood estimation (MLE) to estimate β. The concept behind MLE is to select the parameter vector β that maximizes the probability of getting the result (i.e., plan selections) observed through the survey.

To illustrate the concept of MLE, consider a coin toss. If tossing a coin 10 times results in four heads and six tails, the binomial probability of arriving at this exact result is:

$$(10) \qquad \Pr(\text{4 heads, 6 tails}) = \binom{10}{4} P^4 (1-P)^6 = \frac{10!}{4!6!} P^4 (1-P)^6 ,$$

where P is the probability of a head (Amemiya, 1993). The MLE estimates the P that maximizes the probability of obtaining four heads and six tails. Specifically, the MLE maximizes the expression $P^4(1-P)^6$, which is referred to as the likelihood function. Thus, the MLE maximizes the likelihood function.

Estimating the MLE for the parameter vector β is not much different than obtaining an estimate for the probability of a head in a coin toss. Much like a coin toss, the researcher treats a decision in a binomial qualitative choice model as a single draw from a Bernoulli distribution (Train, 1993). There are two observed outcomes under a Bernoulli distribution—a one if the decision maker chooses alternative i and a zero otherwise (Greene, 2008). If there were only two choice alternatives and if the researcher observed that alternative i was chosen four times, then the probability of selecting alternative i is identical to the probability of getting heads in a coin toss, as shown in equation (10). Consequently, the likelihood function would also be identical. Where a multinomial qualitative choice model deviates from a simple coin toss is in the number of choice alternatives. A coin toss can have only two possible outcomes (i.e., heads or tails), whereas a choice set often consists of more than two choice alternatives and thus yields more than two possible outcomes. Additionally, a choice model involves numerous decision makers, who assumingly make independent purchase decisions.

Per Train (1993), the probability of one decision maker n selecting alternative i equals:

$$(11) \qquad \prod_{i \in J_n} P_{in}^{\delta_{in}}, \text{ where } \delta_{in} = \begin{cases} 1 \text{ if decision maker } n \text{ chose alternative } i \\ 0 \text{ otherwise} \end{cases}$$

and P_{in} equals the probability of decision maker n selecting alternative i. The expression $\prod_{i \in J_n}$ is the product operator. Equation (11) is the product of the marginal or choice probabilities.

To illustrate this equation, consider the probability of selecting one of two available mobile service plans (Plan A and Plan B). In this example, the expression in equation (11) is the probability of decision maker n selecting mobile service Plan A over mobile service Plan B, given that the decision maker selects Plan A. It is the mathematical product $\prod_{i \in J_n}$ of the probability of selecting Plan A and the probability of selecting Plan B. Raising the selected alternative by the power of one and the nonselected alternative by the power of zero yields the conditional binomial probability of the selected Plan A.

Expanding this expression beyond one decision maker, the probability of all decision makers making the choice that the researcher observed in the sample is simply the mathematical product $\prod$ of the expression in equation (11) over all decision makers N:

$$(12) \qquad L(\beta) = \prod_{n \in N} \prod_{i \notin J} P_{in}^{\delta_{in}} \,.$$

Equation (12) is the likelihood of all decision makers N selecting alternative i from choice set J. As shown in equation (1), the probability of decision maker n selecting alternative i is, among other things, a function of the parameter vector β. Hence, $L(\beta)$ is the joint probability function, or likelihood function, of the parameter vector β. Specifically, the likelihood function for β assigns a probability to each value of β that the sampled decision makers would make the decisions that they actually did. Louviere, Hensher, and Swait (2000) described the joint likelihood function as the probability of having observed the particular decisions, given a set of parameters. The parameter vector that yields the highest probability is the maximum likelihood estimator of β. Hence, in order to estimate the parameter vector β, the maximum likelihood function is maximized.

As described by Train (1993) and Louviere et al. (2000), instead of maximizing the likelihood function directly, it is often easier to maximize the log-likelihood function. The log-likelihood function $LL(\beta)$ of equation (12) is:

$$(13) \qquad LL(\beta) = \sum_{n \in N} \sum_{i \in J} \delta_{in} \log P_{in},$$

where $\sum_{i \in J}$ is the sum over all alternatives and $\sum_{n \in N}$ is the sum over all decision makers.

Because δ_{in} is zero for the nonselected alternatives, the log-likelihood function is simply the log of the probability of the selected alternatives summed over all decision makers. As shown in Figure 2, the log-likelihood is a function that reaches its maximum when it gets as close as possible to zero. This is because the likelihood function is a probability, which is maximized as it approaches unity. The log of one, however, is zero.

Figure 2. Log-likelihood Function

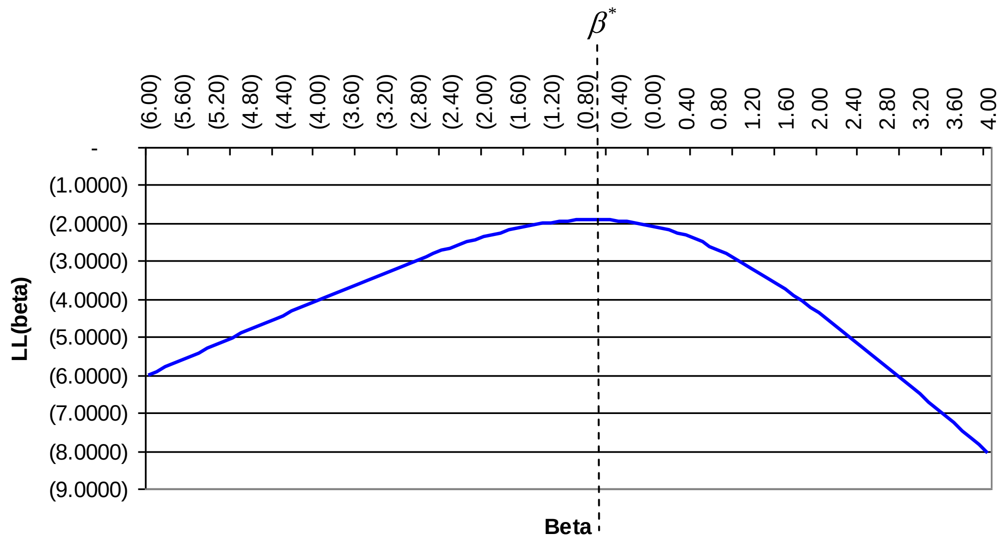

Figure 2. Illustrated here is the log-likelihood function for a hypothetical choice scenario of three decision makers facing three choice alternatives.

A useful statistical tool in evaluating the goodness of fit of the maximized log-likelihood function is the likelihood ratio (LR) index used to determine how well the models fit the data. Analogous to an R^2 in a regression model, the LR index compares the model with the parameter estimates against the same model where these parameters are zero. Train (1993) defines the LR index μ as:

$$(14) \qquad \mu = 1 - \frac{LL(\beta^*)}{LL(0)},$$

where $LL(\beta^*)$ is the value of the log-likelihood function evaluated at the maximum likelihood estimators of the parameter vector and $LL(0)$ is the value of the log-likelihood function evaluated at the point where all parameters are assumed to be zero. In essence, the likelihood ratio evaluates the percentage improvement of the maximum likelihood estimator over a world with no information. In a world of perfect information, $LL(\beta^*) = 0$ and the index is one. In a world of no information, $LL(\beta^*) = LL(0)$ and the index is zero. Louviere et al. (2000) found a likelihood ratio index for MNL models of between 0.2 and 0.4 to be indicative of an excellent fit.

Thus far, the discussion about the derivation and evaluation of the logit model has been restricted to individual decision making. It produced the probability of a group of individuals N selecting an alternative i. However, most studies, including this one, are interested in market behavior, not individual behavior. Because market behavior is a direct consequence of individual behavior, individual probabilities provide information about market behavior. Therefore, the researcher calculates market behavior by taking the simple average of a random and representative sample of the market participants. If there is doubt that the sample is random, the researcher can weight individual market decisions to arrive at the market average. Alternatively, the researcher can forecast market behavior by forecasting the probability of an average decision maker. As noted by Train (1993), however, although common, this method yields inconsistent results due to the nonlinearity of the cumulative probability function.

In contrast to these desirable features of the logit model, Train (1993) also discussed a distinct flaw of the model—the independence of irrelevant alternatives, or IIA. The IIA problem is the logit model's inability to distinguish between irrelevant alternatives. Louviere et al. (2000) define IIA as "the ratio of the probabilities of choosing one alternative over another (given that both alternatives have a non-zero probability of choice) is unaffected by the presence or absence of any additional alternatives in the choice set" (p. 44).

The classical example to illustrate the IIA problem is the red bus/blue bus example. In this example, a decision maker selects first between traveling by car or a blue bus. Assuming that both travel options have the same representative utility V, the probability of selecting the car is 0.5. Assume now that the choice set includes a red bus so that the traveler must decide whether to take the car, a blue bus, or a red bus. Common sense would predict that the mere difference in bus color would not influence the decision maker's selection. However, the addition of this third (irrelevant) alternative alters the logit probabilities. It reduces the probability of selecting the car to $0.33\overline{3}$, thereby potentially producing unrealistic probability results.

The IIA property of the logit model also could be a potential limitation to the present mobile demand survey. Remember that the survey respondents must select from among three mobile service plans. If a survey respondent is indifferent between two plans (i.e., one of the plans is irrelevant), then a logit model would produce inaccurate probabilities for this respondent. To avoid this potential problem, the survey data were evaluated using an advanced form of the logit model, the mixed logit model. Among other desirable features, the mixed logit model remedies the IIA problem.[10]

Exploded Logit Modeling

The exploded logit model (also called the logit with ranked choices) is identical in all aspects to the standard logit model discussed thus far with the exception of its treatment of the underlying data. A standard logit model relies on one observation from each decision maker. It only uses the alternative that the decision maker actually selects. The exploded logit model, on the other hand, uses the rankings of some or all of the available choices. Consequently, the exploded logit model uses several choice decisions per decision maker whereas the non-exploded logit model relies only on the decision of the most preferred choice alternative.

For instance, consider a decision maker who must select from among four cars to purchase, Cars A, B, C, and D. The decision maker selects Car A with a second choice of Car B followed by Car C. Car D is the least preferred car. A standard logit model relies only on the fact that the decision maker selected Car A. It ignores the rejection of Cars B, C, and D, in particular the fact that the decision maker values Car B over Car C and both Cars B and C over Car D, the least preferred car. This is valuable information that further explains the decision maker's preferences. The exploded logit model makes use of this additional information. Obviously, without structuring the survey accordingly, the researcher does not know whether Car A was preferred to Car C, and so on. Hence, in order to use an exploded logit model, the researcher has to structure the survey in one of two ways. The first way to extract ranked data is to ask the decision maker to rank Cars A through D according to desirability (i.e., 1 = most desirable to 4 = least desirable). This is the simultaneous method of obtaining the rankings. The sequential way is to ask the decision maker to select the top pick of the alternative cars, then to ask for the second pick, and finally the third pick. The first pick reveals that the decision maker prefers Car A rather than Cars, B, C, and D. The second pick reveals that the decision maker prefers, say Car B, rather than Cars C and D. Finally, the third pick demonstrates the decision maker's preference of Car C over Car D. Either method extracts the ranking of the alternatives.

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[10] Note that conditional on a given set of preference parameters for an individual, the IIA property continues to hold.

The ranking provides the researcher with additional data points, which, in turn, allows for more accurate parameter estimates (Beggs, Cardell, & Hausman, 1981). For example, if there are 200 respondents to a survey, the standard logit model will have 200 observations. The exploded logit model, however, "explodes" these data and has three observations for each respondent, resulting in 600 (3 x 200 = 600) observations. Train (2009) showed that the researcher could treat the ranking of J alternatives as though the decision maker had $J-1$ independent choices. The model treats the rankings of each survey respondent as an individual (pseudo) observation. The researcher can then use a standard logit model to fit the ranked, or exploded, data. As shown by Beggs et al. (1981), the logit probability for an exploded logit model (as shown in equation (9) for the case of the standard logit model) is the joint probability of the particular ranking:

$$\text{(15)} \qquad \Pr(U_{1n} > U_{2n} > U_{3n} > \ldots > U_{Hn} \text{ for } H \leq J) = \prod_{h=1}^{H} \left[e^{V_{hn}} \Big/ \sum_{m=h}^{H} e^{V_{mn}} \right],$$

where H is the number of selections made. To illustrate this equation, the probability of the ranking of the four Cars, A, B, C, and D is:

$$\text{(16)} \qquad \Pr(\text{ranking A, B, C, D}) = \frac{e^{\beta x_{An}}}{\sum_{j=\text{A, B, C, D}} e^{\beta x_{nj}}} \frac{e^{\beta x_{Bn}}}{\sum_{j=\text{B, C, D}} e^{\beta x_{nj}}} \frac{e^{\beta x_{Cn}}}{\sum_{j=\text{C, D}} e^{\beta x_{nj}}}.$$

As stated by Train (2009), this particular expression is unique to the logit model and does not apply to other models, such as the probit model. Practically, the expression implies that the exploded logit model treats the ranked data as if they were H independent observations from decision maker n.

Although the exploded logit model is desirable in that it allows the extraction of information about alternatives other than the first choice, it does not address the IIA problem discussed above. The exploded logit model also introduces a new assumption that may not be realistic. Specifically, by treating each survey respondent's rankings as individual observations, it assumes that $J-1$ observations from one respondent are identical to $J-1$ observations from $J-1$ respondents. In order to remedy this potential problem as well as the IIA problem, there is the mixed logit model or more specifically the exploded mixed logit model. This is the subject of the next two sections.

Mixed Logit Modeling

The mixed logit model is a highly flexible derivative of the standard logit model (Train, 2009). The flexibility of this model is a direct consequence of relaxing the assumption that the parameters β are point estimates. In lieu, the mixed logit model assumes that the parameters are random variables, each with a certain probability distribution, mean, and standard deviation. Researchers also refer to mixed logit models as random parameter logit (RPL) models. Their first application was around 1980 (see, e.g., Boyd & Mellan, 1980; Cardell & Dunbar, 1980).

The mixed logit model follows the same building blocks as the standard logit model. Thus far, the parameter vector consists of nonrandom values that do not vary by decision maker. The implication of this is that the observed utility V_{in} varies only by the attributes of the choice alternative and the decision maker. The relationship by which these attributes relate to the observed utility remains constant. Practically, this assumes that all decision makers have the same preferences. By making the parameter estimates random values, the researcher relaxes this constraint, thereby allowing for respondent-specific parameters β_n. Hence, in contrast to equation (6), the utility expression for a mixed logit model is:

(17) $$U_{in} = U(x_{in}, r_n) = V(z_{in}, s_n, \beta_n) + e_{in}.$$

As in the standard logit model, e_{in} is independent and an identically distributed (iid) Extreme Value (Weibull). However, given that the parameter vector β_n varies by survey respondent, it is distributed with density $f(\beta)$. Consequently, the analogous relationship shown for the standard logit model in equation (9) becomes:

(18) $$P_{in} = \frac{e^{\beta_n x_{in}}}{\sum_{j \in J_n} e^{\beta_n x_{jn}}}, \text{ for all } i \text{ in } J_n,$$

where $\beta \sim f(\beta|b,W)$, and b is the mean vector for all β and W is the covariance matrix of all β. Because β_n is not known, the probability P_{in} is the integral of β_n over all its possible values (Train, 2009):

$$(19) \qquad P_{in} = \int L_{in}(\beta) \cdot f(\beta|b,W) d\beta = \int \left(\frac{e^{\beta x_{in}}}{\sum_{j \in J_n} e^{\beta x_{jn}}} \right) f(\beta) d\beta.$$

Train (2009) found that the most common distributions selected for the parameter vector are normal and lognormal distributions, thus he recommends the lognormal distribution in instances where the coefficient is known to have the same sign for each survey respondent. Other distributions in use are the triangular distribution and the uniform distribution (see, e.g., Hensher & Greene, 2003; Revelt & Train, 2000; Train, 2001).

Mixed Exploded Logit Modeling

An exploded logit model also can be applied to the mixed logit model, yielding the mixed exploded logit model. Because the mixed logit model allows for respondent-specific-parameter estimates, the pseudo-observations created by the ranking now are correlated (Train, 2009). This correlation is a significant improvement over the standard exploded logit model as it allows the researcher to take into account that pseudo-observations are not entirely new observations but observations from the same survey respondent. Therefore, the mixed exploded logit model incorporates the fact that survey respondents have different preferences, and it accounts for the correlation in unobserved factors over repeated choices by each respondent. Train (2009) also demonstrated that the mixed logit model allows for the relaxation of the IIA.[11]

Model Specification

The objective of this study is to identify the demand drivers of mobile demand when services are bundled. Although regression analysis could potentially be used for this type of analysis (see, e.g., Tripathi & Siddiqui, 2009), a discrete

[11] The mixed logit is not the only remedy to the IIA problem. For instance, Burda, Harding and Hausman (2008) estimated the preference parameters non-parametrically, allowed for correlation among the parameters, and relaxed the IIA assumption.

choice model replicates more closely the subscriber's purchase decision. A key consideration in this decision is the fact that purchase decisions are binary and thereby noncontinuous. The theoretical discussion above highlights a number of discrete model candidates. Among them are logit and probit models. Logit models contain a number of desirable features, particularly when the standard logit model is extended. For instance, extending the standard logit model to use exploded data is straightforward for logit models as researchers can treat the pseudo-observations as new observations. This is not the case for probit models (Train, 2009). Hence, the model for this study is a logit model. More specifically, it is an MNL model as the decision makers face more than two choice alternatives. However, the MNL model is not the optimal model for this study because the model requires extension in several dimensions.

First, in order to address the IIA problem and the fact that decision makers for mobile service plans do not all have the same preferences, a mixed logit model yields potentially more accurate probability estimates. Second, using an exploded version of the logit model can be more efficient as it requires information from less decision makers. For studies such as this one where survey data are required, using multiple observations from the same decision maker optimizes both time and resources. Thus, an appropriate model for this study is a mixed exploded logit model. Given the three choices faced by the decision maker, the best model for this study is a multinomial mixed exploded logit model. A final consideration in this model is the specific distribution for the stochastic parameter vector β. Statistical software typically limits the number of available distributions to normal, lognormal, exponential, and triangular. Each type of distribution requires a set of starting values in order to maximize the log-likelihood function. Practical tests show that lognormal, exponential, and triangular distributions require highly accurate starting values for the existing software to be able to maximize the log-likelihood function. Thus, the study started with normal distributed variables, which has one clear disadvantage. Depending on the sizes of the standard deviation and the mean of parameter β, a mixed logit model with normal distributed variables might produce parameter estimates that contradict economic theory. For instance, assume a normal distributed price coefficient with a mean of -0.2 and a standard deviation of 0.2. In this example, the mixed logit model forecasts positive price coefficients for some 22% of the draws. Some mixed logit software reports the percentage of draws that have opposite signs instead of the mean as the “share<0.” In the example above, the share<0 is 78%, indicating that 22% is above zero. A lognormal distribution is left-bound at zero. Hence, its share<0 is necessarily zero, thus the problem of forecasting coefficients with signs that are opposite to its mean is avoided. Consequently, relative to normal distributed parameters, lognormal distributed parameters promise to produce more accurate coefficients and thus probability forecasts.

Before specifying the theoretical model for this study, the number of choice alternatives, choice situations, and number of decision makers were decided upon and then defined. As explained later, the data for this model come from a consumer survey. In this survey, respondents ranked three hypothetical mobile service plans (Plan 1, Plan 2, and Plan 3). Each plan represented a choice alternative, denominated by j_n. The subscript indicates that choice situations differed over the decision makers; that is, not all decision makers faced the same three choice alternatives. Hence, the number of choice alternatives faced by the decision maker (the survey respondent) was three. The three choice alternatives considered together represent a choice situation, denominated by t_n. In a choice situation, the decision maker ranked the desirability of the three choice alternatives from high to low. In reality, there are many more mobile service plans from which to choose. Setting the number of choice alternatives at three assumes that mobile subscribers narrow their selection to three plans before making a decision. It also takes into account that given the complexity of mobile service plans consumers might not be capable of comparing more than three plans at once. This assumption seems to be consistent with the findings of U.S. mobile service providers. For instance, on its website, Verizon Wireless offers potential subscribers a choice of three voice plans and three data plans.

Each survey respondents faced six different and independent choice situations. That is, survey respondents made six independent trade-off exercises, each with three choice alternatives. Limiting the number of choice situations to six also took into consideration survey respondent fatigue that might occur if there were too many choice situations offered. The number of completed surveys was set at 500. With three choice alternatives, the respondent made ranking decisions per choice situation. In the first ranking decision, the respondent faced all three choice alternatives and decided which among the three was most desirable based on its relative attribute levels. In the second ranking decision, the respondent indicated which of the remaining two alternatives was least desirable. With six choice situations, this provides 2 x 6 x 500 = 6,000 observations. Consensus does not seem to exist among researchers as to the number of required observations for a study. This is particularly the case for discrete choice models. A rule of thumb offered by Draper and Smith (1998) and Ryan (2009) suggests that the number of observations should be at least 10 times the number of independent variables. As explained below, there is a maximum of 10 choice attributes and a maximum of nine sociodemographic variables providing 29 potential independent variables. This requires a minimum of 290 observations. Hence, 6,000 observations are sufficient and allow for data stratification.

Based on these considerations, the fundamental question underlying this model is, Given three mobile service plans, what is the probability that a consumer will select a particular plan? Mathematically, the expression for the selected model is:

$$(20) \qquad P_{itn} = \int \left(\frac{e^{\beta q_{itn}}}{e^{\beta q_{itn}} + e^{\beta q_{jtn}}} \right) f(\beta) d\beta = \int \left(\frac{1}{1 + e^{\beta q_{itn} - \beta q_{jtn}}} \right) f(\beta) d\beta .$$

The matrix q_{itn} consists of observed survey respondent characteristics s_n and observed mobile service plan characteristics z_{itn}. The respondent characteristics s_n serve two distinct purposes. The first purpose is to ensure that the selected sample represents the average U.S. consumer. As such, it includes current consumption patterns to compare the responses to publicly and commercially available benchmark data. Second, sociodemographic variables are a subset of the respondent characteristics. Although the relevant literature provides no clear guidance as to whether sociodemographic variables should be included, collecting them provides the flexibility to test their significance (or lack thereof). In the present survey, the information collected from the survey respondents s_n included:

- Whether the respondent had a mobile phone at the time of the survey
- Whether the respondent had ever been financially responsible for a mobile phone service account
- The number of minutes included in the respondent's current monthly voice plan

- Whether the respondent subscribed to a monthly data plan that allowed access to the Internet and the ability to send emails via the mobile phone
- Whether the respondent subscribed to a plan that contained an SMS allowance
- Whether the respondent used the mobile phone to send and receive emails
- The approximate monthly mobile phone service expenditure
- Whether the respondent had a fixed-line phone in the main residence
- Age
- The state of residency
- Whether the respondent lived in a metropolitan area, suburban community, small town, or farming area
- The highest level of education completed
- Employment status
- Gender
- Marital status
- Number of children
- Annual income from all sources before taxes

Also consistent with the economic literature, the present survey collected all relevant price and non-price attributes. In contrast to the literature, the survey included price and non-price attributes for all mobile plan components rather than only voice or voice and SMS. The mobile service plan attributes z_{itn} contained the following price and non-price attributes:[12]

- Price of the mobile phone (*phone_price*): price of the mobile phone
- Monthly recurring charge (*mrc*): fixed-plan price component per month
- Voice minutes (*v_allowance*): total number of voice minutes included in the monthly charge
- Data allowance (*d_allowance*): total number of kilobytes of downloads and uploads included in the monthly charge
- Data download speed (*download*): speed in seconds that a file can be downloaded from the Internet (the higher the speed, the faster the download)[13]
- Fee for excess minutes (*v_over*): per-minute charge for each minute in excess of the monthly voice allowance
- Fee for excess date usage (*d_over*): per-kilobyte charge for each kilobyte of data in excess of the monthly data allowance

[12] The variable names are provided in parentheses and italicized throughout the study.

[13] As reference point, standard dial-up service provides a speed of 56 kilobits per second (kbps), digital subscriber line (DSL) between 3,000–7,100 kbps, and coaxial cable Internet access between 8,000 and 20,000 kbps.

- SMS fee (*text*): charge for each text message sent and received
- Type of phone (*phone_type*): a Smartphone (e.g., iPhone, Blackberry) or a regular non-Smartphone
- Length of contract (*term_length*): contract length in months with an ETF of $150

Table 3 is an example of a choice set faced by a respondent.

Table 3
Illustrative Choice Set

S1G6	Plan 1	Plan 2	Plan 3
Price of mobile phone	$ 200	$ 50	$ 400
Monthly charge	$ 120	$ 60	$ 20
Voice minutes allowance per month	400	3,000	2,000
Data allowance per month (kilobytes)	5,000	200	50
Data download speed (kilobits per second)	3,000	500	2,000
Fee for excess minutes	$ 0.40	$ 0.10	$ 0.10
Fee for excess data usage	$ 0.40	$ 0.25	$ 0.10
SMS fee (per message sent and received)	$ 0.30	$ 0.25	Free
Type of phone	Smart	Smart	Non-smart
Length of contract (months)	30	18	12
Assuming that these three plans are the only way you can obtain wireless telephone service, which plan are you <u>most likely</u> to purchase?	○ Plan 1	○ Plan 2	○ Plan 3
Assuming that these three plans are the only way you can obtain wireless telephone service, which plan are you <u>least likely</u> to purchase?	○ Plan 1	○ Plan 2	○ Plan 3

As Table 3 illustrates, each plan has identical attributes, but the attribute levels differ among the plans. For instance, Plan 1's monthly charge is $120 and Plan 2's $50. Decision makers decide based on the relative value placed on each attribute. For example, a low mobile phone price is more important than the length of the term contract for some subscribers. For others, they prefer paying more for the mobile phone and being free to switch service providers at any time. As decision makers base their decisions on the level of the various attributes, setting them is of utmost importance. The setting of attributes within and among choice alternatives is the topic of the next chapter.

Experimental Survey Design

With the model specified, the attention focused on how to obtain the data to populate the model. The theoretical model discussed above can be estimated using either revealed-preference (RP) or stated-preference (SP) data. RP data are actual market data (Louviere et al., 2000). RP data in this study would consist of actual mobile subscriber choices. Specifically, the observations in an RP database would consist of actual subscriber accounts. The columns would consist of the specific plan attributes and the account holder's personal information. The advantage of RP data is its high reliability as the data are the result of actual market transactions (Louviere et al., 2000). SP data, on the other hand, are the result of an experiment, specifically a consumer survey. As indicated by the name, the resulting data are not actual (revealed) choices but responses to hypothetical choice situations. SP data in this study would consist of asking survey respondents which mobile plan they would select if offered a plan with a set of specific attributes. Another name for SP data is stated-choice (SC) data.

There are various trade-offs between RP and SP data. The main advantage of RP data is that subscribers actually made those choices and accepted the consequences (e.g., they are paying for the selected mobile service plan). In practice, however, RP data present a number of difficulties and complexities. First, RP data provides information on the actual choices made; however, no data are available on the other choices offered, if any, or on the conditions under which the respondents made their choices. Second, mobile service providers (as well as most other firms) are reluctant to supply their subscriber data (which are contained in billing databases) for third-party studies. Although mobile service providers frequently study subscriber behavior, these studies are typically confidential as they could provide valuable insights to competitors if revealed. Third, and related to the first point, RP data are embedded within highly complex billing systems, consisting of several terabytes of data and thousands of tables. For this particular study, several North American mobile service providers declined the request to provide data. A fourth practical disadvantage of RP data is that the data contain much "noise." That is, subscribers make purchase decisions based on a wide number of decision factors with a change in service attributes being only one factor. Fifth, given the competitive environment of the U.S. mobile sector, price variations are minimal as mobile service providers are price takers and thus cannot widely experiment with changes in service plan offerings. The implication of this lack of variation is that a choice model cannot evaluate the interaction between demand determinants and sufficient information does not exist on how consumers react to attribute changes (Louviere et al., 2000). Finally, even if there are changes in attributes, these might be across all plans, thereby making it difficult to isolate statistically the impact.

The fundamental disadvantage of SP data is that survey respondents make choices without actually having to accept the consequences of their choices. This raises the question of whether consumers in the real world would behave as they claim they would in an experiment. On the other hand, SP data allow researchers to control the experiment, deciding the number of choice alternatives and attributes upon which respondents make their decisions.

In light of these considerations, this study uses a combination of RP and SP data. The objective of this hybrid approach is to maximize the advantages of RP and SP data and minimize their respective disadvantages (Louviere et al., 2000). Practically, the combination simply required a survey consisting of an RP and an SP section. In the RP section, the survey respondents provided information about their actual consumption patterns. This included questions such as the size of the average monthly mobile phone bill, the type of services (e.g., voice, SMS, MMS) used, and whether they purchased fixed-line service. The SP section of the survey came from an SP experiment (i.e., a trade-off exercise). SP experiments generate SP data by asking survey respondents to state their most preferred choice or to rank the choices by preference from a set of carefully drafted choice alternatives. Experimental design refers to the methods by which the choice alternatives and choice sets are drafted. First proposed by Louviere and Woodworth (1983) and Hensher (1983), SP experiments are widely used in many different fields but most applications are in economics and marketing.

The fundamental objective of SP experiments, and thus experimental design, is to determine the impact that different product or service attributes have on an outcome, such as the purchase of the product or service (Louviere et al., 2000). In this study, the objective is to determine the impact that several mobile service plan attributes have on the probability P_{in} that plan i is selected by decision maker n. Specifically, analysts vary these attributes over a number of choice situations and survey respondents in order to ascertain the impact that the attributes have on the probability P_{in}.

The design of SP experiments has a direct impact on the accuracy of the probability estimate P_{in}. In designing an SP experiment, the analyst must decide the number of choice alternatives J_n faced by each decision maker n, the number of choice situations T_n, the number of attributes Z_{jn}, the number of attribute levels, and the levels for each attribute in the survey. As explained previously, the present choice experiment has three choice alternatives repeated in six choice situations. A choice alternative is a mobile service plan. A shown above, 10 attributes describe each plan. The number of attribute levels, in particular the distribution of these levels across the SP experiment, further influence the accuracy of the probability estimate P_{in}. Consider, for example, a scenario where only two mobile plans with MRCs of $120 and $100 per month are included in a survey. The resulting responses to such a survey would likely be meaningless in terms of MRCs because there is insufficient variation in this particular plan attribute. Alternatively, consider a survey that includes only very inexpensive options for mobile phones (e.g., free or $25) and only very expensive options for the MRC (e.g., $120, $100, and $90). Such a survey would likely overestimate the respondents' sensitivity to price changes in the MRC and underestimate the sensitivity relative to mobile phones. Thus, the levels of the attributes as well as their distribution across the experiment are a critical aspect of experimental design.

The economic literature provides only general guidelines on how to determine the number of attributes and attribute levels. For instance, Churchill (1995) found that attributes must be important to decision makers in making their purchase decisions. To determine what constitutes an important attribute, Churchill listed expert opinions, focus groups, and surveys but found that any other explanatory research technique also could be valid. The present survey draws its attributes from market observation. Specifically, U.S. mobile service providers list their service bundle choices on their corporate websites. Service bundles differ in a number of aspects, such as MRC and the price of the mobile phone. Given the high level of competition in the U.S. mobile sector, the attributes by which the service plans differ provide a good indication as to what matters to U.S. consumers when purchasing a mobile service plan. Additionally, the U.S. Congress and the FCC have highlighted various mobile service plan attributes that allegedly affect a mobile service provider's market share. These attributes include the pricing of SMS and the length of the term contract. Hence, it is also reasonable to include those attributes even if only to test the hypothesis that they are statistically significant. Based on these considerations, the present SP experiment relies on the 10 mobile service plan attributes Z_{in} listed above.

With respect to the attribute levels, Churchill (1995) found that attribute ranges should extend beyond what researchers typically observe in the market; however, they should not be so excessive as to make them unrealistic. Similarly, Bliemer and Rose (2009) found that a wide range of attribute levels yields parameter estimates with smaller standard errors.

For the present SP experiment, attribute levels observed in the actual market served as the starting point with the observed ranges expanded by increasing the upper limits, decreasing the lower limits, or both. For instance, mobile phone prices typically range from $0 to $300. To measure the decision makers' sensitivity to changes in the mobile phone price, the upper limit of this range was expanded to include hypothetical mobile phone prices of $400 and $500. Some attributes, such as the type of mobile phone, are dummy variables and take on either a one or a zero. Others, such as the MRC, can take on seven different dollar amounts. Table 4 presents the attributes and attribute levels for this study.

Table 4
Design Matrix Attribute Levels

Attribute	Price of mobile phone	Monthly charge	Voice minute allowance	Data allowance	Data download speed	Fee for excess minutes	Fee for excess data usage	SMS fee	Type of phone	Length of contract
Attribute unit	*($)*	*($ per month)*	*(min per month)*	*(kb per month)*	*(kbps)*	*($ per min)*	*($ per kb)*	*(per message)*	*(dummy)*	*(months)*
Values begin	$0	$20	400	0	250	$0	$0	$0	1	0
	$50	$40	800	50	500	$0.10	$0.10	$0.05	0	6
	$100	$60	1,200	200	1,000	$0.15	$0.15	$0.10		12
	$200	$80	1,600	500	1,500	$0.20	$0.20	$0.20		18
	$300	$100	2,000	1,000	2,000	$0.25	$0.25	$0.25		24
	$400	$120	3,000	5,000	3,000	$0.30	$0.30	$0.30		30
Values end	$500	$160	9,999	9,999	6,000	$0.40	$0.40	$0.40		36

The attribute levels for an SP survey are contained in the design matrix shown in Appendix B. Each column in the design matrix represents the attribute levels for each attribute in a given choice situation. The total number of columns is equal to the product of choice alternatives (i.e., service plans) and choice attributes. In the design matrix for this survey, there are 10 choice attributes and three choice alternatives, resulting in 30 columns. Each row is a set containing three different mobile service plans (i.e., choice situations). The total number of rows is equal to the total number of unique conjoint exercises in the SP experiment. Depending on the specific experimental design, analysts can elect to use unique trade-off exercises for all choice situations and decision makers or repeat a certain number of choice situations across survey respondents. If unique experiments are used, the number of rows in the design matrix is equal to the product of the number of decision makers and the number of choice situations. With 500 decision makers and six choice situations each, this would yield 3,000 rows. For reasons discussed below, the present SP experiment uses only 42 unique choice situations. With six choice situations per survey, this yields seven unique surveys. The resulting design matrix has a dimension of 30 x 42 and is included in Appendix B. The first column of this matrix, entitled “Survey,” lists which of the seven unique surveys the particular choice situation (row) belongs. The second column, entitled “Game,” lists the number of the choice situation. For instance, the row where Survey=3 and Game=6 contains the attribute levels for the sixth choice situation faced by all survey respondents that received the third unique survey.

In deriving the design matrix, attribute levels are typically not presented in their actual units. Rather, they are coded according to the attribute levels L as 0, 1, 2, 3, … $L-1$ (Louviere et al., 2000). For instance, the price of the mobile phone in Table 4 has seven levels; therefore, a free phone would be coded “0,” a $50 phone would be coded “1,” and so on. The specific distribution of attributes across this matrix can have a material impact on the model outputs and the statistical power of the experiment, particularly when small numbers of observations are involved (Rose & Bliemer, 2010).

The literature on SP design discusses two main streams for determining the attribute levels in the SP design matrix or, more specifically, the correlation between the attributes. One method is the orthogonal experimental design method (see Louviere et al., 2000). However, recent research has raised several concerns as to whether orthogonal design is the most accurate method for nonlinear models, such as the logit model (e.g., Huber & Zwerina, 1996; Kanninen, 2002; Kessels, Goos, &

Vandebroek, 2006; Sandor & Wedel, 2001, 2002, 2005). Because of these concerns, a different method known as efficient or optimal design was recently developed. The following sections provide an overview of orthogonal design and experimental design and explain why the efficient design method is more appropriate for nonlinear models, including the present study.

Orthogonal Design

In designing an SP experiment, a researcher could include all possible combinations of attribute levels in the attribute matrix and present the resulting survey to each decision maker. This full factorial design would allow the researcher to obtain a specific response from each decision maker for each combination of attribute levels thereby ruling out the possibility of biasing the study results through the administration of a subset of these combinations. It further provides the researcher with full information on the effects of a change in the attributes on the dependent variable (i.e., the probability of decision maker n purchasing mobile service plan j). However, implementing a full factorial design is highly challenging to the decision making of the survey respondent and only practical for the simplest of SP experiments due to the large number of possible combinations and thereby the large number of choice situations that would need to be presented to survey respondents. Per Louviere et al. (2000), equation (21) calculates the number of choice situations T for a full factorial design:

$$(21) \qquad T^{ff} = \prod_{j=1}^{J} \prod_{z=1}^{Z_j} l_{jz} = l^{Z \cdot J},$$

where l_{jz} is the number of attribute levels for attribute z in choice alternative j. For instance, in an SP experiment with three choice alternatives ($J = 3$), three attributes ($Z = 3$), and three attribute levels for each of the attributes ($l = 3$), there are $3^{3\times 3} = 19,683$ choice situations in the full factorial design. Full factorial design for this hypothetical SP experiment would imply that all survey respondents would need to state their preferences in all 19,683 choice situations. In the present study, there are three choice alternatives ($J = 3$), 10 attributes ($Z = 10$) of which nine have seven attribute levels ($l = 7$), and one attribute with two attribute levels $(l = 2)$. Using the same equation as above, this yields over 525 sextillion choice situations that would be faced by all 500 decision makers n. Clearly, this is not practical, which shows that full factorial design is practical only for surveys with very few alternatives, attributes, and attribute levels.

Given the practical limitation of full factorial design, researchers have opted to present only a subset of all possible choice situations to each survey respondent, that is, fractional factorial design. Various methods exist from which a researcher can select the subset. A commonly used method is to select randomly a number of choice situations from the full factorial design and present this subset to survey respondents. Another method is to divide the number of choice situations in the full factorial design by the number of survey respondents and administer the choice situations in sequential blocks. In contrast to these two random selection methods, statistical design theorists have developed a number of other design methods, each aimed at producing accurate parameter estimates with the least number of observations. One such method is the orthogonal method. Similar to the random selection and sequential methods described, the orthogonal method also selects from the full factorial design method. However, it does so efficiently (instead of randomly), where efficiency is assessed through a particular statistical property (i.e., D-optimality). The objective of the orthogonal method is to produce parameter estimates with the smallest standard errors. A design matrix is orthogonal if the sum of the inner product of any two columns of the orthogonal coded matrix is zero (Louviere et al., 2000).

Finding its roots in operations engineering, fractional factorial design investigates a system's input-output relationship. It has a direct application to the present study that is investigating the impact that a set of attributes (input) has on the probability of a mobile service plan being selected (output). Starting with the full factorial design, fractional factorial design focuses only on the subset of combinations (often referred to as "runs") with the most desirable statistical properties, a process referred to as screening where the resulting design is called the screening design (DeVeaux, 2001). To select the subset that yields the most desirable statistical properties, the analyst creates an effect matrix from the full factorial matrix. The effect matrix breaks the full factorial matrix into main effects and interaction effects using contrast coding with pluses and minuses (+/−). An effect is the response of a change in attribute levels on the dependent variable (Box, Hunter, & Hunter, 2005). Main effects measure the impact that one attribute has on the dependent variable, whereas cross effects measure the combined effect of two or more attributes on the dependent variable (DeVeaux, 2001). To arrive at the fractional factorial design, the analyst determines how many of the combinations can reasonably be observed in a survey. Using the effect matrix, the analyst then can examine the type of effects (main effect or interaction) observed with the subset of combinations (Louviere et al., 2000). Alternatively, the analyst can select a subset of combinations and transform the selection into orthogonal codes (−1 for low values and +1 for high values) such that each column of combinations sums to zero and the inner products are also zero (Louviere et al., 2000). Appendix C illustrates this concept with an example.

The use of orthogonal SP design was primarily justified by its property to maximize the D-efficiency of linear models (e.g., Kuhfeld, Tobias, & Garratt, 1994; Lusk & Norwood, 2005). Statistical efficiencies are measures of design "goodness" indicating the precision of the parameter estimates for a fixed sample size (Rose & Bliemer, 2010). Among these efficiency measures is "D-efficiency," which measures the size of the standard error. Specifically, it measures the size of the determinant of the asymptotic variance covariance (AVC) matrix for a single respondent or the so-called D-error. A design with a lower D-error indicates a higher level of precision. Hence, with a higher level of statistical efficiency, more precise estimates can be obtained with a given sample size. Alternatively, a smaller sample size provides equally precise estimates. A design with the lowest D-error is D-optimal. In practice, however, D-optimal designs are often difficult to find. Furthermore, as the D-error declines asymptotically with the sample size, increasing the sample size for a single respondent yields decreasing marginal returns. Specifically, the standard error decreases at a rate of $1/\sqrt{N}$, where N is the sample size (Rose & Bliemer, 2010).

Figure 3 demonstrates that by selecting a D-optimal design over a nonoptimal design the researcher can achieve a lower standard error with the same number of observations or obtain the same level of accuracy with fewer observations (thereby saving money because fewer respondents need to be surveyed).

Figure 3. Asymptotic Standard Error

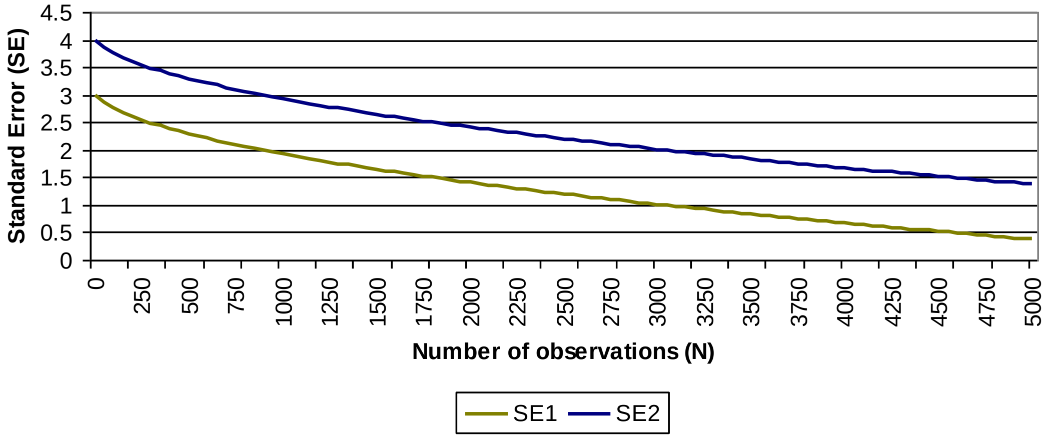

Figure 3. This figure illustrates the standard errors of two designs. The first design, SE1, is the default design, whereas the second design, SE2, is D-optimal.

Given the decreasing marginal returns from D-optimization, instead of minimizing the D-error generating a low D-error is often sufficient. A design that yields a low D-error is D-efficient, defined as:

(22) $$\text{D-efficiency} = \frac{100}{|C|^{1/K}},$$

where C is the AVC of the parameter vector β (Rose & Bliemer, 2006). K is the number of attributes in the design and serves to normalize the efficiency measure by number of attributes. Thus, the smaller the determinant of the AVC is, the higher the D-efficiency. Consider a linear model of the following form:

(23) $$Y = Z\beta + e,$$

where Z is the matrix of observed attributes, β is the parameter vector, and e is the error term. For linear models (and linear models only), the AVC is:

(24) $$AVC = \delta^2 (Z'Z)^{-1},$$

where Z' is the transpose of the matrix of observed attributes Z and δ^2 is the model variance (Ruud, 2000). Thus, D-efficiency equals:

(25) $$D-efficiency_{linear} = \frac{100}{\left|\delta^2 (Z'Z)^{-1}\right|^{1/K}}.$$

Multiplying and dividing the AVC for linear models by the number of observations F yields:

(26) $$\delta^2 (Z'Z)^{-1} = \frac{\delta^2}{F}\left(\frac{Z'Z}{F}\right)^{-1}.$$

Substituting equation (26) into equation (25) produces the following relationship:

(27) $$\text{D-efficiency}_{\text{linear}} = \frac{100}{\left|\frac{\delta^2}{F}\frac{(Z'Z)^{-1}}{F}\right|^{1/K}} = \frac{100}{\left(\frac{\delta^2}{F}\right)^{1/K}\left|\left(\frac{(Z'Z)^{-1}}{F}\right)\right|^{1/K}}.$$

The expression $\left(\frac{\delta^2}{F}\right)^{1/K}$ is simply a scalar, which is composed of the standard deviation of the model variance and the number of observations. The economic literature discussing D-efficiency for linear designs simplifies the expression in equation (27) by removing this scalar (see, e.g., Kuhfeld et al., 1994; Rose & Bliemer, 2010). The simplification seems justified. Removing F from the expression makes D-efficiency a relative measure, whereas removing δ^2 still maintains the proportional relationship with the model's AVC. Simplifying yields:

(28) $$\text{D-efficiency} \approx \frac{100}{\left|\left(\frac{Z'Z}{F}\right)^{-1}\right|^{1/K}}.$$

Hence, D-efficiency for linear models implies minimizing the determinant of the AVC, which, in turn, minimizes the standard error. Under orthogonal design, the independent variables are uncorrelated. Hence, $V = \left(\frac{Z'Z}{F}\right)^{-1}$ is an identity matrix with unit diagonal elements and zero off-diagonal elements. Thus:

$$\text{(29)} \quad \text{D-efficiency}_{\text{linear+orthogonal}} \approx \frac{100}{\left|I^{-1}\right|^{1/K}} = \frac{100}{\left|I\right|^{1/K}} = \frac{100}{1^{1/K}} = \frac{100}{1} = 100.$$

As noted by Rose and Bliemer (2010), under orthogonal design, D-efficiency yields a value of (approximately) 100%. This result, in turn, implies that for linear models orthogonal design is D-efficient.

Efficient Design

In the mid-1990s, scholars started to question the efficiency of orthogonal design for SP experiments (e.g., Bunch, Louviere, & Anderson, 1996; Huber & Zwerina, 1996; Kanninen, 2002; Kessels et al., 2006; Sandor & Wedel, 2001, 2002, 2005). For instance, Bunch et al. (1996) compared a variety of SP design alternatives for logit models and pointed out that traditional conjoint methods employed linear models. Along the lines explained above, these models were statistically efficient and supported by a large economic literature. Bunch et al., however, noted that these desired properties did not extend to nonlinear applications, such as logit models. This can be demonstrated by substituting V in equation (22) with the AVC for a nonlinear model estimated by maximum likelihood. For such models, the AVC is the second derivative of the log-likelihood function with respect to the parameter vector β:

$$\text{(30)} \quad V = \frac{\frac{\partial^2 LL}{\partial\beta\partial\beta'}}{F},$$

where LL is the log-likelihood function (Ruud, 2000). D-efficiency for such models equals:

$$\text{(31)} \quad \text{D-efficiency}_{\text{MNL}} = \frac{100}{\left|\left(\frac{\frac{\partial^2 LL}{\partial\beta\partial\beta'}}{F}\right)^{-1}\right|^{1/K}}.$$

Equation (31), however, reveals that the efficient survey design for nonlinear models estimated by maximum likelihood, such as logit models, depends on the true parameter vector β. This creates a "chicken-or-egg" problem because the purpose of the conjoint study is to estimate the vector β; yet, in order to estimate this vector, the true parameter values β must be known. The literature refers to the a priori knowledge required by such models as non-zero priors (see, e.g., Rose & Bliemer, 2010). The practical implications of the non-zero prior requirement seem to be straightforward in that orthogonal design might still yield D-efficient results if no information on priors is available. More often than not, however, some information is available, thereby rendering orthogonal design possibly not D-efficient. For instance, as explained in the literature, prior information is available from pilot studies (e.g., Rose, Bliemer, Hensher, & Collins, 2008). In these instances, D-efficiency is frequently indexed with a "p," indicating non-zero priors. If no information is available, D-efficiency is indexed with a "0," indicating zero priors (e.g., Burgess & Street, 2005). Finally, instead of assuming fixed non-zero priors, $\hat{\beta}$ can take on the form of a random variable. This Bayesian approach is typically indexed with a "b" (e.g., Bliemer, Rose, & Hess, 2006; Sandor & Wedel, 2001).

Another obstacle with using nonorthogonal design for nonlinear models is the complexity of the AVC and thereby D-optimality. As detailed by Bunch et al. (1996), a closed form of D-efficiency for nonlinear models does not seem to exist. Specifically, Bunch et al. used the information matrix for a logit model as a proxy for the model's AVC and expressed it in relative terms (comparing one default design, d, to an alternative design). They defined the following form:

$$(32) \qquad AVC(\beta,\xi) = -\frac{1}{F}\sum_{f=1}^{F} P_{df}(\beta)P_{af}(\beta)(z_{df} - z_{af})(z_{df} - z_{df})',$$

where *N* indicates the number of observations, P_{dn} is the logit probability of observation n in the default design, P_{an} is the logit probability of observation n in the alternative design, β is the parameter estimates, and z is the choice attributes. From equation (32), Bunch et al. derived a relative D-efficiency measure for a logit model (comparing two designs at a time) taking on the following form:

$$\text{(33)} \quad \text{Relative-D-efficiency}(\beta^0, \xi, \xi^*)_{MNL} \equiv \left\{ \frac{\det\left[AVC(\beta^0, \xi) \right]}{\det\left[AVC(\beta^0, \xi^*) \right]} \right\}^{1/K},$$

where β^0 is the parameter estimate priors and ξ^* and ξ are two comparative designs.

Several other researchers have attempted to define D-efficiency for nonorthogonal linear and nonlinear models. For instance, Chaloner and Larntz (1989) attempted to define D-efficiency for logistic regressions. Atkinson (1988) used a paired comparison design. However, as pointed out by Bunch et al. (1996), practical applications of efficiency measures for these models are still missing. Bunch et al. also noted that the lack of practical solutions, rather than the theoretical concepts, for measuring nonorthogonal D-efficiency might explain why orthogonal design remains the prevalent method even for nonlinear models.

Given the mathematical complexity of D-optimality for nonlinear models, researchers have proposed a number of methods that attain D-efficiency instead (e.g., Huber & Zwerina, 1996; Kuhfeld et al., 1994; Rose et al., 2008). Specifically, Rose et al. (2008) proposed a Monte Carlo simulation-based method. In this method, the analyst populates the design matrix randomly. Using parameter priors from a properly specified pilot model, the analyst calculates the choice probabilities for this particular design and then constructs the AVC matrix. To evaluate the statistical efficiency of this initial design, the initial D-error is calculated. This is simply the determinant of the AVC matrix from the initial design. In a next step, Rose et al. proposed a design change (i.e., changing one or more attributes in the SP design matrix) and then recalculating the D-error. If the D-error of the second run is smaller than the D-error of the initial run, the second design is retained; if not, it is rejected. This looping procedure is repeated R times up to the point where the researcher is satisfied with the D-error of the design.

Ideally, the simulation should evaluate all combinations of attribute levels and retain the combination that yields the lowest D-error. This requires a full factorial design from which N choice situations can be sampled. However, in all but the simplest SP surveys, this requires the evaluation of an enormous number of designs, making it practically infeasible. A number of "smart" methods have been proposed on how to change the SP matrix design for each round. For instance, Cook and Nachtsheim (1980) proposed the modified Fedorov algorithm. This method starts with a full factorial design (for simple SP problems) or a fractional factorial design (for more complex problems) and between iterations replaces entire rows in the design matrix. The algorithm selects from a candidate set of possible design rows from either the full factorial matrix or the fractional factorial matrix. The fractional factorial matrix is selected in such a way that attribute levels are distributed approximately equally across the design matrix. For instance, if there are three attribute levels for the price of a mobile phone, the Fedorov method selects a fractional factorial candidate matrix that ensures that each of these three levels appear approximately an equal amount. The Monte Carlo simulation then evaluates all designs in the candidate set and selects the set with the lowest D-error.

Huber and Zwerina (1996) and Sandor and Wedel (2001) proposed the "RSC algorithm," which stands for relabeling, swapping, and cycling. The RSC method encompasses three methods in one. Instead of replacing rows in consecutive designs (as done in the Fedorov method), this algorithm replaces attributes. The RSC method replaces these attributes in three ways. First, relabeling refers to replacing a column in the design matrix. As discussed above and shown in Appendix B, a column in the design matrix is the vector of attribute levels for one attribute. The relabeling option in the RSC method replaces an entire attribute column by switching attribute levels. For instance, a column in the design matrix for the present study is the price of the mobile phone for the first choice (i.e., *plan1.phone_price*). The RSC method would replace this column by substituting all mobile phone prices of $100 with free mobile phones. Swapping is a similar concept, but it involves changing only a subset of attribute levels. Finally, cycling refers to changing all attribute levels for each choice situation by replacing them with the next higher or lower value. The RSC method can be used simultaneously or in sequence.

To complete the discussion on efficient design, it is important to note that the economic literature discusses design evaluation measures other than D-efficiency. One of these alternative measures is A-efficiency that, as implied by its name, minimizes the A-error. Whereas D-efficiency minimizes the determinant of the AVC, in contrast, A-efficiency minimizes the trace of the AVC, which is the sum of the elements on the main diagonal of the AVC. Specifically as shown by Rose and Bliemer (2005) and Kuhfeld et al. (1994):

(34) $$\text{A-efficiency} = \frac{100}{F\Omega(\beta, z_{jn})},$$

where $\Omega\left(\beta, z_{jn}\right)$ is the trace of a nonlinear model's AVC. As found by Scarpa and Rose (2008), relative to D-efficiency A-efficiency is less commonly used by researchers and is less discussed in the economic literature. One possible cause, as found by Scarpa and Rose, is that unlike D-efficiency A-efficiency only considers the elements on the AVC's main diagonal thereby ignoring off-diagonal elements. As discussed above, the off-diagonal elements play an important role in determining efficiency. The reason why orthogonal design is D-efficient is that the off-diagonal elements are zero.

Another alternative efficiency measure is the C-error criterion. This less-known efficiency measure minimizes the variance of the ratio of two parameters. Scarpa and Rose (2008) define the C-error as:

(35) $$\begin{aligned} &\text{C-error} = Var\left(\frac{\beta_v}{\beta_w}\right) \approx Var\left(\frac{\beta_W}{-\beta_v}\right) \cong \\ &\beta_v^{-2}\left[Var(\beta_w) - 2\beta_w\beta_v^{-1}Cov(\beta_w, \beta_{v)} + (\beta_w / \beta_v)^2 Var(\beta_v)\right] \end{aligned}$$

where *v* and *w* are two different parameters in the choice model. To minimize the C-error, the sum of the $J-1$ attribute parameters must be minimized. A Monte Carlo simulation such as the simulation described above for the D-efficiency design can be applied.

A more recent alternative efficiency measure is S-efficiency. Introduced by Bliemer and Rose (2005), S-efficiency minimizes the sample size required for the experiment and improves the accuracy of parameters with a high standard error. The distinguishing factor between D-efficiency and S-efficiency is that D-efficiency minimizes the overall standard error (i.e., the determinant of the AVC), whereas S-efficiency examines the t-ratios of each estimated parameter and seeks to improve parameters with high t-ratios while minimizing the sample size. Bliemer and Rose defined the t-ratios as the ratios of the non-zero priors and their corresponding standard error. They derived the lower bound for a statistically significant parameter estimate for that parameter as:

$$M \geq \left(\frac{1.96 \cdot se_1(\beta_w^*)}{\beta_w^*} \right)^2, \quad (36)$$

where se_1 is the standard error for the first alternative and β_k^* is the non-zero prior of parameter *w*. With different parameters having different lower bounds, S-optimality seeks the minimum number of observations where all individual parameters are statistically significant. Hence, although D-efficiency minimizes the D-error, S-efficiency minimizes the sample size. Stated differently, a D-efficient design might require more observations than an S-efficient design, but, on the other hand, an S-efficient design might result in an overall lower level of accuracy.

Two other alternative design metrics are G-optimality and V-optimality. These metrics are optimality measures not efficiency measures. Efficiency measures minimize a design's AVC, whereas optimality measures seek to minimize the average prediction variance (Kessels et al., 2006). However, as noted by Kessels et al. (2006), G-optimality and V-optimality have not been applied yet in the experiment choice context. Thus, they are not discussed further.

The economic literature and practitioners seem to favor D-efficiency as the preferred efficiency measure for efficient design. Specifically, Bunch et al. (1996) found D-efficiency particularly useful for logit models. Similarly, Rose and Bliemer (2009) found D-efficiency to be the most commonly used method. The principal advantages of D-efficiency are that it accounts for both model variance and covariance and that it is normalized by the number of attributes. Based on these considerations, the present study uses D-efficiency as its relevant efficiency measure for its design matrix. Because D-optimality cannot be shown for logit models due to its nonlinearity, the design matrix for this study uses efficient design instead of orthogonal design.

Implementing Efficient Design

To implement the design choices discussed above, various software packages are available. Among them are *SAS* by SAS Institute Inc., *Ngene* by ChoiceMetrics, *DOE++* by Reliasoft, and *SPC* by BPI Consulting. Any of these software packages, as well as several more, can produce the selected design options. In this study, *Ngene 1.0.2* was used to estimate the design matrix. *Ngene* is dedicated experimental design software that is relatively easy to use. Other software packages, such as *SAS*, are much broader in their capabilities and applications; therefore, they require a deeper understanding of their programming commands.

Ngene requires a number of critical input parameters to design a D-optimal matrix. The first input requires defining the number and names of the choice alternatives (alts). There are three choice alternatives labeled Plan1, Plan2, and Plan3.

Next, the number of rows in the design matrix is specified. Because a row is a unique choice situation, the number of rows in the design matrix is the number of unique choice situations. A researcher can opt to administer unique choice situations to each survey respondent. Given 500 survey responses and six choice situations each, this would require a minimum of 3,000 rows. Realistically, the number of unique choice situations needs to exceed this number because it is highly likely that not all potential survey respondents will reply to the survey. Considering surveys not completed, this survey started with 800 unique surveys. For this number of surveys, 4,800 design matrix rows were required, resulting in a matrix with a dimension of 30 by 4,800. However, current computing power cannot handle designs of this magnitude. Therefore, the practical implication is that instead of surveying consumer responses to unique choice situations, the study incorporated a set of choice situations. This design choice is consistent with the relevant literature (e.g., Rose & Bliemer, 2009; Scarpa & Rose, 2008). With repeating choice situations, the design matrix in theory could consist of six rows only defined as one block, implying that all respondents would select from the same six choice situations. However, such a design would not allow for attribute balance because each attribute level only has a one-seventh (14%) chance of being included in the design. With all attributes having seven or fewer levels, a design of seven blocks with each block containing six choice situations is the minimum number of rows to attain attribute balance. To test whether specifying the design matrix beyond this minimum level would yield lower D-errors, designs with more than 42 rows were tested. These tests showed no material reduction in the D-error, although they added significant time to each run. Hence, the specification of the design matrix was 42 rows over seven blocks. *Ngene* randomly assigns block numbers to each of the 42 choice situations. Combining the block numbers, in turn, generates seven unique SP surveys, each consisting of six choice situations. The surveys are labeled sequentially from one to seven.

Ngene allows the researcher to select from several efficiency measures, including D-, A-, B-, and S-efficiency (ChoiceMetrics, 2010). The efficiency measures vary depending on the type of model, including logit and error-component (EC) models. For the reasons discussed above, the model for this study is a logit model and the design objective is D-efficiency. Although *Ngene* employs a Monte Carlo simulation to generate the D-efficient design, it allows users to select from several replacement algorithms. Specifically, *Ngene* is capable of optimizing according to the Fedorov method, the RSC method, modified Fedorov methods, and the Nelder-Mead method (ChoiceMetrics, 2010). Each of these methods draws from the full factorial design matrix and differs only in how it replaces attributes between iterations. With a large level of iterations, the choice of algorithm seems to be secondary. In addition, no literature exists that discusses the relative advantages and disadvantages of these methods. Therefore, this study uses the swapping method in the RSC procedures, which is also the default method in *Ngene*.

In designing the survey, the analyst must pay particular attention not to create choice situations that are either dominant or nonsensical. A dominant alternative is a choice alternative that is superior to the other two alternatives in the choice situation in one or more attributes and inferior in none. As such, it provides no information about the decision maker's preferences. D-optimality removes dominant alternatives through the process of minimizing the AVC. Specifically, dominant alternatives have a very high choice probability, whereas all other alternatives have a small probability. This leads to large differences in the model's covariances, which in turn yields high values for the determinant of the AVC. In minimizing the determinant of the AVC, D-optimality achieves probability (utility) balance, thereby removing dominant alternatives. D-optimality, however, has no way to ascertain whether a choice alternative makes sense to the decision maker. *Ngene* allows the user to condition the matrix design, thereby ensuring that nonsensical alternatives are not included. Conditioning consists of coding specific attribute level combinations that *Ngene* is to ignore. For the present survey, there were the following four conditions:

(1) If the monthly voice minute allowance (*v_allowance*) is unlimited, then the plan's voice overage charges (*v_over*) must also be zero.

(2) If the monthly data allowance (*d_allowance*) is unlimited, then the plan's data overage charges (*d_over*) must also be zero.

(3) If the monthly voice minute allowance (*v_allowance*) is limited, then the plan's voice overage charges (*v_over*) cannot be zero.

(4) If the monthly data allowance (*d_allowance*) is limited, then the plan's data overage charges (*d_over*) cannot be zero.

Next, *Ngene* requires the specification of the model. This step is critical as *Ngene* optimizes the design matrix based on a specific model. This creates a challenge for the analyst because the model's final specification is subject to the statistical significance (or absence thereof) of the attributes and its various interaction terms. Similarly, *Ngene* optimizes the design based on parameter estimate priors. The model specification and the parameter priors are necessary as D-efficiency minimizes the determinant of the AVC. The AVC is a function of the model's specification and in nonlinear models is a function of the parameter priors. This chicken-or-egg problem poses a challenge as differences between the parameter priors and the final parameters stand to nullify at least some of the promised benefits from D-optimization. As discussed below, one can measure this inadvertent loss of efficiency by comparing the D-error of the design matrix under the model's final specification and parameter estimates to the D-error of the original design and the parameter priors.

The parameter priors for this model are the result of a pilot study. In the pilot study, 25 coworkers responded to six choice situations each. At two observations per choice situations, this resulted in 300 observations. *Stata* (statistical software from StataCorp) labels these observations "Group Observations" indicating that there are 300 groups of unique choice observations. Each group consists of multiple observations. Specifically, in selecting the most preferred mobile plan, the decision maker selects one plan and rejects two plans. This generates three model observations in the exploded logit model, one for each mobile plan. The dependent binary dummy variable (*select*) indicates the decision maker's first choice of plans and the two rejected. Similarly, indicating which of the rejected two mobile plans is the least preferred plan generates two observations. Hence, the group observations total is 300, 150 of which contain three observations each, whereas the remaining 150 contain two observations each. This results in 750 model observations. It is important to note that when referring to "exploded data" the reference is to increasing the number of observations from one observation per choice situation (generating 150 choice observations) to two observations per choice situation (generating 300 choice observations). The latter step of increasing the number of observations from 300 to 750 is merely a consequence of the method used to fit the logit model to the 300 observations. The additional 450 observations do not generate additional information about the decision makers' preferences. Table 5 summarizes the results of the fitted pilot model.

Table 5
Exploded Logit Model for Pilot Data

Number of obs:	750					
Number of groups:	300					
Obs per group						
min:	2					
avg:	2.5					
max:	3					
Log likelihood:	-199.98					
LR chi2(10):	137.56					
Prob > chi2:	0					
select	Coef.	Std. Err	z	P>z	[95% Conf. Interval]	
phone_price	-0.0021	0.0005	-4.38	0.00	-0.0030	-0.0012
mrc	-0.0167	0.0021	-7.76	0.00	-0.0209	-0.0125
v_allowance (per 100)	0.0066	0.0042	1.58	0.12	-0.0016	0.0148
d_allowance (per 100)	0.0112	0.0038	2.98	0.00	0.0038	0.0186
download (per 100)	0.0034	0.0048	0.71	0.48	-0.0060	0.0128
v_over	-0.0838	0.7544	-0.11	0.91	-1.5623	1.3948
d_over	-0.3807	0.7668	-0.50	0.62	-1.8836	1.1223
text	-1.6333	0.6137	-2.66	0.01	-2.8362	-0.4305
phone_type	1.0785	0.1869	5.77	0.00	0.7122	1.4449
term_length	-0.0032	0.0072	-0.45	0.65	-0.0173	0.0109

The pilot coefficients serve only as starting values for the D-optimization routine. Accordingly, it would be premature to examine their significance levels, measured in the z-statistic, and possibly respecify the model. The pilot coefficients, however, have the expected signs.

In the absence of any information of statistically significant interaction terms, the initial model, including the parameter priors from the pilot study, takes the following form:

$$
\begin{aligned}
& U(\text{Plan})= \\
& \text{b1}[-0.0020992]\cdot \text{phone\_price}[0, 50, 100, 200, 300, 400, 500] + \\
& \text{b2}[-0.0166683]\cdot \text{mrc}[20, 40, 60, 80, 100, 120, 160] + \\
& \text{b3}[0.0000659]\cdot \text{v\_allowance}[50, 100, 200, 500, 1000, 2000, 99999] + \\
& \text{b4}[0.0001119]\cdot \text{d\_allowance}[0, 50, 200, 500, 1000, 5000, 99999] + \\
& \text{b5}[0.000034]\cdot \text{download}[250, 500, 1000, 1500, 2000, 3000, 6000] + \\
& \text{b6}[-0.0837528]\cdot \text{v\_over}[0, 0.1, 0.15, 0.2, 0.25, 0.3, 0.4] + \\
& \text{b7}[-0.3806611]\cdot \text{d\_over}[0, 0.1, 0.15, 0.2, 0.25, 0.3, 0.4] + \\
& \text{b8}[-1.63345]\cdot \text{text}[0, 0.05, 0.1, 0.2, 0.25, 0.3, 0.4] + \\
& \text{b9}[1.078538]\cdot \text{phone\_type}[0, 1] + \\
& \text{b10}[-0.0032271]\cdot \text{term\_length}[0, 6, 12, 18, 24, 30, 36]
\end{aligned} \tag{37}
$$

where b1-b10 are the model parameters, the number in the brackets following the parameter name are the parameter priors, and the numbers in the brackets following the independent variable names are the attribute levels. Appendix D presents the resulting *Ngene* optimization code for this study.

Per the recommendation from ChoiceMetrics, the number of Monte Carlo iterations was not limited. Rather, the optimization routine ran until it produced no incremental improvement for a prolonged period. As shown in Table 6, the routine ran 1,479,737 iterations. At approximately 30 seconds per 1,000 iterations, this took approximately 12 hours of run time. Of the total 396,541 iterations, approximately 27% improved the D-error statistic, thus they were retained. Overall, the optimization routine reduced the D-error by 40%. Several alternative optimizations yielded similar improvements.

Table 6
Ngene Optimization Results

Statistics	Value
D-error start	0.00022523557
D-error end	0.00013464514
Total iterations	1,479,737
Last iteration with improvement	396,541
Improvement (%)	40%

Appendix E displays the resulting logit model choice probabilities. These are the estimated probabilities for a certain choice alternative (mobile plan) in the design to be selected. The more balanced the probabilities for choice alternatives within a choice situation are, the more balanced the overall design. Appendix E illustrates that there are still a few unbalanced choice situations although they are approximately D-optimal. For instance, choice situation 31 forecasts the probability for Plan 1 at 1%, Plan 2 at 41%, and Plan 3 at 58%, whereas other choice situations are balanced. For instance, choice situation 24 forecasts the probabilities at 32%, 43%, and 25% for Plan 1, Plan 2, and Plan 3, respectively.

Survey Administration

With the theoretical model specified, the survey developed, and the design matrix D-optimized, the next step was to decide on the proper data collection method. Several online and offline primary data collection methods were available. Among the offline methods were focus groups, mail surveys, mall intercepts, and phone interviews. Online primary research methods included online panel surveys, discussion groups, and click data. Each method has advantages and disadvantages (Mohammed, Fisher, Jaworksi, & Cahill, 2002).

In selecting the proper data collection method, researchers aim to minimize sampling biases, costs, and turnaround and to maximize data quality (Mohammed et al., 2002). Sampling biases arise when the sampled population is not representative of the general population. Online data collection methods require a survey respondent to have an Internet connection, a computing device to connect to the Internet, and to be Internet literate. Conversely, offline data collection methods require survey respondents to have listed phone numbers and to allow research firms to contact them (i.e., not be listed on the FCC’s Do Not Call Registry). Even focus groups and mail surveys potentially have biases because they might attract responses from individuals with relatively more free time thus distorting the survey. No method of data collection is entirely unbiased (Postoaca, 2006). Hence, researchers seek to minimize sampling biases and specifically test for such biases after the survey. Costs can vary significantly among research methods with offline methods generally being more costly than online methods (Mohammed et al., 2002). Turnaround time, or completion speed, is another key consideration in selecting a data method (Postoaca, 2006). Postoaca (2006) estimated that online surveys require 25% to 50% less time to complete than offline surveys. In terms of quality, Postoaca found that both online and offline methods can yield high quality data. Postoaca, however, cautioned that online panels with less than two surveys per year on average are prone to poor quality. Mohammed et al. (2002) found that online methods yield higher data quality than offline methods as the latter requires manual data entry.

The present SP survey lends itself well to an online data collection method and a panel survey in particular. At approximately $8 per completed online survey compared to $40 to $60 per completed offline survey, the online survey is considerably less expensive. Further, there are potential biases present in both methods. Therefore, because online surveys significantly minimize turnaround time, are less expensive, and do not have any more biases than offline surveys, the relative advantages of an online method outweigh its relative disadvantages. The choice of online panels seems consistent with the general trend of market research. Callegaro and Disogra (2008) found that market, social, psychological, and medical research is increasingly using online panels. Specifically, Comley (2007) found that one-third of all market research conducted in the United States used online panels as the data collection method. Comley also observed similar trends in Europe.

In panel surveys, pre-recruited panel members respond to a set of surveys each year. Research firms recruit these panels, typically by offering some form of compensation for the completed survey. There are two general types of online panels, probability panels and volunteer panels (Callegaro & Disogra, 2008). Probability panels consist of individuals recruited using some form of randomization. A common method to recruit probability panels is through random-digit-dial (RDD) telephone sampling (Callegaro & Disogra, 2008). Volunteer panels are opt-in panels consisting of members who voluntarily join the panel. There are no generally accepted metrics to evaluate the quality of online panels (Callegaro & Disogra, 2008). Chang and Krosnick (2009) compared the sample representativeness and response quality of three data collection methods: RDD telephone surveys, opt-in panels, and probability panels. Chang and Krosnick found that probability panels generated the most accurate response data out of the three methods. The data from the telephone surveys were least biased; however, they contained the largest measurement error. The data from the opt-in surveys were the most biased data, although the data yielded the most accurate self-reports. Self-reports are survey questions that ask the respondent to describe actual behavior. As such, they are a measure of data accuracy.

Link and Mokdad (2005), on the other hand, found that offline surveys generate more accurate data than online surveys. Windle and Rolfe (2011) also compared online and offline data collection methods and noted that Internet surveys are increasingly gaining in popularity because they are quicker and less costly. In contrast to the findings of Chang and Krosnik (2009), Link and Mokdad (2005) and Windle and Rolfe (2011) concluded that there were no differences between the methods when forecasting the dependent variable (maximum willingness to pay). Windle and Rolfe did find that there were differences in the sample's sociodemographic composition and the survey respondents' attitudes. Hence, although the economic literature offers some guidance as to the increasing popularity of online data collection methods, online and offline methods seem to perform differently depending on the specific circumstances of the study.

In selecting an online panel for the present SP survey, the focus was on experience, panel size, and panel reputation. SurveySavvy™, an online survey company established by Luth Research met all three criteria. With over 3.5 million members, it is one of the largest global online communities (Luth Research, n.d.). Introduced in 1999, SurveySavvy™ is an experienced company that conducts numerous surveys throughout the year. It also has a reputation of being of the highest quality. SurveySavvy™ is a hybrid panel, consisting of both opt-in and invited members. Hence, it could potentially be subject to sample biases. However, with 3.5 million members, the chance of a selection bias is minimal. Nevertheless, the resulting data were subjected to various tests prior to fitting a logit model to the data.

Luth Research coded the D-optimized design matrix shown in Appendix B, the survey shown in Appendix F, and administered the survey to the members of SurveySavvy™. Prior to collecting the data, Luth Research conducted a soft launch. In this test run, 44 surveys completed by the online panel were examined for errors. The review revealed that the screening question needed to be moved to the beginning of the survey. Specifically, the population of interest for this study consists of individuals 18 years of age or older. The original survey screened for age at the end of the survey. Placing screening questions at the end of the survey increases the risk of false self-reports as respondents might report an incorrect age after completing the survey. Therefore, the screening question was moved to the beginning and the survey was terminated when a respondent entered an age of 17 years or less. The soft launch also revealed that at least one survey respondent completed the survey within a very short time (i.e., 92 seconds). This raised the concern that survey responses with short completion times might not be accurate because the respondents might not have carefully considered the questions. Thus, based on the minimum completion time from the pilot study, all surveys completed in less than 3.5 minutes were removed from the final dataset. With these two modifications, the data collection proceeded to the full launch.

The full data collection launch generated 653 survey responses. Of these, 164 surveys were eliminated due to either incomplete responses or completion times of less than 3.5 minutes. The remaining 489 completed surveys form the database for this study.[14] With seven unique SP surveys, D-optimality of the database is preserved if the responses are equally distributed across these surveys. Table 7 shows an approximately equal distribution across surveys. Hence, D-optimality is preserved.

Table 7

Response Distribution by Survey

Survey number	Frequency
1	72
2	71
3	68
4	70
5	70
6	69
7	69
Total	489

[14] If despite the incomplete responses and/or short completion times, the dropped survey responses provided accurate information on the respondents' decision-making and if the preferences of these eliminated observations differ from the observations of the remaining respondents, removing the observations could potentially introduce a sample selection bias. At a minimum, the removal limits the sample to respondents that did complete all questions and required longer than 3.5 minutes.

Survey Results Analysis

This section presents the results of the D-optimized SP survey. The survey results and the fitted model form the statistical base of any inferences drawn from this study. Inferences are only as accurate as the statistical base. Hence, in order to ensure valid inferences, the survey data must be unbiased and of high quality and the econometric model must fit the data optimally. The descriptive statistics of the survey results and the estimation results are the subjects of this section.

Descriptive Statistics

The SP survey for this study consisted of three sections: RP, SP, and sociodemographic. In the RP section, the survey respondents provided information about their actual consumption patterns. The SP section recorded the survey respondents' ranked preferences of three mobile service plans in six different choice situations. The sociodemographic section collected personal information about the survey respondents. The sociodemographic data and RP data were jointly tested for quality and potential biases by examining the sample characteristics. The SP data from the survey responses were analyzed separately.

Sample characteristics. Table 8 presents various descriptive statistics for the survey sample. For each of the 19 survey questions in the SP and sociodemographic sections, Table 8 presents the mean, standard deviation, minimum value, maximum value, median, skewness, kurtosis, the 25th percentile, and the 75th percentile. The number of observations (489) is the number of completed and valid surveys. For Q4–Q9, the number of observations is 417. The difference is due to 28 respondents who indicated that they did use a mobile phone at the time of the survey and 44 survey respondents who indicated that they were not financially responsible for their mobile service plan.

Table 8

Sample Descriptive Statistics

Variable	Obs	Mean	Std. dev.	Min	Max	Median	Skew.	Kurtosis	25%	75%	Attribute levels
Q1: Age	489	44.43	15.45	18	82	42	0.31	2.11	31	55	
Q2: Wireless	489	1.06	0.23	1	2	1	3.81	15.53	1	1	Yes=1, No=2
Q3: Fin. responsibility	489	1.13	0.33	1	2	1	2.24	6.03	1	1	Yes=1, No=2
Q4: Plan minutes	417	3.93	2.01	1	8	4	0.31	1.85	2	6	<400 = 1, 400-699=2, 700-899=3, 900-1399=4, 1400-2099=5, Unlim=6, Prepaid=7, Don't know=8
Q5: Data plan subscription	417	1.58	0.49	1	2	2	(0.34)	1.11	1	2	Yes=1, No=2
Q6: SMS plan subscription	417	1.54	0.50	1	2	2	(0.15)	1.02	1	2	Yes=1, No=2
Q7: Mobile Internet usage	417	1.60	0.49	1	2	2	(0.41)	1.17	1	2	Yes=1, No=2
Q8: Mobile email usage	417	1.62	0.49	1	2	2	(0.48)	1.23	1	2	Yes=1, No=2
Q9: Monthly expenses	417	2.13	1.00	1	5	2	0.72	2.90	1	3	<$50=1, $50-$99=2, $100-$149=3, >$150=4, Don't know=5
Q10: Term contract	417	1.32	0.51	1	3	2	1.23	3.45	1	2	Yes=1, No=2, Don't know =3
Q11: Landline subscriber	489	1.28	0.45	1	2	1	0.98	1.96	1	2	Yes=1, No=2
Q12: State of residence	489	25.45	16.00	1	51	24	0.04	1.46	10	43	
Q13: Residence density	489	2.30	0.84	1	4	2	0.01	2.29	2	3	Metropolitan=1, Suburban=2, Small town=3, Farming =4
Q14: Education	489	3.18	1.03	1	5	3	0.03	1.77	2	4	<High school =1, High school=2, Vocational =3, College = 4, Post-graduate = 5
Q15: Employment status	489	1.90	0.92	1	3	2	(0.15)	1.02	1	3	Full-time = 1, Part-time = 2, Not employed = 3
Q16: Gender	489	1.53	0.50	1	2	2	(0.41)	1.17	1	2	Male = 1, Female = 2
Q17 Marital status	489	1.79	0.75	1	4	2	(0.48)	1.23	1	2	Single = 1, Married = 2, Partnered = 3, Other = 4
Q18: Number of children	489	1.56	0.93	1	4	2	0.72	2.90	1	2	Zero = 1, One = 2, Two = 3, More than three = 4
Q19: Annual income	489	2.34	1.11	1	6	1	1.23	3.45	1	3	<$30K=1, $30K-$49K=2, $50K-$74K=3, $75K-$149K=4, >$150K=5, No answer=6

To ensure that the survey respondents accurately represented U.S. consumers, the sample statistics were compared to the various population statistics. This examination took on four stages. In the first stage, the sample demographics were compared to data from the U.S. Census Bureau and other benchmarks. In the second stage, the sample's subscription levels (e.g., data plan, SMS, and landline subscriptions) were compared to similar metrics for the average U.S. consumer. The third stage examined the survey respondents' use of mobile phone service (e.g., mobile Internet and email usage) and compared it to similar metrics for the average U.S. subscriber. In the fourth stage, monthly consumptions (e.g., monthly expenditure and plan minutes) were benchmarked against the consumption patterns of the U.S. consumers. The objective of the first examination stage was to ensure that the survey sample represented the U.S. consumers in terms of sociodemographic attributes. The remaining stages served to ensure that in addition to sociodemographic attributes, the sample's mobile phone plan consumption appropriately mirrored U.S. consumers' consumption patterns. The sociodemographic variables for the first data examination stage included the following variables:

- **Age:** With a mean age of 44.42 years and a median age of 42 years, the sample population accurately represents the U.S. population over the age of 18 years. According to the U.S. Bureau of Census, the mean and median age of the U.S. population over the age of 18 years is 45.20 years and 43 years, respectively (U.S. Census Bureau, n.d.). The sample skewness and kurtosis is 0.31 and 2.11, respectively, compared to same metrics for the U.S. population of 0.51 and 2.48.

- **Gender:** Of the survey respondents, 47.03% were male and 52.97% were female. This compares well to the 49.27% male and 50.73% female estimated by the U.S. Bureau of Census (n.d.).

- **Annual income:** Table 9 compares income levels among survey respondents to income levels earned by the U.S. population, as estimated by the U.S. Bureau of Census (n.d.).

Table 9
Annual Household Income Comparison

Annual household income	Sample statistics	Bureau of Census (est.)
Less than $30,000	27.20%	30.15%
$30,000 to just under $50,000	31.29%	19.45%
$50,000 to just under $75,000	25.15%	17.90%
$75,000 to just under $150,000	14.52%	22.15%
$150,000 and more	0.61%	10.35%
Decline to answer	1.23%	0.00%
Mean income category	$30K–$50K	$30K–$50K

Table 9 reveals that although the sample represents some income categories accurately others are oversampled or undersampled. In particular, the survey sample does not include sufficient respondents with annual household incomes in excess of $75,000. However, the mean income category is accurate.

- **State of residence:** The survey sampled all 50 U.S. states and the District of Columbia. Indexing the states, including the District of Columbia, from 1–51 by alphabetical order produced a sample distribution with a mean of 25.45, a standard deviation of 16.18, skewness of 0.0360, and kurtosis of 1.4604. The population counts by state, as reported by the U.S. Bureau of Census (n.d.), follow a distribution with a mean of 24.76, a standard deviation of 15.18, skewness of 0.0289, and kurtosis of 1.6110. Hence, the distribution of survey respondents closely mirrors the U.S. population distribution.
- **Residence density:** Of the survey respondents, 18.40% indicated that they mainly lived in a metropolitan city, 39.06% listed their main residence in a suburban community of a larger city, 36.40% lived in a small town or rural city, and the remaining 6.13% lived in a farming area. The most recent count from the U.S. Bureau of Census (n.d.) found that 30.30% of the U.S. population lived in metropolitan cities, 49.00% lived in urban areas outside a city, and 20.70% lived in rural areas. A direct comparison of these counts is not possible as the U.S. Census Bureau uses a well-defined classification system based on calculated population density, whereas the survey relied on the interpretation of the respondents.
- **Education:** Indicating their highest level of education, 1.04% had less than a high school education, 33.95% ended their education with graduation from

high school, 19.02% terminated with vocational schooling, 37.83% had a college degree, and the remaining 8.18% had a post-graduate degree. The U.S. Bureau of Census tracks educational levels differently and does not list vocational schooling. Hence, a direct comparison is not possible. However, in its latest survey of individuals 18 years of age and older, the U.S. Bureau of Census (n.d.) reported that 15.72% had less than a high school education, 52.99% ended their education with a high school degree, 22.73% had a college degree, and the remaining 8.75% had a post-graduate degree. Based on this comparison, it is possible that the level of education in the sample is higher than the level of education of the general U.S. population.

- **Employment status:** Of the survey respondents, 47.85% worked full time, 14.72% worked part time, and the remaining 37.42% were not gainfully employed. The U.S. Bureau of Census (n.d.) reported that, as of 2009, 65% of individuals over the age of 16 years were in the labor force. Although this includes two additional years relative to the survey sample (which only sampled individuals over the age of 18 years), this implies that 35% were not gainfully employed. This corresponds well with the sample observations.
- **Marital status:** Of the survey respondents, 37.42% were single, 50.72% were married, 7.77% had a partner, and the remaining 4.09% indicated another relationship status. The U.S. Bureau of Census (n.d.) estimated that 50.3% of the U.S. population is married, 30.80% has never been married, 10.4% is divorced, 2.2% is separated, and 6.3% is widowed. Although a direct comparison to the survey sample is not possible, the percentage of survey respondents that were married matches the forecasts by the Bureau of Census well.
- **Number of children:** Of the survey respondents, 67.89% had no children. Among the 32.11% of respondents that had children, the average number of children was 1.75. The U.S. Bureau of Census (n.d.) reported that 63.74% of households had children. Among those, the average number of children was 1.86. The U.S. Bureau of Census defines a household as the total number of individuals living in a housing unit. It does not track the number of children by individual. Hence, a direct comparison of the percentage of the U.S.

population without children is not possible. However, the average family size in the sample matches the figure for the U.S. population well.

This first examination stage demonstrates that the survey sample represents the U.S. population generally well in terms of sociodemographic variables. Notwithstanding, a few limitations apply. In particular, the survey sample represents households with incomes of less than $75,000 per annum better than households that exceed this level.

The subscription level variables for the second data examination stage included the following variables:

- **Mobile:** The mobile penetration rate in the sample is 94.27%. This is higher than the 88.9% mobile penetration rate reported by the FCC (2010b) and the 93% reported by the wireless association CTIA (2011) for 2010 and slightly lower than the 95.9% reported by the market research firm TeleGeography (2011).

- **Data plan subscription:** Of the survey respondents, 41.73% indicated that they subscribed to a mobile data plan. The market research firm Nielsen found that of the 28% of U.S. mobile subscribers with Smartphones (Nielsen, 2010b) only 66% subscribed to a mobile data plan (Nielsen, 2010a). Not counting the mobile subscribers with non-Smartphones that subscribe to data plans this indicates that less than 20% of mobile subscriber have a data plan subscription. Conversely, it would require that approximately 15% of non-Smartphone subscribers subscribe to a data plan. This figure is plausible considering that 89% of the mobile phones currently registered are capable of browsing the Internet (CTIA, 2011) and thereby might require a data plan. Furthermore, the market research firm comScore (2011, p. 5) found that 47% of December 2010 mobile subscribers were media users, which it defined as browsing the Internet. Although comScore did not report the percentage of these users that also subscribed to a data plan, Nielsen (2010a) estimated this number at 91.7%. This implies that 43.1% of U.S. mobile subscribers had a monthly data plan, which is consistent with the sample data.

- **SMS plan subscription:** Of the survey respondents, 46.28% reported subscribing to an SMS plan. The FCC (2010b) cited a study by the Pew Research Center that found that 43% of mobile subscribers used SMS. The

FCC and Pew Research provided no information as to the percentage of SMS users that subscribed to an SMS plan. According to the Verizon Wireless website, there is large price difference between SMS with and without an SMS plan. Without a plan, a mobile subscriber pays $0.20 for each SMS sent. With a plan, a text message costs approximately $0.02. The FCC (2010b) reported average SMS revenue at $0.014 per message. This indicates that the large majority of the reported 43% SMS users also subscribe to an SMS plan. Hence, the sample seems generally consistent with the population.

- **Landline subscription:** Of the survey respondents, 71.98% reported having a landline in their home. This implies that 28.02% live in mobile-only households. The FCC (2010b) reports this percentage at 21.1%. The wireless association CTIA (2011) estimated the figure at 26.6%.

Based on these considerations, the sample also appropriately represents the U.S. consumers' communications subscription levels. The plan components variables for the third data examination stage included the following variables:

- **Mobile Internet usage:** Of the survey respondents, 40.05% indicated that they currently used their mobile phones to access the Internet. This percentage is lower than the 47% found by comScore (2011). However, it is close to the 41.73% of survey respondents that subscribe to a data plan.

- **Mobile email usage:** Of the survey respondents, 38.38% indicated that they currently used their mobile phones to send and receive emails. This is lower than the 40.05% of respondents that use their mobile phone for Internet browsing and lower than the 41.73% of respondents that subscribe to mobile data plan. This, however, is expected because mobile phones, particularly non-Smartphones, make sending emails difficult. comScore (2011) found that 30.5% of mobile users used their mobile phones to send and receive emails. Hence, the sample is generally consistent with the population.

- **Term contract:** Of the survey respondents, 69.78% reported having a term contract with the current provider. The FCC (2010b) found that 70.9% of subscriber net additions in 2010 had postpaid service. Term contracts typically only apply to postpaid service plans. Given the significant mobile phone discounts offered by mobile service providers for postpaid service plans, it is reasonable to assume that all, or almost all, postpaid service plans are subject to a term contract. Hence, the observed figure is in line with the figure reported by the FCC.

Again, the sample data represents U.S. consumers well. Finally, the mobile expenditures variables for the fourth data examination stage included the following variables:

- **Monthly expenses:** Median monthly mobile expenditures for the survey respondents are between $50 and $99. This is slightly higher than the $47.09 reported by the FCC (2010b) but might be the result of the slightly higher plan minutes observed in the sample.
- **Plan minutes:** The average plan minutes category in the sample is 3.93 minutes, which equals 900–1,400 minutes per month. This is higher than the 709 minutes per month found by the FCC (2010b) and higher than the 726 minutes found by the wireless association CTIA (2011) for 2010. Hence, the survey sample might reflect higher volume subscribers more accurately than subscribers with low plan minutes per month.

Thus, the sample performed well in all four examination stages and is deemed to reasonably accurately represent the U.S. consumers.

To test the accuracy of the self-reporting, various consistency checks were performed. First, survey respondents who currently have prepaid mobile service plans should not have a term contract. Approximately 12% of the survey respondents stated that they currently had prepaid mobile service. Of those, none indicated that they were under a term contract. Specifically, 98% responded in the negative with the remaining 2% stating that they did not know. Second, respondents with monthly data plans are expected to access the Internet and/or send and receive emails. Of the 41.73% of the respondents who stated that they currently had a data plan, 86.21% responded that they accessed the Internet and 80.46% used their mobile phones to send and receive emails. Curiously, 17 respondents indicated that they subscribed to a data plan, yet they did not use their mobile phone to access the Internet or send and receive emails. Some service providers require subscribers to purchase a data plan with certain mobile phones. For instance, the Apple iPhone when purchased in a service bundle requires subscribers to purchase a data plan. Hence, the observation is theoretically possible. Finally, survey respondents that did not use a mobile phone were not expected to respond to the questions about their consumption patterns.

Twenty-eight respondents did not use a mobile phone at the time of the survey. As expected, of those respondents, none answered any questions about their current consumption patterns.

Survey responses. In this section, the data from the SP survey are analyzed. The objective of this review is to ensure that the survey responses are indicative of actual consumer choices. It further tests that the D-optimization of the design matrix did not create unrealistic mobile plan choices. There is no single test to ensure the accuracy of the survey responses. Rather, several examinations had to be conducted.

The first test examined whether the survey respondents always preferred one mobile plan better than the remaining two choice alternatives. Although D-optimal design does not create any dominant or near dominant alternatives, revealed dominance could still occur if a choice situation is superior in one important aspect or inferior in an attribute that bears no weight in the purchase decision. Similarly, the test examined whether any choice situations were clearly inferior and thus never selected. There is nothing inherently wrong with the presence of inferior alternatives. In fact, they provide a useful test to ensure that survey respondents select rationally.

Appendix G shows the frequency by which each choice alternative was accepted and rejected. The first column in Appendix G indicates which of the seven unique surveys the respondent answered. A respondent faced six choice situations, as listed in the second column of Appendix G. As discussed, the respondent answered two questions in the ranking exercise. In the first question, the respondent selected the preferred plan from three plan alternatives. In the second question, the respondent selected the least preferred plan from the remaining two alternatives. Hence, there are two rankings per choice situation. The third column in Appendix G contains these rankings. The three plans and the number of times each was selected and rejected are shown in the remaining columns of Appendix G.

There were no mobile plans that were always accepted. Hence, there are no revealed dominant alternatives. However, four plan choices were never selected. Specifically, survey respondents never selected the third choice alternative in the first choice situation of the third survey. Similarly, the first plan of the fourth choice situation and the third plan in the sixth choice situation of the fourth survey also were never selected. Finally, the respondents never selected choice alternative two of the fourth choice situation in the fifth survey. This behavior is expected. For instance, the first of these three choice alternatives had an MRC of $160 and provided only 50 voice minutes per month. The other two choice alternatives offered lower MRCs and higher voice allowances. The three specific choices also had low design choice probabilities (shown in Appendix E) of 5%, 9%, and 3%.

The second test examined whether the presentation order of the choice alternatives was correlated with the responses. For this, the selected choice alternatives were regressed on the order in which the respondents saw them. The respondents' choices were recorded in the variable *select*, and the variable *plan* indicated the position in which the choice was presented. Table 10 shows the results of regressing *select* on *plan.* The regression coefficient for *plan* is statistically insignificant. Therefore, the survey responses were not influenced by the order in which the plan alternatives were presented.

Table 10
Choice Alternative Order Regression Results—All Choice Situations

Source	**SS**	**df**		**MS**		
					Obs	14,670
Model	0.2526	1		0.2526	F(1, 14668)	1.0500
Residual	3,520.55	14668		0.2400	Prob > F	0.3049
Total	3,520.80	14669		0.2400	R-squared	0.0001
					Adj R-sq.	–
					Root MSE	0.4899
select	Coeff.	Std	t	P>t	[95% Conf. interval]	
plan	-0.0050729	0.0049446	-1.03	0.305	-0.0147651	0.0046192
_cons	0.4101656	0.0107023	38.32	0	0.3891877	0.4311435

A third test examined whether some respondents made their selection based on a prespecified rule that was independent from the choice alternative characteristics. For instance, a respondent might always select the first offered plan. Evidence of such behavior would indicate that the respondent did not make the trade-off exercise. Listing the selection choices by plan number and respondent identifier indicated no such behavior, although short of a case-by-case analysis such behavior cannot entirely be ruled out.

A fourth test involved examining the completion times for the various survey sections. Table 11 shows the completion times for each of the six choice situations and the RP and sociodemographic (non-choice) sections. As explained above, surveys completed in less than 3.5 minutes were removed from the dataset. Despite removing these observations, Table 11 still shows minimum values for several choice situations and the non-choice section that appears low. However, as respondents might have based their decisions on a few attribute levels only (e.g., price), these observations should not be removed. Empiricism implies that respondents learn the concept of the trade-off exercise in Choice Situation 1 and become increasingly experienced throughout the survey. Thus, one would expect a negative correlation between the number of the choice situation and the completion time. The data weakly confirmed this expectation as beyond Choice Situation 1, there was a monotonic decrease in mean competition times. The exception to this general trend is Choice Situation 3, which required almost as much time to complete as Choice Situation 1. This, however, is due to the fact that one respondent was logged into the system for over 1,440 minutes (approximately 24 hours). In fact, without this observation, the mean completion time for Choice Situation 3 was 0.80 minutes. Maximum completion times offer no insights as respondents might have temporarily stopped completing the survey, yet remained logged into the survey server.

Table 11
Survey Completion Times in Minutes

Completion time	Obs	Mean	Std. dev.	Min	Max
Choice situation 1	489	3.55	39.88	0.25	879.65
Choice situation 2	489	0.93	1.06	0.05	18.28
Choice situation 3	489	3.75	65.04	0.10	1,440.08
Choice situation 4	489	0.75	2.34	0.08	45.98
Choice situation 5	489	0.62	0.65	0.10	7.52
Choice situation 6	489	0.67	1.23	0.08	16.30
Non-choice sections	489	8.96	5.95	0.08	1,173.42

A significant percentage decline in completion times for the last choice situations might indicate the presence of respondent fatigue. This occurs when respondents select their plan choices based not on the attribute levels but on nonsystematic (e.g., pick any plan) or systematic (e.g., pick a plan in order of appearance) reasons. Respondent fatigue is widely discussed in the survey literature (see, e.g., Backor, Golde, & Nie, 2007; Bennett & Nair, 2008; Biderman, 1967; Hart, Rennison, & Gibson, 2005). Respondent fatigue can manifest itself in many different ways, and no one method exists to test for it. The completion times for Choice Situation 5 and Choice Situation 6 were 18% and 11%, respectively, below the time for Choice Situation 4. Some decline in completion time is expected, and the differences in time are not necessarily indicative of respondent fatigue. However, repeating the regression of *select* on *plan* for only Choice Situation 5 and Choice Situation 6 revealed the presence of respondent fatigue.

Table 12 shows that the order in which the survey respondents saw the plans was a statistically significant factor in their selection of mobile plan. Although not large in magnitude, the negative parameter sign indicates that the respondents favored the plan alternatives in descending order in which they saw them. This dependency is not present if all choice situations are considered. It also is not present for the first four choice situations. Hence, respondent fatigue seems to be limited to Choice Situation 5 and Choice Situation 6. This finding must be taken into consideration when fitting a model to the data. The order in which the mobile plans were presented to the survey respondents was random. Consequently, respondent fatigue will likely not bias the results. However, it also might not add any further information to the model, thus it could be removed from the dataset.

Table 12
Choice Order Regression Results—Choice Situations 5 and 6

Source	**SS**	**df**	**MS**			
					Number of obs	4890.00
Model	2.63	1.00	2.63		F(1, 4888)	10.99
Residual	1170.97	4888.00	0.24		Prob > F	0.00
					R-squared	0.00
Total	1173.60	4889.00	0.24		Adj R-squared	0.00
					Root MSE	0.49
select	Coefficient	Std. err.	t	P>t	[95% Conf. interval]	
plan	-0.03	0.01	-3.31	0.00	-0.04	-0.01
_cons	0.46	0.02	24.64	0.00	0.42	0.49

Model Fitting

This section fits various versions of the MNL to the survey data. The analysis commences with a general (non-mixed) exploded logit model. The LR index along with several other considerations serves to compare its results to the results of a mixed exploded logit model. The LR index is only meaningful when comparing models where one model is a subset of the other model. For instance, the LR index increases with the number of model variables. Hence, unlike the R^2, it cannot be used to compare models with different variables. The standard exploded logit model is a special case of the mixed exploded logit model in that the former assumes the parameter variances to be zero. Hence, the LR index can be used to compare the two models. For all other model comparisons, a likelihood-ratio test (LRT) must be used. This test takes the following general form (Train, 2009):

$$\text{(38)} \qquad \mathrm{LRT} = -2(LL(\beta^{R}) - LL(\beta^{U})),$$

where $LL(\beta^{R})$ is the maximum of the log-likelihood function of the restricted model and $LL(\beta^{U})$ is the maximum value of the unrestricted model. The restricted model is the model under the null hypothesis H_0. For instance, in order to analyze whether interaction terms are statistically significant, the restricted model is a model where the coefficients of the interaction terms under consideration are zero. The unrestricted model is the alternative hypothesis H_A. It is a model that includes the interaction terms. The difference in equation (38) is chi-squared distributed with degrees of freedom equal to the number of restrictions (Train, 2009). In this example, it is the number of interaction terms excluded from the restricted model. Because the log-likelihood function is always negative, the LRT is simply twice the difference in maximum values of the restricted and unrestricted model. If this value exceeds the critical value of the chi-square distribution with the appropriate degrees of freedom, then the null hypothesis is rejected (Train, 2009).

Model fit. In the search for the best model, several models are fitted to the survey data. A first model (Model 1) examines core pricing variables, including the variables described in the theoretical model (and to which the design matrix was optimized to), in addition to a dummy variable that distinguishes high volume voice minute plans from low volume voice minute plans. While economic theory might suggest a negative coefficient for voice overage charges, the sample contains both high and low voice minute volume users. Low voice minute users by definition have no overage charges and therefore voice overage charges are likely irrelevant. High voice minute users might select plans with high monthly allowances, thereby avoiding overage charges. Thus, the coefficient for the voice overage charges might be statistically insignificant. In lieu, subscribers might place a premium on high volume plans, relative to low volume plans.

Model 2 is identical to Model 1 with the exception that it examines the removal of the variable for voice overage charges. With the core specifications settled, Model 3 relaxes the assumption of zero coefficient variances that is embedded in the standard logit model. Specifically, it assumes that all coefficients are distributed normal. A mixed exploded logit model achieves this objective, assuming that preference parameters are independent of each other. A drawback of Model 3 is that due to the symmetry of the normal distribution, a certain percentage of subscribers might have coefficients with signs opposite to the signs of the coefficients for the mean subscriber. For price coefficients, this would mean that a percentage of subscribers might have positive price coefficients. This is counter to economic theory. To remedy this potential shortfall, Model 4 examines to augment Model 3 by replacing the normal distribution with the lognormal distribution. This change in coefficient distribution ensures price coefficients to be fully negative. Finally, Model 5 introduces sociodemographic variables in the form of gender and age.

Table 13 presents the results of Model 1. It fits the data using a general (non-mixed) exploded logit model. This model focuses on the choice behavior of the average consumer. Thus, it does not consider sociodemographic variables, which serve to forecast beyond the mean, addressed separately. In an effort to derive the demand determinants, all mobile service plan attributes are included in this model. Furthermore, economic theory postulates that consumers consider all price attributes when making the purchase decision. This is particularly true for non-voice mobile services, such as Internet browsing and texting. In contrast to mobile voice services, subscribers generally do not know how to calculate their consumption of data services on a monthly basis. For instance, subscribers do not know the size of an email or an Internet browsing session. Consequently, subscribers might react adversely to high prices for these services, whereas subscribers understand mobile voice services, which they consume on a per-minute basis. Additionally, mobile phones typically include a counter that further informs subscribers of the length of a mobile voice call. The hypothesis is that subscribers purchase mobile service plans that include sufficiently large monthly voice allowances, thereby minimizing the probability of incurring voice overage charges. For instance, *Consumer Reports* (2011) found that 33% of U.S. mobile subscribers consume less than half of their monthly voice allowance. Thus, the expectation is that voice overage charges are statistically insignificant. Furthermore, with an average monthly mobile voice consumption of approximately 700 minutes (FCC, 2010b; CTIA, 2011), the marginal utility that subscribers derive from plans that offer less minutes than this consumption level might differ from plans that exceed this level. To test this latter hypothesis, Model 1 includes a dummy variable (*dummy_high*) that takes the value of one if the monthly voice allowance exceeds 700 minutes and zero otherwise.

Table 13
Model 1: Exploded Logit

Number of obs	14670					
Number of groups	5868					
Obs per group						
min	2.00					
average	2.50					
max	3.00					
LR chi2(10)	1018.17					
Prob > chi2	0.00					
Log likelihood	-4747.94					
select	Coefficient	Std. Error	z	P>|z|	95% Conf. interval	
phone	-0.0026	0.0001	-24.390	0.000	-0.0028	-0.0024
mrc	-0.0084	0.0004	-19.070	0.000	-0.0093	-0.0075
voiceallow (per 100)	0.0045	0.0012	3.740	0.000	0.0021	0.0068
dataallow (per 100)	0.0034	0.0007	4.530	0.000	0.0019	0.0048
download (per 100)	0.0019	0.0009	2.100	0.036	0.0001	0.0036
v_over	0.0365	0.1644	0.220	0.824	-0.2858	0.3588
d_over	-0.3083	0.1489	-2.070	0.038	-0.6001	-0.0165
text	-0.6225	0.1212	-5.140	0.000	-0.8601	-0.3849
phone_type	0.2956	0.0351	8.420	0.000	0.2268	0.3644
term_length	-0.0097	0.0014	-7.160	0.000	-0.0124	-0.0071
dummy_high	0.3972	0.0475	8.360	0.000	0.3041	0.4904

There are 2 x 6 = 12 choice observations per survey respondent. In fitting the data to the logit model, *Stata* requires reshaping and entering of the survey data in the "long format." Consequently, the number of observations as reported by *Stata* and shown in Table 13 differs from the number of choice situations discussed thus far. In the long format, each row is a choice alternative. The variable *select* indicates whether the survey respondent selected or rejected the alternative. In selecting the first choice, the survey respondent faced three choice alternatives, selecting one. In the long format, this translates into three observations—one for each choice alternative faced. In the second choice, the survey respondent faced the remaining two alternatives, again selecting one. This results in two additional observations. Hence, the long format has five observations per choice situation for a total of 5 x 6= 30 observations per completed survey. With 489 valid surveys, this results in 14,670 observations. In fitting the exploded logit model, *Stata* requires a group identifier that links all choice alternatives that the decision maker considered jointly. In selecting the most preferred mobile plan, the survey respondent compared three choice alternatives. In selecting the least preferred plan, the survey respondent compared the remaining two choice alternatives. Hence, there are two groups of unique decisions per choice situation—one with three observations and one with two observations. At 489 surveys and six choice situations each, this results in 5,868 groups.

Considering several diagnostic tests, this model fits the data well. The z-score tests the null hypothesis of the coefficient to be zero. It is the ratio of the parameter estimate and the corresponding standard errors (Kennedy, 2008). With the parameter estimate distributed normal over repeated samples, this ratio also is distributed normal. Table 13 lists both the z-score for each logit coefficient as well as the probability for the null hypothesis to be accepted. Of the 11 coefficients, eight are significant at the 99% confidence level and two are significant at 95%. As expected, at 18%, the overage charge for voice service (*v_over*) is statistically insignificant.

A Hausman-McFadden test of IIA (Hausman & McFadden, 1984) indicates no presence of IIA. Specifically, consistent with IIA failure, the coefficient estimates for a two-choice conjoint exercise are larger in magnitude than the estimates for the full set of alternatives. Furthermore, the following Hausman-McFadden IIA test statistic yields a negative value:

(39) Hausman-McFadden IIA test $= \left(\beta_C - \beta_A\right)' (\Omega_A - \Omega_C)^{-1} (\beta_C - \beta_A)$,

where Ω_A and Ω_C are the AVC matrices for a two-choice conjoint exercise (eliminating choice alternative 3) and for the full set of alternatives, respectively. β_A and β_C are the respective vectors of parameter estimates. If IIA holds, this test statistic is distributed chi-square with 11 degrees of freedom. The negative value indicates that the test statistic is not chi-square distributed, hence, confirming the absence of IIA in Model 1.

The signs of the model coefficients correspond with economic theory. Specifically, the price for the mobile phone (*phone*) is negative, indicating a downward sloping demand function for mobile phones. Similarly, the other statistically significant price coefficients are also negative. These include the monthly recurring charge (*mrc*), data overage charges (*d_over*), and SMS charges (*text*). Voice and data allowances, download speed, phone type, and the dummy indicating plans with high voice minutes (*dummy_high*) all carry positive signs. For these variables, an increase in attribute level translates into higher utility and, ceteris paribus, a decrease in price. Thus, a positive coefficient is expected. The length of the term contract is similar to a price, and, ceteris paribus, longer-term contracts are akin to a price increase. Hence, one expects a negative sign. Finally, the variable for voice overage charges (*v_over*) is statistically not different from zero and not considered further. This finding confirms the hypothesis that subscribers understand the pricing of mobile voice minutes and purchase mobile service plans with a sufficiently large monthly voice allowance as to avoid the relatively high overage charges. *Consumer Reports* (2011) further confirms this hypothesis in its finding that 33% of U.S. mobile subscribers consume less than half of their monthly allowance. In contrast, data overage charges are statistically significantly. This implies that the per kilobyte pricing is not well understood by consumers as they are not aware of how much data allowance is consumed by a data application, such as Internet browsing of emailing. Table 14 summarizes the results of Model 2, which excludes the voice overage charge.

Table 14
Model 2: Exploded Logit

Number of obs	14670					
Number of groups	5868					
Obs per group						
min	2.00					
average	2.50					
max	3.00					
LR chi2(10)	1018.12					
Prob > chi2	0.00					
Log likelihood	-4747.96					
select	Coefficient	Std. error	z	P>|z|	95% Conf. interval	
phone	-0.0026	0.0001	-24.44	0.00	-0.0028	-0.0024
mrc	-0.0084	0.0004	-19.23	0.00	-0.0093	-0.0076
voiceallow (per 100)	0.0043	0.0011	4.03	0.00	0.0022	0.0065
dataallow (per 100)	0.0034	0.0007	4.60	0.00	0.0020	0.0048
download (per 100)	0.0019	0.0009	2.10	0.04	0.0001	0.0036
d_over	-0.3068	0.1487	-2.06	0.04	-0.5984	-0.0153
text	-0.6228	0.1212	-5.14	0.00	-0.8603	-0.3853
phone_type	0.2950	0.0350	8.43	0.00	0.2264	0.3636
term_length	-0.0097	0.0014	-7.20	0.00	-0.0124	-0.0071
dummy_high	0.3991	0.0468	8.53	0.00	0.3074	0.4908

Model 1 and Model 2 assumed a zero variance for all parameter estimates. Model 3 relaxes this assumption by fitting a mixed exploded logit model, thereby remedying the IIA problem and allowing for consumer-specific parameters. Unlike the general (non-mixed) exploded logit model, statistical software packages typically do not provide integrated commands for this model. *Stata* provides a downloadable add-in, *mixlogit*, which allows fitting mixed logit models. However, the procedure requires the same group specification as the standard logit model discussed above. Consequently, it treats the 12 decisions made by one survey respondent as if 12 different survey respondents made them. This particular treatment might lead to inaccurate estimators for the parameter means and standard deviations. Hence, software code for *Matlab* by MathWorks and provided by Train (2006) is used instead. Table 15 presents the results of Model 3, a mixed exploded logit model with all parameters distributed normal. While mean coefficient estimates differ from the estimates in Model 2, there is no apparent drift in values and only a slight change in statistical significance.

Table 15
Model 3: Mixed Exploded Logit—Normal

	Mean			Standard deviation			95% Conf. int.		
Variable	**Coeff.**	**Std. error**	**z**	**Coeff.**	**Std. error**	**z**	**Low**	**High**	**Share<0**
phone	-0.0037	0.0002	-18.50	0.0028	0.0002	14.00	-0.0092	0.0018	0.91
mrc	-0.013	0.0008	-16.25	0.0122	0.0009	13.56	-0.0369	0.0109	0.86
voiceallow	0.0082	0.0018	4.56	0.0123	0.0034	3.62	-0.0159	0.0323	0.25
dataallow	0.0053	0.0011	4.82	0.0088	0.0017	5.18	-0.0119	0.0225	0.27
download	0.0015	0.0013	1.15	0.0062	0.0033	1.88	-0.0107	0.0137	0.40
d_over	-0.6504	0.1983	-3.28	0.4571	0.4559	1.00	-1.5463	0.2455	0.92
text	-0.8379	0.1709	-4.90	1.3157	0.3585	3.67	-3.4167	1.7409	0.74
phone_type	0.4629	0.0572	8.09	0.7706	0.0731	10.54	-1.0475	1.9733	0.27
term_length	-0.0125	0.0021	-5.95	0.0236	0.0029	8.14	-0.0588	0.0338	0.70
dummy_high	0.5224	0.0672	7.77	0.6393	0.0795	8.04	-0.7306	1.7754	0.21
log-likelihood (at convergence)									-4516.84

As shown in Table 15, the mixed exploded logit model estimates two coefficients per independent variable. The first coefficient estimates the mean value of the coefficient, whereas the second coefficient estimates its standard deviation. As the estimates themselves are random variables, the two coefficient estimates have standard errors and z-scores. The general (non-mixed) exploded logit model is a subset of the mixed exploded logit model in that the former assumes the coefficients for the standard deviation to be zero. Hence, the LR index compares the fit of Model 3 relative to Model 2. The denominator of the value *LR-Index* is the value of the log-likelihood function at the first iteration with all starting values set at zero. The LR index for Model 2 is:

$$(40) \qquad \text{LR-Index}_{\text{Model2}} = 1 - \frac{-4747.96}{-5257.02} = 0.097.$$

The LR index for Model 3 is:

$$(41) \qquad \text{LR-Index}_{\text{Model3}} = 1 - \frac{-4516.84}{-5257.02} = 0.141.$$

Because the value *LR-Index* for Model 3 is larger than for Model 2, Model 3 explains the decisions taken by the survey respondents more accurately and therefore provides a superior fit relative to Model 2. All the coefficients for the mean parameters in Model 3 carry the expected signs and with the exception of *download* are all statistically significant. The coefficients for the standard deviations are statistically significant, with the exception of *d_over* and *download*. Individual univariate Wald tests examine the hypotheses of the *download* and *d_over* standard deviation coefficients to be zero. Since variance estimates are constraint to be positive, the testing of these hypotheses involves inequalities. An LRT with inequality constraints in nonlinear models is not chi-square distributed (Wolak, 1991) and thus is not the appropriate test. Univariate one-sided Wald tests are used instead:

$$\omega = \frac{(\beta_x - \beta_0)^2}{\text{var}(\beta_x)}, \tag{42}$$

where β_x is the coefficient estimate of the standard deviation of attribute x and β_0 is the value of the same under the null hypothesis (Enders, 2010). Since the test examines whether the coefficient of a particular standard deviation is zero, $\beta_0 = 0$. Thus:

$$\omega = \frac{(\beta_x - 0)^2}{\text{var}(\beta_x)} = \left(\frac{\beta_x}{\sqrt{\text{var}(\beta_x)}} \right)^2, \tag{43}$$

which is simply the square of the z-score reported in Table 15. The univariate Wald statistic is chi-square distributed with one degree of freedom. With 10 possible individual Wald tests in Model 3, a Bonferroni correction leads to a significance level of the chi-square distribution of 0.005 or 0.01 for a one-sided test.[15] This, in turn, yields a critical value of 6.635. Table 16 lists the Wald statistics for each of the standard deviation coefficients.

[15] A Bonferroni correction adjusts the significance level of a hypothesis test by allowing individual comparisons while maintaining the model's overall error rate (Galambos, 1977). The correction simply divides the typical significance level of 5% by the number of individual tests.

Table 16

Wald Statistics—Standard Deviation Coefficients

Variable	z-score	Wald statistic
phone	14.00	196.00
mrc	13.56	183.75
voiceallow	3.62	13.09
dataallow	5.18	26.80
download	1.88	3.53
d_over	1.00	1.01
text	3.67	13.47
phone_type	10.54	111.13
term_length	8.14	66.23
dummy_high	8.04	64.67

The table reveals that the null hypothesis (of *download* and *d_over* having standard deviations of zero) cannot be rejected. This finding implies that decision makers do not differ materially in their preferences for differences in download speeds and data overage charges. Practically, it means that the coefficients for these two attributes should remain nonstochastic. Table 17 reports the results of this modified Model 3 in which all variables, except *download* and *d_over* are stochastic and assume a normal distribution.

Table 17

Model 3-1: Mixed Exploded Logit Model—Normal

	Mean			Standard deviation			95% Conf. int.		
Variable	Coeff.	Std. error	z	Coeff.	Std. error	z	Low	High	Share< 0
phone	-0.0037	0.0002	-18.50	0.0028	0.0002	14.00	-0.0092	0.0018	0.9004
mrc	-0.0127	0.0008	-15.88	0.0122	0.0009	13.56	-0.0366	0.0112	0.8504
voiceallow	0.0080	0.0017	4.71	0.0123	0.003	4.10	-0.0161	0.0321	0.2582
dataallow	0.0052	0.0010	5.20	0.0055	0.0022	2.50	-0.0056	0.0160	0.1725
text	-0.7467	0.1729	-4.32	-1.5102	0.3145	-4.80	2.2133	-3.7067	0.6892
phone_type	0.4860	0.0584	8.32	0.8177	0.0753	10.86	-1.1167	2.0887	0.2754
term_length	-0.0122	0.0021	-5.81	0.0256	0.0028	9.14	-0.0624	0.0380	0.6835
dummy_high	0.5236	0.0682	7.68	0.7132	0.0821	8.69	-0.8743	1.9215	0.2312

	Coeff.	Std. error	z
download	0.0016	0.0013	1.23
d_over	-0.5985	0.1980	-3.02

Finally, an LRT examines the hypothesis of nonstochastic variable *download* to be zero. A model without *download* is the restricted model. It forms the null hypothesis. Model 3-1, as shown in Table 17, is the alternative model, or unrestricted model. Per equation (38), the LRT for these models is:

(44) $\quad \text{LRT} = -2(-4520.50 - (-4519.68)) = 1.64$.

The mathematical difference in equation (44) is distributed chi-square with one degree of freedom. The critical value of a chi-square (1) for a 95% confidence level is 3.84. Because 1.64 < 3.84, the null hypothesis cannot be rejected. Consequently, under the model specifications of Model 3-1, removing the variable *download* provides a superior fit.

Model 3 assumes that coefficients follow a normal distribution. Given the symmetry of this distribution type, model coefficients close to zero or with a relatively large standard deviation will necessarily result in economic theory not supporting the selection of some subscribers. Table 17 reports the share of the normal distribution that is smaller than zero. For instance, the estimated mean for the price coefficient of a mobile phone (*phone*) is −0.0037 and the estimated standard deviation of the same coefficient is 0.0028. The reported share below zero is 0.90, which implies that 90% of subscribers have negative price coefficients. Conversely, given the relationship between the estimated mean and standard deviation, 1 – 0.90 = 10% of subscribers seem to prefer mobile phones that are more expensive. Similarly, the share of the normal distribution for the coefficient of SMS prices (*text*) that is below zero is 69%, implying that 31% of subscribers appear to prefer higher SMS prices. These and other similar observations are clearly unreasonable. Subscribers might prefer higher priced phones relative to lower priced phones if it also means that the higher priced phone offer more functionality or prestige. However, given the D-optimal design matrix, higher priced phones are not correlated with more functionality.

To remedy this apparent shortfall, Model 4 fits a mixed exploded logit model with all parameters distributed lognormal. The lognormal distribution has positive values only and eliminates the possibility of a sign change within a random parameter estimate. In essence, it ensures that the share < 0 is always zero. To fit this model, all variables with negative coefficients were multiplied by −1.[16] Software code by Train (2006) for *Matlab* was used to execute Model 4. A summarized understanding of this algorithm follows as it assists in interpreting the model's specifications and results.

[16] The extension "_neg" indicates variables such as *phone_neg and mrc_neg*.

By definition, the log of a lognormal distribution is a normal distribution. A lognormal distribution is typically defined by the parameters of this underlying normal distribution (Mood, Graybill, & Boes, 1974). Hence, the code by Train (2006) derives the lognormal coefficients by maximizing the log-likelihood function of the log value of the lognormal coefficients. These parameter estimates serve as the basis for the lognormal coefficients. Specifically, the algorithm draws from a standard normal distribution for each of the 20 coefficients specified in Model 3 and 489 survey respondents. The algorithm multiplies the resulting matrix by a vector of starting values for the standard deviation of the underlying normal distribution and sums it with a vector of starting values for the mean for the same distribution. The resulting matrix is exponentiated, thereby becoming a draw from a lognormal distribution. Based on these values, the algorithm computes the average logit probabilities for each survey respondent. These average probabilities are the simulated approximation of the mixed logit probabilities, evaluated at the starting value vectors. The log-likelihood function is calculated as the sum of the logged average probabilities over all survey respondents. The algorithm maximizes the log-likelihood function numerically by repeating these calculations with different mean and standard deviation vectors for the underlying normal distribution. The looping procedure ends when no further improvement in the log-likelihood function is found (e.g., the log-likelihood function of the lognormal model is maximized).

In order for the model to estimate the lognormal coefficients, it is necessary to specify the most accurate starting values for the means and standard deviations of the normal distributions that give rise to the lognormal model.[17] Model 3 provides vectors for the estimated means μ_n and standard deviations σ_n of normal distributed coefficients. These vectors serve as starting values for the estimated means and standard deviations of lognormal distributed coefficients. As explained, the simulated maximum likelihood estimation routine maximizes a normal distribution upon which it derives estimates for lognormal distributed coefficients. Thus, rather than setting starting values equal to the vectors μ_n and σ_n, the means and standard deviations of the normal distribution underlying the lognormal model must be derived. Solving the

[17] In deriving the lognormal coefficients, the software code by Train (2006) makes 100 draws per survey respondent maximizing the log-likelihood function of a normal distribution. The code converts the individual values of this underlying normal distribution by calculating the exponent values from which it calculates lognormal means and standard deviations.

equation of the mean of a lognormal distribution for the mean of the underlying normal distribution μ yields:

$$(45) \qquad \mu = \ln(\mu_n) - \frac{\sigma_n}{2}.$$

Similarly, solving the equation of the variance of a lognormal distribution for the variance of the underlying normal distribution σ yields:

$$(46) \qquad \sigma = \sqrt{\frac{\ln(\sigma_n)}{3}}.$$

Based on these starting values, Model 4 fits a mixed exploded logit model with all coefficients distributed lognormal. Following Train (2009), Table 18 presents the estimated parameters of the underlying normal distribution of Model 4. These coefficients are the log values of the lognormal coefficients. As such, they have no direct interpretation by themselves and only serve to examine the specifications of the resulting lognormal coefficients.

Table 18
Model 4: Mixed Exploded Logit—Parameter Estimates

	Mean of log-coefficients			Standard deviation of log-coefficients		
	Estimate	**Std. error**	**z**	**Estimate**	**Std. error**	**z**
phone_neg	-5.8077	0.0691	-84.0478	0.8481	0.0653	12.9877
mrc_neg	-4.7468	0.0976	-48.6352	1.1018	0.0926	11.8985
voiceallow	-6.0218	0.5553	-10.8442	2.7094	0.308	8.79675
dataallow	-6.0708	0.4371	-13.8888	1.4404	0.2851	5.05226
download	-7.6611	1.1188	-6.8476	1.7945	0.3488	5.14478
d_over_neg	-1.2328	0.7544	-1.63415	0.8723	0.5337	1.63444
text_neg	-1.1938	0.4339	-2.75133	1.5716	0.2346	6.69906
phone_type	-1.8847	0.3511	-5.36799	1.8261	0.282	6.47553
term_length_neg	-5.0726	0.2695	-18.8223	1.4567	0.1603	9.08734
dummy_high	-1.5618	0.3581	-4.36135	1.0577	0.2437	4.34017
log likelihood (at convergence)						- 4437.43

With a log-likelihood at convergence of −4437.43, Model 4 is superior to Model 3. Interestingly, while Model 3 finds download insignificant, in Model 4, the variable is significant at the 95% level. The variable *d_over_neg*, however, remains statistically insignificant at 95%. A Wald test examines whether specifying the coefficient for *d_over_neg* as nonstochastic (null hypothesis) yields a model that is superior to Model 4. The critical value for the chi-square distribution with one degree of freedom at 1% significance level is 6.635. The Wald test finds a score of 2.67 and thus cannot reject the null hypothesis. Hence, as in Model 3, the variable *d_over* remains nonstochastic.

Table 19 presents the results of Model 4-1, which specifies *d_over* as a fixed coefficient variable.

Table 19
Model 4-1: Mixed Exploded Logit—Parameter Estimates

	Mean of log coefficients			**Standard deviation of log coefficients**		
	Estimate	Std. error	z	Estimate	Std. error	z
phone_neg	-5.8280	0.0681	-85.58	0.8190	0.0765	10.71
mrc_neg	-4.8055	0.1004	-47.86	1.1618	0.0836	13.90
voiceallow	-5.8815	0.5537	-10.62	2.5982	0.2963	8.77
dataallow	-5.8697	0.3718	-15.79	1.2935	0.2873	4.50
download	-9.7343	2.2184	-4.39	2.8566	0.8833	3.23
text_neg	-1.5093	0.5571	-2.71	1.9231	0.3250	5.92
phone_type	-1.8609	0.3804	-4.89	1.7261	0.3083	5.60
term_length_neg	-4.8968	0.2109	-23.22	1.2797	0.1063	12.04
dummy_high	-1.3616	0.2936	-4.64	0.8014	0.2275	3.52
log likelihood (at convergence)			-4,448.87			

Table 20 presents the estimated medians, means, and standard deviations that result from this underlying normal distribution.

Table 20
Model 4-1: Mixed Exploded Logit—Lognormal

Variable	**Distribution**	**Median**	**Mean**	**Std. dev.**
phone	Lognormal	-0.0029	-0.0041	0.0040
mrc	Lognormal	-0.0082	-0.0161	0.0268
voiceallow	Lognormal	0.0028	0.0773	1.1046
dataallow	Lognormal	0.0028	0.0064	0.0128
download	Lognormal	0.0001	0.0034	0.0774
text	Lognormal	-0.2211	-1.4140	6.4312
phone_type	Lognormal	0.1555	0.6856	2.5155
term_length	Lognormal	-0.0075	-0.0169	0.0323
dummy_high	Lognormal	0.2563	0.3535	0.3324
		Coefficient	**Std. error**	**z**
d_over	Fixed	0.4242	0.191	2.22

Consistent with the existing literature, the standard errors of the underlying normal distribution serve to examine the specifications of the lognormal model (e.g., Revelt & Train, 1998; Train 2009). Further, given the asymmetry of the lognormal distribution, the standard deviations offer only a general indication of the data spread.[18] A large standard deviation relative to its mean indicates that subscribers have different opinions about the value of certain mobile plan attributes. For instance, subscribers seem to have diverging views on the value of the monthly voice allowance, the price of SMS, and the type of phone offered.

Addressing respondent fatigue. Table 12 revealed respondent fatigue for Choice Situation 5 and Choice Situation 6. For these choice situations, the order in which the survey presented the mobile plans contributed in a statistically significant manner with regard to the probability of a respondent selecting a choice alternative. With a random presentation of mobile service plans, this finding should theoretically not bias the results. Model 4-2 removes Choice Situation 5 and Choice Situation 6 and fits the remaining data with the specifications of Model 4-1. As in Model 4-1, all coefficients are distributed lognormal, with the exception of *d_over*, which is nonstochastic.

Table 21 and

Table 22 present the results of this derivative of Model 4-1.

Table 21
Model 4-2: Mixed Exploded Logit—Parameter Estimates

	Mean of log coefficients			Standard deviation of log coefficients		
	Estimate	**Std. error**	**z**	**Coefficient**	**Std. error**	**z**
phone_neg	-5.8565	0.0838	-69.89	0.9738	0.094	10.36
mrc_neg	-4.5873	0.0987	-46.48	0.9313	0.0924	10.08
voiceallow	-6.9949	0.8954	-7.81	3.4166	0.5483	6.23
dataallow	-5.4206	0.2992	-18.12	-0.1433	0.7548	-0.19
download	-5.4841	0.4074	-13.46	0.0573	1.3231	0.04
text_neg	-0.4245	0.2931	-1.45	1.2262	0.1661	7.38
phone_type	-1.1215	0.2419	-4.64	1.2571	0.2281	5.51
term_length_neg	-4.9017	0.3167	-15.48	1.4897	0.1849	8.06
dummy_high	-2.3256	0.7346	-3.17	1.8456	0.4915	3.76
log likelihood (at convergence)			-2,975.79			

[18] Importantly, the standard deviations are not indicative of the accuracy of the estimators. The accuracy of the estimators is measured in the standard error shown in Table 18.

Table 22

Model 4-2: Mixed Exploded Logit—Lognormal

Variable	Distribution	Median	Mean	Std. dev.
phone	Lognormal	-0.0029	-0.0046	0.0058
mrc	Lognormal	-0.0102	-0.0157	0.0183
voiceallow	Lognormal	0.0009	0.3642	17.5625
dataallow	Lognormal	0.0044	0.0045	0.0006
download	Lognormal	0.0042	0.0042	0.0002
text	Lognormal	-0.6541	-1.4134	2.9259
phone_type	Lognormal	0.3258	0.7147	1.3501
term_length	Lognormal	-0.0074	-0.0227	0.067
dummy_high	Lognormal	0.0977	0.5226	2.1873
		Coefficient	**Std. error**	**z**
d_over	Fixed	0.5464	0.2688	2.03

A Hausman specification test examines the null hypothesis of Model 4-2 and Model 4-1 to produce both consistent estimators. If the Hausman specification test accepts the null hypothesis, Model 4-2 and Model 4-1 produce identical results. If so, removing Choice Situations 5 and 6 does not improve the fitted model. Under the alternative hypothesis, only Model 4-2 is consistent. If the Hausman specification test rejects the null hypothesis, Model 4-1 estimates are inconsistent, and removing Choice Situations 5 and 6 improves the fitted model. Following Hausman (1978), the Hausman test statistic is:

$$m = (\beta_{M4-2} - \beta_{M4-1})' (AVC_{M4-2} - AVC_{M4-1})^{-1} (\beta_{M4-2} - \beta_{M4-1}), \quad (47)$$

where AVC_{M4-2} and AVC_{M4-1} are the asymptotic covariance matrices of Model 4-2 and Model 4-1, respectively. This statistic is chi-square distributed with k degrees of freedom. With 10 independent variables and two coefficients each (mean and standard deviation) for the present models, k = 20. The null hypothesis is rejected when the Hausman test statistic exceeds the critical value of 31.4. Calculating m for Model 4-2 and Model 4-1 produces a Hausman test statistic of 4.14, thereby accepting the null hypothesis. Thus, the removal of Choice Situations 5 and 6 is not necessary to produce consistent estimators and Model 4-1 remains.

Considering sociodemographic differences. Thus far, the fitted models focused on the attributes of the hypothetical choices only. The standard deviations of Model 4-1 indicated that with the exception of *d_over*, survey respondents differed in their reactions to changes in attribute levels. This raises the question whether sociodemographic differences explain these taste variations and whether adding these variables to Model 4-1 would improve further the model fit. By adding sociodemographic variables, the standard and mixed exploded logit models reflect potential sociodemographic differences in the selection of a mobile service plan. However, the sociodemographic information for a respondent n does not vary across choice alternatives. Thus, V_{in} also does not vary, provided there is no new information for the logit model specified in equation (9), P_{in} in particular. Consequently, if entered as standalone independent variables, the logit model omits them. In order to consider sociodemographic variables in logit models, these variables must be interacted with the main effect variables, thereby creating the required variation across alternatives (Train, 2009). By interacting the sociodemographic variables with choice attributes, the z-statistic does not provide information as to the significance, or lack thereof, of the sociodemographic variables. Instead, it only provides information on the interaction term. Hence, in order to examine whether the sociodemographic variables are statistically significant, hypothesis testing is required.

As discussed in the literature review section, the existing literature provides little guidance as to which sociodemographic variables should be included in the model, if any. Although different in significant aspects, the present study is most similar to Iimi (2005) and Tripathi & Siddiqui (2009). Neither of these studies found sociodemographic variables to be statistically significant. The latter study, however, reported different coefficient estimates by age and gender. As shown in Table 1, age and gender appear to be the most frequently considered sociodemographic variables in the literature. Income is also frequently considered, but only in studies that examine aggregate levels of mobile demand, such a cross-country comparison (e.g., Garbacz & Thompson, 2007). Importantly, income has not been considered in studies where the consumer is the unit of analysis. Thus, Model 5 adds age and gender as fixed coefficient variables to Model 4-1. The variable *age* is interacted with *phone* and divided by 10,000. The variable *gender* is interacted with *mrc* and divided by 1,000.[19] Table 23 and Table 24 present the parameter estimates and lognormal medians, means, and standard deviations for Model 5.

[19] The divisions are necessary in order to generate absolute starting values (and thus logit coefficients) larger than 0.1. At starting values smaller than 0.1, the *Matlab* code is unable to maximize the log-likelihood function.

Table 23

Model 5: Mixed Exploded Logit—Parameter Estimates

	Mean of log of coefficients			Standard deviation of log-coefficients		
	Estimate	Std. error	z	Estimate	Std. error	z
phone_neg	-5.7965	0.0679	-85.37	0.82	0.0662	12.39
mrc_neg	-4.6687	0.1265	-36.91	1.0516	0.1017	10.34
voiceallow	-6.0014	0.5472	-10.97	2.6886	0.3008	8.94
dataallow	-6.0589	0.4379	-13.84	1.4302	0.2844	5.03
download	-7.9043	1.2902	-6.13	1.8707	0.387	4.83
d_over_neg	-0.8453	0.9434	-0.90	0.2329	3.6754	0.06
text_neg	-1.1783	0.4404	-2.68	1.538	0.2447	6.29
phone_type	-1.8838	0.3539	-5.32	1.8195	0.2897	6.28
term_length_neg	-5.0683	0.2681	-18.90	1.4503	0.1603	9.05
dummy_high	-1.5656	0.361	-4.34	1.0414	0.2504	4.16
log likelihood (at convergence)						-4428.73

Table 24

Model 5: Mixed Exploded Logit—Lognormal

Variable	Distribution	Median	Mean	Std. dev.
phone	Lognormal	-0.0030	-0.0042	0.0041
mrc	Lognormal	-0.0094	-0.0162	0.0225
voiceallow	Lognormal	0.0025	0.1065	2.1191
dataallow	Lognormal	0.0023	0.0064	0.0163
download	Lognormal	0.0004	0.0021	0.0106
d_over	Lognormal	-0.4294	-0.4413	0.1043
text	Lognormal	-0.3078	-0.9897	2.8644
phone_type	Lognormal	0.1520	0.7825	3.5619
term_length	Lognormal	-0.0063	-0.0181	0.0475
dummy_high	Lognormal	0.2090	0.3599	0.5193
		Coefficient	Std. error	z
age_interaction	Fixed	-0.4450	0.1085	4.10
gender_interaction	Fixed	1.1306	1.2703	0.89

The LRT score that compares Model 4 (restricted) to Model 5 (unrestricted) is 50.60, clearly exceeding the critical value of 5.99, thereby rejecting the null hypothesis that these socioeconomic variables have coefficients of zero. A univariate one-sided Wald test cannot reject the null hypothesis of *d_over* being nonstochastic. Hence, Model 5-1 respecifies Model 5 by defining *d_over* as a fixed coefficient variable. Table 25 and Table 26 present the parameter estimates and lognormal medians, means, and standard deviations for Model 5-1. Appendix H contains the covariance matrix for Model 5-1.

Table 25

Model 5-1: Mixed Exploded Logit—Parameter Estimates

	Mean of log of coefficients			Standard deviation of log-coefficients		
	Estimate	Std. error	z	Estimate	Std. error	z
phone_neg	-5.7816	0.0674	-85.78	0.8043	0.0715	11.25
mrc_neg	-4.6736	0.1262	-37.03	1.0518	0.0967	10.88
voiceallow	-5.9611	0.5215	-11.43	2.6188	0.3043	8.61
dataallow	-6.1022	0.5578	-10.94	1.4831	0.4493	3.30
download	-8.0862	1.4286	-5.66	1.9329	0.4253	4.54
text_neg	-1.3937	0.5098	-2.73	1.7141	0.2827	6.06
phone_type	-1.8069	0.3046	-5.93	1.7144	0.2283	7.51
term_length_neg	-5.1307	0.2957	-17.35	1.5041	0.1881	8.00
dummy_high	-1.4487	0.3150	-4.60	0.9079	0.2642	3.44
log likelihood (at convergence)						-4,427.584

Table 26

Model 5-1: Mixed Exploded Logit—Lognormal

Variable	Distribution	Median	Mean	Std. dev.
phone	Lognormal	-0.0031	-0.0043	0.0040
mrc	Lognormal	-0.0093	-0.0161	0.0224
voiceallow	Lognormal	0.0026	0.0913	1.6604
dataallow	Lognormal	0.0022	0.0067	0.0183
download	Lognormal	0.0003	0.0020	0.0110
text	Lognormal	-0.2482	-1.0786	4.1441
phone_type	Lognormal	0.1642	0.6997	2.6406
term_length	Lognormal	-0.0059	-0.0182	0.0505
dummy_high	Lognormal	0.2349	0.3553	0.4044
		Coefficient	Std. error	z
age_int	Fixed	-0.4479	0.1085	-4.13
gender_int	Fixed	1.0965	1.2696	0.86
d_over	Fixed	-0.4371	0.196	-2.23

The LRT rejects removing *gender_int*, which shows a low z-score in its parameter estimate. Consequently, adding the sociodemographic variables to Model 4 further improves the model fit. This finding also provides some resolution to the relevant literature as it provides direct proof of the relevancy of sociodemographic variables.

The age interaction term (*age_int)* is calculated as follows:

(48) $$\text{age\_int}_n = \frac{(age_n - \overline{age}) \cdot phone_{in}}{10000},$$

where $\overline{age}$ is the mean age of the survey respondents. Hence, *age_int* measures the sensitivity on *phone* for each year a respondent's age differs from the mean age. Specifically, the coefficient of −0.4479 indicates that for each year of age, the coefficient for *phone* decreases by $-0.4479/10000 = -0.00004479$, approximately 1%. For instance, a consumer 50-years old has a phone coefficient of $-0.0043 - ((0.4479/10000) \cdot (54 - 44.4)) = -0.00473$, which is 10% higher than at the age of 44.4 years. Alternatively, a person 20-years old has a phone coefficient of $-0.0043 - ((0.4479/10000) \cdot (20 - 44.4)) = -0.00321$, which is 25% lower than at the age of 44.4 years.

The interpretation of the gender interaction term is straightforward. Gender is a dummy variable with "0" indicating man, and "1" indicating woman. The variable is interacted with *mrc* and divided by 1,000. The resulting coefficient of 1.0965 indicates that the coefficient for *mrc* for men and women is −0.0161 and $-0.0161 + (1.0965/1000) = -0.0150$, respectively. Stated differently, the survey indicates that women are 7% less sensitive to *mrc* than men are.

D-optimality of fitted model. A compelling aspect of this study was the application of efficient design to telecommunication services. As demonstrated with the significant reduction in D-error through the efficient design routine, D-efficient design has the potential of significantly improving the accuracy of the parameter forecasts. A core requirement of D-efficient design is prior knowledge of the ultimate model's specification, including its parameter values. In most instances, however, prior knowledge of the model specification and/or coefficients is not available. In fact, if it were, it might render a subsequent study redundant. This, in turn, raises the question whether the gains from optimization are robust to deviations in model specifications.

Table 5 provides the specifications of the ex-ante model upon which *Ngene* optimized the design matrix for the SP survey. Table 6 lists the D-error of the optimized design matrix for the specification of the ex-ante model at 0.0001346 at approximately 1.5 million iterations, which is a 40% improvement over its starting value. Appendix B shows the optimized design matrix for this study.

Model 5-1 differs from the ex-ante model in two aspects. First, instead of a standard logit model, Model 5-1 is a mixed logit model with lognormal distributed coefficients. Second, the coefficients estimated by Model 5-1 differ from the pilot study coefficient because the pilot study produced different estimates than the actual survey and due to the inclusion of three additional variables in the final model (e.g., *dummy_high*, *age_int*, and *gender_int*). To test the robustness of the benefits from D-optimization, the D-error of the optimized design matrix is calculated using the specifications of Model 5-1 (rather than the pilot model). This error measure then is compared to the D-errors of 30 randomly created design matrices that are also evaluated using the specifications of Model 5-1. Rather than optimizing the attribute levels across the design matrix, these “chance matrices” draw their attribute levels at random.

Ngene allows mixed logit models in its optimization routine. However, at present, the software can only optimize mixed logit models for uniform and normal distributions. In the absence of lognormal distributions in *Ngene’s* optimization routine, the D-errors of the design matrix and the 30 chance matrices are evaluated under two model specifications. The first specification is Model 5-1, as presented above with all variables distributed lognormal. The second specification is Model 5-1 with all variables distributed normal. Although not used, this second specification normalizes for any optimality loss due to differences in the coefficient distribution. Table 27 presents the results of this comparison.

Table 27
D-Optimality Comparisons

Design	D-error (Model 5-1—Lognormal)	D-error (Model 5-1—Normal)
Chance1	0.1209	0.0075
Chance2	0.0876	0.0076
Chance3	0.0704	0.0078
Chance4	0.0635	0.0075
Chance5	0.0854	0.0078
Chance6	0.0805	0.0073
Chance7	0.0710	0.0071
Chance8	0.0791	0.0080
Chance9	0.0943	0.0080
Chance10	0.0908	0.0068
Chance11	0.1032	0.0077
Chance12	0.1043	0.0071
Chance13	0.0919	0.0068
Chance14	0.0804	0.0070
Chance15	0.0864	0.0072
Chance16	0.0858	0.0067
Chance17	0.0729	0.0072
Chance18	0.0784	0.0071
Chance19	0.0781	0.0071
Chance20	0.0886	0.0067
Chance21	0.0940	0.0074
Chance22	0.0773	0.0082
Chance23	0.0811	0.0077
Chance24	0.0810	0.0075
Chance25	0.0778	0.0075
Chance26	0.0986	0.0076
Chance27	0.0984	0.0070
Chance28	0.0712	0.0076
Chance29	0.0841	0.0075
Chance30	0.1328	0.0078
Av_chance	0.0870	0.0074
Optimized	0.0878	0.0088

The first column shows the D-error of 30 randomly drawn design matrices evaluated under Model 5-1 with nine of the 10 design variables distributed lognormal. The remaining design variable (*d_over*) is fixed. The second column shows the D-errors of the same design matrices evaluated under a derivative of Model 5-1. Under this derivative, instead of the lognormal distribution, the nine design variables are distributed normal. The average D-error value of these evaluations is then compared to the D-error of the design matrix initially optimized under the ex-ante model. The average D-error of the chance matrices evaluated under the lognormal version of Model 5-1 is 0.0870. This compares to the D-error of 0.0878 of the optimized design matrix evaluated under the same model. Similarly, as evaluated under normal version of Model 5-1, the average chance D-error is 0.0074 compared to the D-error of the optimized matrix of 0.0088. The D-error for the optimized matrix is higher when evaluated against the average of both benchmark models. This indicates that for the present study the potential benefits from D-optimization could not be retained due to differences between the pilot model and the final model (i.e., Model 5-1). Under the fitted model, a chance design would have generated equally accurate forecasts as the optimized design did.

Notwithstanding, Table 28 illustrates that if the model specification is known at the survey design stage, efficient survey design stands to significantly improve the D-error of the design matrix and thereby the accuracy of the study. There is an 83% improvement in the D-error when the design matrix is optimized based on the specifications of Model 5-1.

Table 28
Ngene Optimization Results with Perfect Foresight

Statistics	Value
D-error start	0.135723
D-error end	0.022749
Total iterations	62,257
Last iteration with improvement	62,041
Improvement (%)	83%

Hence, for D-efficient design to be applied successfully to other studies, fundamental research needs to address how the potential benefits can be retained.

Results Interpretation

The findings of this study, summarized in Table 26, clearly demonstrate that subscribers consider far more than the mobile phone when selecting a mobile service plan. In fact, subscribers consider most, if not all, of the pertinent aspects of the mobile service bundle, including:

- The price of the mobile phone where higher mobile phone prices make a service bundle less attractive (mean: -0.0043, standard deviation: 0.0040)

- The monthly recurring charge where higher monthly charges make a service bundle less attractive (mean: -0.0161, standard deviation: 0.0224)
- The number of monthly voice minutes included in the mobile service plan where more minutes make a service bundle more attractive (mean: 0.0913, standard deviation: 1.6604)
- The amount of monthly data uploads and downloads included in the mobile service plan with more kilobytes making a service bundle more attractive (mean: 0.0067, standard deviation: 0.0183)
- The speed of data downloads where higher speeds make a service bundle more attractive (mean: 0.0020, standard deviation: 0.0110)
- The charge per kilobyte of data uploads and downloads in excess of the monthly data upload and download allowance where higher prices make a service bundles less attractive (mean: -0.4371, standard deviation: n/a)
- The charge for SMS where higher prices make a service bundle less attractive (mean: -1.0786, standard deviation: 4.1441)
- The type of mobile phone offered with the service bundle with Smartphones being more desirable than non-Smartphones (mean: 0.6997, standard deviation: 2.6406)
- The length of the term contract where a shorter term makes a service bundle more attractive (mean: -0.0182, standard deviation: 0.0505)
- Whether the monthly voice minutes included in the mobile service plan offer more than the national average of 700 minutes per month where plans in excess of this level make a service bundle more attractive (mean: 0.3553, standard deviation: 0.4044)

In addition, consumers place additional value on mobile plans that offer more voice minutes than the average consumption level of 700 minutes per month. Decision making differs by age and gender. For each additional year of age, subscribers become approximately 1% more sensitive to changes in mobile phone prices. Women are approximately 7% less sensitive to changes in MRCs.

The significance of this first set of findings is that researchers and policy makers must examine mobile demand as part of a bundled offering instead of analyzing bundle components on a standalone basis, as has been the case thus far. Alternatively, if justifiable, researchers must ensure that other service attributes are constant throughout the study. For instance, in estimating the impact of term contracts on consumers, Mierzwinski et al. (2005) treated contract length as the single determinant of consumer welfare. Not surprisingly, Mierzwinski et al. found that consumers preferred short-term contracts or no contract at all. Based on this finding, Mierzwinski et al. concluded that term contracts hurt consumers. Counter to the empirical evidence presented herein, Mierzwinski et al. assumed that consumers selected contract lengths independently from other plan attributes. Model 5-1, however, shows that consumers trade-off several plan attributes when selecting a mobile service plan and term length is only one attribute among several that affects consumer choice. Similarly, none of the relevant literature on mobile demand determinants treated demand from a service bundle perspective.

Beyond interpreting the number of significant independent variables and the signs of the coefficients, independent interpretation of the coefficients provides little insight. Based on equation (6), the logit coefficients measure the change in *utils* based on a change in one or several independent variables. However, the change in *utils* is difficult to understand, which is counter to other regression models, such as OLS where a change in the dependent variable often provides direct applicability. Further, per equation (9), an increase in *utils* does not translate into a linear increase in the logit probability. Instead, the forecasted *utils* for a mobile service plan requires insertion into the probability equation for logit models. Based on this complexity, relative interpretation of the logit coefficients is required. Relative interpretation assesses the impact on *utils* of one independent variable compared to the impact on *utils* of another independent variable. It allows for a richer interpretation of core issues than individual coefficient analysis and provides unique practical insights. Table 29 presents all possible relative coefficient interpretations for Model 5-1.

Table 29
Relative Coefficient Interpretation Model 5-1

	phone	mrc	voice allow	data allow	down load	d_over	text	phone type	term length	dummy high
phone	1.00	0.27	-0.05	-0.64	-2.15	0.01	0.00	-0.01	0.24	0.01
mrc	3.74	1.00	-0.18	-2.40	-8.05	0.04	-0.01	-0.02	0.88	0.05
voiceallow	-21.23	-5.67	1.00	13.63	45.65	-0.21	0.08	0.13	-5.02	-0.26
dataallow	-1.56	-0.42	0.07	1.00	3.35	-0.02	0.01	0.01	-0.37	-0.02
download	-0.47	-0.12	0.02	0.30	1.00	0.00	0.00	0.00	-0.11	-0.01
d_over	101.65	27.15	-4.79	-65.24	-218.55	1.00	-0.41	-0.62	24.02	1.23
text	-250.84	-66.99	11.81	160.99	539.30	-2.47	1.00	1.54	-59.26	-3.04
phone_type	-162.72	-43.46	7.66	104.43	349.85	-1.60	0.65	1.00	-38.45	-1.97
term_length	4.23	1.13	-0.20	-2.72	-9.10	0.04	-0.02	-0.03	1.00	0.05
dummy_high	82.63	22.07	-3.89	-53.03	-177.65	0.81	-0.33	-0.51	19.52	1.00

Relative coefficient interpretation reveals the subscriber's marginal willingness to pay for an attribute relative to another attribute. Not all comparisons are meaningful or find applicability in the marketplace. Hence, this analysis focuses only on a subset of the possible combinations. The core issues in strategy, policy, and regulation often include the price for the mobile phone and the MRC. This is not a coincidence as these price attributes represent the highest unit charge in a mobile service plan. Other price components, such as the price of an SMS, are mainly usage driven. Hence, the natural argument is to examine the trade-off space or util-equivalent space relative to these price attributes. Specifically, the relative interpretation of *mrc* relative to *phone* is examined first. This analysis is followed by the relative interpretation of *phone_type* and *phone*, and *term_length* and *phone*. The variables *voice_allow*, *data_allow*, *download*, *d_over*, and *text* are evaluated relative *mrc*.

The MRC coefficient reveals that 44-year-old male subscribers are indifferent between a $1 change in the MRC and a $3.74 equidirectional change in the mobile phone price. As the cost of a mobile phone is a one-time fee and the MRC is a recurring charge, this implies that such subscribers amortize their mobile phones over approximately four months. Over the life of a two-year contract, a total discount in MRC of $24 is equivalent to an upfront discount of $3.74. This implies a discount rate of 25.9%. This result is consistent with the previous relevant literature. For instance, Hausman (1979), in examining individual discount rates in the purchase and utilization of energy-using durables, found a discount rate of 20%. Similarly, Dubin and McFadden (1984) found a discount rate of 20.5% for electric appliances. Hausman (2002) discussed the importance of these tradeoffs in the development of mobile telecommunications demand.

As illustrated in Figure 4, due to the sociodemographic interaction terms, this amortization period changes by age and gender.

Figure 4. Mobile Phone Amortization Period by Age and Gender

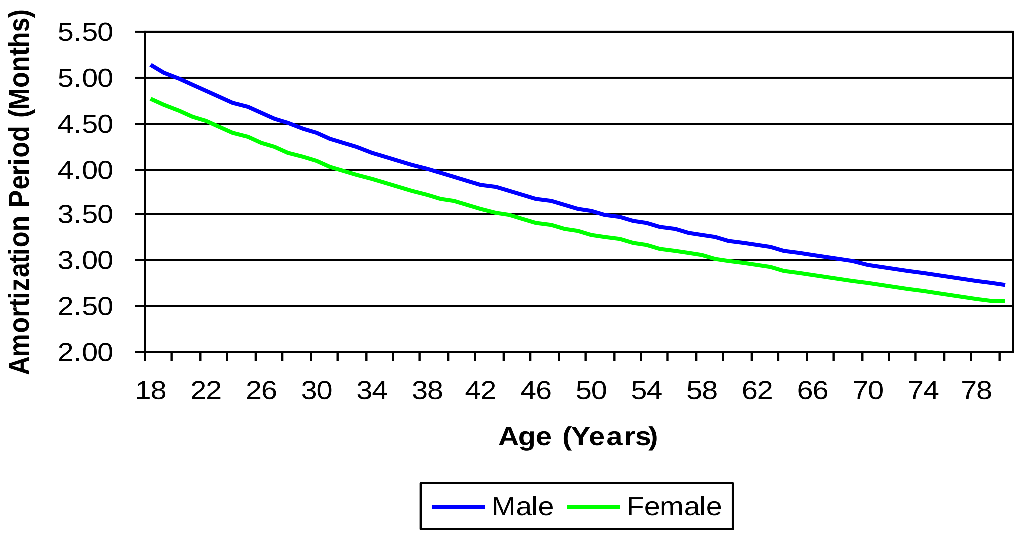

Figure 4. For male subscribers, the mobile phone amortization period decreases by 1% for each additional year beyond the average age and increases by the same amount for each year below this age level. The sensitivity for female subscribers also varies by age, but the difference in gender offsets this curve by 7% relative to men.

The corollary of this finding is that service providers can recover mobile phone discounts by increasing the MRC. However, only a fraction of the mobile phone discount is recoverable over any given month. For instance, for 44-year-old male subscribers, a maximum of 1 ÷ 3.74 = 0.27, or 27%, is recoverable over any given month. Hence, service providers must ensure that these subscribers remain with them for at least four months in order to recover the mobile phone discount. If a subscriber remains with the service provider for more than four months, the service provider stands to make a profit from the initial discount. Alternatively, with most U.S. mobile subscribers being contractually obligated to remain with a service provider for 24 months, the service provider can opt for a lesser increase in the MRC and recover the discount over a longer period.

The relative interpretation of the coefficient for the mobile phone price and the mobile phone type finds a marginal willingness to pay for Smartphones of $163 over non-Smartphones. This finding is generally consistent with the price differential between Smartphone and non-Smartphones observed in the marketplace. For instance, Verizon Wireless offers most of its Smartphones for $99 to $299 and its non-Smartphones for $0 to $99—a differential of approximately $200. As before, this figure is specific to 44-year-old male subscribers. Younger subscribers are willing to pay more for a Smartphone than older subscribers are. For instance, an 18-year-old subscriber is willing to pay $224 for a Smartphone, whereas the maximum willingness to pay for a 70-year-old subscriber is merely $128.

Service providers commonly impose term contracts with ETFs to compensate for mobile phone subsidies. The relative interpretation of the mobile phone price and the term-length coefficients reveals that the average-aged subscribers are willing to pay an additional $4.23 for each month deducted from a term contract. A typical term contract is 24 months. This implies that average-aged subscribers are willing to pay an additional 24 x $4.23 = $101.52 for the mobile phone in order to avoid a term contract. Conversely, the average subscriber prefers a term contract of 24 months to paying the full retail price for a mobile phone for all mobile phones offered at a discount of $101 or more. For instance, Verizon Wireless offers a 32-Gigabyte (GB) iPhone 4 for $299 with a 24-month term contract. Without the term contract, Verizon Wireless sells the same phone for $750. The discount of $450 implies that subscribers prefer to purchase the mobile phone in conjunction with a term contract. Again, the sensitivity to term contracts varies by age. Eighteen-year-old subscribers are willing to pay $140 in order to avoid a term contract, whereas 70-year-old subscribers are willing to pay $80.

Closely linked to the MRC is the number of monthly voice minutes included in a mobile service plan. Model 5-1 finds that male subscribers are willing to pay an additional $5.67 a month for each additional 100 minutes of voice usage. Female subscribers are willing to pay $6.08 for each additional 100 minutes of voice usage. Ceteris paribus, Verizon Wireless offers 450 voice minutes for $39.99 per month and 900 voice minutes for $59.99 per month. Thus, Verizon Wireless charges $0.09 per minute under the first plan and $0.07 per minute under the second plan. AT&T Mobility and other service providers charge $0.45 per minute for each minute beyond the monthly voice allowance. Model 5-1 reveals a willingness to pay of approximately $0.06 for male and female subscribers. This is almost eight times the voice overage charge but consistent with the price subscribers pay on average under their monthly voice allowance. Consequently, subscribers are not willing to pay a premium for voice minutes consumed beyond their monthly voice allowance. This means that subscribers purchase service plans that include a sufficient number of voice minutes. Hence, as observed, voice overage charges do not contribute in a statistically significant manner to mobile service plan selection. Related to this finding, male consumers are willing to pay an additional $22.07 for mobile service plans with a voice allowance in excess of 700 minutes. Female subscribers are willing to pay $23.68. This maximum willingness to pay for high-volume voice plans is consistent with the pricing differentials between low- and high-volume voice plans. For instance, Verizon Wireless and other service providers offer their 450-minute (low) voice plans for $20 less than their 900-minute (high) voice plans.

Model 5-1 finds that male and female subscribers are willing to pay an additional $0.42 and $0.45, respectively, in the MRC for each additional 100 kilobytes (kB) of data allowance. AT&T charges subscribers without a data plan $2.00 per Megabyte (MB) of data (http://www.att.com). At 1,024 kB per MB, this translates to $0.20 per kB. Similarly, Verizon Wireless charges $0.19 per kB of data for pay-as-you-go data subscribers. Hence, Model 5-1 finds a maximum willingness to pay for additional data allowances that is higher than prices in the marketplace. Similarly, male subscribers are willing to pay an additional $2.71 a month for each $0.10 change in the per kB data overage charge. The maximum willingness to pay for female subscribers for the same is $2.91. Unlike voice overage charges (which are invoiced per minute), service providers typically invoice data overage charges in rather large increments. For instance, for subscribers who exceed the 75 MB data allowance of the $10 data plan, Verizon Wireless bills the subscriber $10 for an additional 75 MBs of data. This overage charge applies regardless of whether the subscriber exceeded the data plan allowance by one byte or the entire additional 75 MBs. Assuming that the average subscriber who incurs a data overage charge uses half of this overage allowance, this implies that Verizon charges $10 ÷ (75 ÷ 2) = $0.27 per MB, or $0.0003 per kB. In order to avoid this data overage charge, subscribers would be willing to pay only a fraction of a cent increase in the MRC. Stated differently, male and female subscribers are not willing to increase their MRC to avoid data overage charges. In contrast to voice overage charges, this result implies that subscribers are willing to incur data overage charges.

As found by Dippon (2010), the current download speed impediments of 3G mobile service are a significant deterrent of 3G take-up. Model 5-1 demonstrates that male subscribers are willing to pay an additional $0.12 in the MRC for each additional 100 kilobits per second (kbps) download speed. Female subscribers are willing to pay $0.13. At current mobile speeds of approximately 1,000 kbps, service providers that can increase their mobile download speeds from the current levels to

5,000 kbps, thus making them comparable to standard DSL service, can charge an additional (4,000 ÷ 100) x 0.12 =$4.80 in the MRC. LTE, often referred to as 4G, promises rates far in excess of standard DSL. Verizon Wireless recently announced that its 4G network delivers 5,000–12,000 kbps when downloading data (http://www.verizonwireless.com). If so, average subscribers are willing to pay a premium ranging from $4.80 to $13.20 per month to enjoy this service.

U.S. service providers offer SMS on both a pay-per-use and a plan basis. For instance, AT&T Mobility, Verizon Wireless, and other service providers offer SMS at $0.20 per SMS sent and received. AT&T Mobility offers a $10 plan that includes 1,000 SMSs and a $20 plan that provides unlimited SMSs. The former plan implies an SMS rate of $0.10 per SMS. Model 5-1 reveals that male subscribers are indifferent between a $0.10 change per SMS and a $6.70 equidirectional change in the MRC. For female subscribers, this amount is $7.19. This implies that non-plan subscribers (who currently pay $0.20) are willing to pay $13.40 (male) and $14.38 (female) for an unlimited plan. Similarly, non-plan subscribers are willing to pay $6.70 (male) and $7.19 (female) to reduce their SMS rate to $0.10. These two findings indicate that AT&T's prices for its SMS plans are higher than the subscribers' maximum willingness to pay for this bundle component, as found by Model 5-1. The findings of Model 5-1 are more in line with the pricing structure of T-Mobile, which offers unlimited SMS for $10 a month, slightly below the indicated maximum willingness to pay.

Strategy Implications

U.S. service providers offer similar service plans. For instance, Verizon Wireless, AT&T Mobility, and Sprint all offer a monthly mobile service plan with 900 voice minutes for $59.99. Additional charges such as $0.40 per minute for voice overage charges, an option for unlimited or almost unlimited data usage (Smartphones) for an additional $25.00 to $29.99, and an SMS plan with almost unlimited messaging at around $20 apply (see http://www.verizonwireless.com; http://wireless.att.com; http://www.sprint.com). Similarly, T-Mobile offers a monthly 1,000-minute plan for $49.99 with a voice overage charge of $0.45, unlimited SMS for $10, and unlimited data for $30 (see http://www.t-mobile.com). The similar offerings, particularly among the three largest service providers (Verizon, AT&T, and Sprint) are indicative of market equilibrium. By deviating from this equilibrium position, service providers can generate a profit, at least in the short run until other service providers follow suit. However, not all deviations are profitable, and some deviation strategies are better than other strategies. Short of trial and error, service providers can measure the price elasticities of demand for the various price (and even non-price) attributes and select the attribute changes that generate the largest demand response.

Elasticities measure the impact on the dependent variable because of a change in one or more independent variables (Silverberg & Wing, 2000). Specifically, the elasticity of demand measures the impact on demand (measured in terms of market share) from a change in price or other product attributes levels. Following Silverberg and Wing (2000), the price elasticity of demand is:

$$(49) \qquad E_d = \lim_{\Delta p \to 0} \frac{\dfrac{(M_1 - M_0)}{\left(\dfrac{M_1 + M_0}{2}\right)}}{\dfrac{(P_1 - P_0)}{\left(\dfrac{P_1 + P_0}{2}\right)}},$$

where M_0 is the market share of a service provider in the default scenario and M_1 is the same providers' market share in the alternative scenario. P_0 and P_1 are the price or attribute levels of the service provider's service plan in the default scenario and in the alternative scenario, respectively. In the alternative scenario, the same service provider alters the attribute levels of one or more attribute of its service plan. If $|E_d| > 1$, demand is elastic; if $|E_d| < 1$, demand is inelastic.

Average logit probabilities generated by Model 5-1 calculate the probability of a subscriber selecting a specific mobile service plan. The median or mean logit probabilities of selecting a service plan are not equal to the logit probability of an average subscriber selecting the same plan (Train, 2009). Hence, the median and mean coefficients for Model 5-1 presented in Table 26 provide no information about the market shares obtained by the service providers offering these plans. Rather, random draws from the underlying normal distribution of the mixed logit model generate the probabilities that an average subscriber will select a specific service plan. Attributing these probabilities to the service providers yields forecasted market shares. Specifically, each coefficient of the standard deviation is multiplied by

η □ (0,1) and added to the corresponding mean coefficient. The exponent of these values generates random coefficients for the lognormal distribution. These, in turn, generate logit probabilities that are averaged to calculate the average probability of selecting a specific plan.

Table 30 summarizes the attribute levels of an illustrative market simulation with four service providers (Provider 1, Provider 2, Provider 3, and Provider 4) along with the average logit probabilities, or market shares. Each service provider is assumed to offer only the plan shown in the default scenario. The objective of this market simulation is to examine the market share gains and losses occurred by Provider 1 from deviating from the default scenario. It is noteworthy that since all plans in the default scenario are actual plans offered in the U.S. market place, this simulation is expected to approximate gains and losses incurred by a U.S. service provider that elects to introduce more innovative mobile service plans.

This simulation assumes that mobile service providers tailor their strategies to average-aged subscribers. Given the higher price sensitivity of male subscribers relative to female subscribers, the simulation further assumes that mobile service providers target male subscribers. To illustrate the simulation concept, it assumes that each service provider offers only this single service plan.

Table 30
Default Scenarios and Market Shares

	Provider 1	**Provider 2**	**Provider 3**	**Provider 4**
phone	99.99	99.99	0.00	199.99
mrc	74.99	54.99	59.99	69.99
voiceallow (in 100s)	9.00	4.50	9.00	10.00
dataallow (in 100s)	20.48	7.68	0.00	20.48
download (in 100s)	14.10	8.77	7.95	8.68
d_over	0.08	0.27	0.03	0.30
Text	0.20	0.02	0.02	0.00
phone_type	1.00	1.00	0.00	1.00
term	24.00	24.00	24.00	24.00
dummy_high	1.00	0.00	1.00	1.00
logit probability	23.16%	29.19%	32.31%	15.34%

Taking Provider 1 as an example, a first possible competitive strategy is to vary mobile phone prices. An increase or decrease in the current illustrative mobile phone price for Provider 1 results in different market shares for the service provider (see Figure 5).

Figure 5. Logit Probability—Provider 1

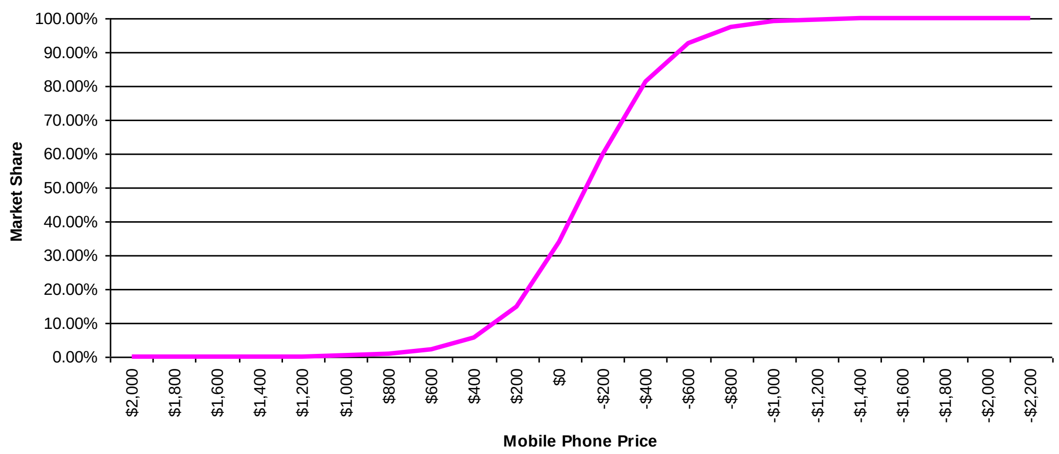

Figure 5. Consistent with Figure 1, Figure 5 presents Provider 1's market share as a function of its mobile phone price. A negative mobile phone price would indicate that Provider 1 would issue a credit to the subscriber's account. Thus, the subscriber would receive the mobile phone free in addition to getting the credit.

Table 31 shows the underlying data for Figure 5 and calculates the elasticity of demand for changes in mobile phone prices. For instance, if Provider 1 decreased its mobile phone price from $99.99 to zero, it could potentially achieve a market share of 34.01%. This is a 47% increase of its market share in the default scenario (23.16%). Alternatively, if Provider 1 raised its price for the mobile phone from $99 to $200, its market share would approach 15%, a decrease of 35%. The price elasticity of demand for Provider 1's service plan reveals that with a mobile phone price of approximately $200 and higher the service provider faces elastic demand.[20] In this range of the demand curve, the percentage of the market share change is greater than the percentage price decrease. Alternatively, for mobile phone prices below $200, Provider 1 faces inelastic demand. Practically, this finding means that if Provider 1 sought to decrease its mobile phone prices it should remain in the elastic range of the demand curve. Alternatively, if the service provider were to increase mobile phone prices, it could minimize the market share impact of this change by remaining in the inelastic range of the demand curve.

[20] Unit elasticity is at $258.

Table 31

Price Elasticity of Demand: Provider 1 Mobile Phone Prices

Price	Market share	% Change	Elasticity
$2,000	0.00%	n/a	n/a
$1,800	0.00%	n/a	n/a
$1,600	0.01%	n/a	-17.00
$1,400	0.03%	200.00%	-7.50
$1,200	0.09%	200.00%	-6.50
$1,000	0.26%	188.89%	-5.34
$800	0.73%	180.77%	-4.27
$600	2.07%	183.56%	-3.35
$400	5.73%	176.81%	-2.35
$200	15.00%	161.78%	-1.34
$0	34.01%	126.73%	-0.39
-$200	60.06%	76.60%	0.28
-$400	81.30%	35.36%	0.45
-$600	92.55%	13.84%	0.32
-$800	97.24%	5.07%	0.17
-$1,000	99.00%	1.81%	0.08
-$1,200	99.64%	0.65%	0.04
-$1,400	99.87%	0.23%	0.01
-$1,600	99.95%	0.08%	0.01
-$1,800	99.98%	0.03%	0.00
-$2,000	99.99%	0.01%	0.00

Alternatively, Provider 1 could change its MRC by increasing or decreasing it. In Table 32, Provider 1 increases and decreases its MRC from its default rate of $74.99. At current prices and above, the service provider faces elastic demand. In this range of the demand curve, the market penalizes service operators that seek to increase the MRC and rewards those that decrease their prices (albeit, possibly only in the short run).

Table 32
Price Elasticity of Demand: Provider 1 MRC

Price	Market share	% Change	Elasticity
$600	0.00%	n/a	n/a
$500	0.01%	n/a	-11.00
$400	0.07%	600.00%	-6.75
$300	0.43%	514.29%	-5.04
$200	2.72%	532.56%	-3.63
$100	15.70%	477.21%	-2.11
$0	56.16%	257.71%	-0.56
-$100	89.47%	59.31%	0.23
-$200	98.17%	9.72%	0.14
-$300	99.70%	1.56%	0.04
-$400	99.95%	0.25%	0.01
-$500	99.99%	0.04%	0.00

Provider 1 could also alter its term contract requirements. Currently, AT&T, Verizon, and Sprint generally require 24-month contracts. Provider 1 could either shorten or prolong its term length. By decreasing the number of required term months, Provider 1 could make its service plan more attractive relative to other service providers, thereby gaining market share. By increasing the term length, Provider 1 would lose market share. However, it could offset this loss by increasing mobile phone subsidies. The longer contract lengths ensure that Provider 1 can profitably recover the larger mobile phone discount. As Table 33 shows, the price elasticity of demand with respect to term length is inelastic in the range of zero to 36 months. This implies that at least as a standalone strategy decreasing the term length from its current 24 months is not an effective competitive strategy. In contrast, the inelastic region of the demand curve between 24 months and 36 months might provide a profit opportunity for Provider 1.

Table 33

Price Elasticity of Demand: Provider 1 Term Reduction

Term	Market share	% Change	Elasticity
0	31.10%	n/a	n/a
1	30.74%	-1.16%	-0.01
2	30.38%	-1.17%	-0.02
3	30.03%	-1.15%	-0.03
4	29.68%	-1.17%	-0.04
5	29.33%	-1.18%	-0.05
6	28.98%	-1.19%	-0.07
7	28.63%	-1.21%	-0.08
8	28.29%	-1.19%	-0.09
9	27.95%	-1.20%	-0.10
10	27.61%	-1.22%	-0.12
11	27.28%	-1.20%	-0.13
12	26.94%	-1.25%	-0.14
13	26.61%	-1.22%	-0.15
14	26.29%	-1.20%	-0.16
15	25.96%	-1.26%	-0.18
16	26.64%	2.62%	0.40
17	25.32%	-4.95%	-0.84
18	25.00%	-1.26%	-0.22
19	24.69%	-1.24%	-0.23
20	24.38%	-1.26%	-0.25
21	24.07%	-1.27%	-0.26
22	23.76%	-1.29%	-0.28
23	23.46%	-1.26%	-0.29
24	23.16%	-1.28%	-0.30
25	22.86%	-1.30%	-0.32
26	22.57%	-1.27%	-0.33
27	22.28%	-1.28%	-0.34
28	21.99%	-1.30%	-0.36
29	21.70%	-1.32%	-0.38
30	21.42%	-1.29%	-0.38
31	21.13%	-1.35%	-0.42
32	20.86%	-1.28%	-0.41
33	20.58%	-1.34%	-0.44
34	20.31%	-1.31%	-0.44
35	20.04%	-1.33%	-0.46
36	19.77%	-1.35%	-0.48

Given Senator Kohl's allegation of price fixing for SMS, it is also informative to examine whether changes in SMS prices prove effective. In the default scenario, Provider 1's service bundle does not include a plan for SMS. Thus, each SMS sent and received costs the subscriber $0.20. Evaluated against the service bundles of other mobile services providers, which all include SMS plans in this illustrative default scenario and thus lower SMS rates, Table 34 examines the market reaction to decreases in Provider 1's SMS rate.

Table 34

Price Elasticity of Demand: Provider 1 SMS Price Reduction

Price	Market share	% change	Elasticity
$0.20	23.16%	n/a	n/a
$0.15	23.89%	3.15%	-0.11
$0.10	24.64%	3.14%	-0.08
$0.05	25.40%	3.08%	-0.05
$0.00	26.18%	3.07%	-0.02

As before, a price decrease leads to inelastic demand responses. This finding is interesting from at least two perspectives. First, given that a monopolist would not set its price in the inelastic region of the demand curve, this finding sheds doubt on Senator Kohl's allegations. Second, it demonstrates that decreasing the SMS rate is not an effective competitive strategy, as subscribers do not sufficiently care about the level of SMS prices for it to be an effective competitive strategy.

Although strategies that are more competitive exist, service providers might want to pursue, an effective strategy could also entail altering more than one service attribute. For instance, in Table 35, a combinational strategy for Provider 1 is examined. In this strategy, Provider 1 increases the term length to 36 months, provides a free mobile phone, and varies increases in the MRC to obtain a positive net effect. In the default scenario, Provider 1 has a market share of 23.16%. Offering free mobile phones and increasing the term length to 36 months boosts the service provider's market share by 28% to 29.65 %. At this rate, Provider 1 must bear the revenue loss from offering free mobile phones. If it increased the MRC by $5 per month over the previous scenario, it would retain a market share of 27.68%. This is still higher than the default market share by 20%. By increasing revenue by $5 per month, Provider 1 increases revenue by $5 x 36 = $180 over the subscriber's lifetime. Offsetting the mobile phone subsidy of $99.99, this yields a net revenue increase of $80.01 per subscriber in addition to the 4.5 points market share gain. Additionally, Provider 1 lowers its churn rate by contractually obligating subscribers to remain with the carrier for an additional 12 months beyond the original 24 months.

Table 35
Combinational Competitive Strategy—Average Male Subscriber

MRC	Mobile phone	Term	Market share
$74.99	$99.99	24	23.16%
$74.99	$0	36	29.65%
$79.99	$0	36	27.68%
$84.99	$0	36	25.79%
$89.99	$0	36	23.99%

Given the high level of competition in the U.S. mobile market, other service providers are likely to follow suit, thereby cancelling the long-term benefits from competitive strategies. However, due to the term-length requirements, service providers that pioneer a profitable strategy stand to enjoy a two- to three-year first-mover advantage.

Policy Implications

The study's findings also provide valuable information on a number of critical policy decisions pending before the FCC and state regulators. Most generally, the regulators must consider the entire service bundle when examining market behavior or alleged market failures. Considering individual service attributes in isolation yields incorrect results and thus incorrect regulation and policy. For instance, the FCC and U.S. Congress still discuss term contracts separate from all other service attributes. Policy makers, as well as several class action plaintiffs, accuse AT&T, Verizon, Sprint, and others of harming subscribers by requiring term contracts with ETFs. The allegations do not consider that these service providers offer term contracts in conjunction with several other attributes. Similarly, MetroPCS, a regional service provider, currently airs advertisements in which it promotes its absences of "stupid term contracts." The relative evaluation of the coefficients for mobile phone price and the MRC has shown a marginal willingness to pay of $101 in terms of mobile phone prices to avoid a term contract. However, a closer look at MetroPCS' mobile phone pricing structure finds prices that exceed by more than $101 the prices of other service providers that demand term contracts. For instance, MetroPCS sells the Smartphone BlackBerry Curve 8530 for $199 without contract (see http://metropcs.com). AT&T Mobility sells the same handset for $0.01 with a two-year contract (see http://www.att.com). Similarly, Verizon Wireless sells the handset for $79.99 (see http://www.verizonwireless.com). Hence, from a welfare perspective, MetroPCS' offering is inferior to the offerings by these other service providers. Yet, due to the incorrect analysis of ETFs, MetroPCS is not subject to the federal investigation. The study also demonstrates that varying term lengths from zero months to 36 months has little impact on subscribers' decisions, as all changes within this range fall in the inelastic range of the demand curve.

The study highlights the importance of offering spectrum that, in turn, will increase mobile upload and download speeds. Specifically, subscribers are willing to pay a premium of up to $13.20 over the current MRC in order to obtain LTE mobile speeds. With most unlimited data plans around $30 per month, this implies that subscribers are willing to increase their MRC by 45% in order to obtain LTE. The high willingness to pay illustrates the high priority that subscribers place on the increase in mobile upload and download speeds. The move to LTE could also have an impact on fixed-line broadband offerings. Currently, fixed-line broadband providers, such as Comcast, offer comparable Internet access at $34.99 per month (http://www.comcast.com). With consumers willing to pay $43.20 for mobile broadband offerings, subscribers place an $8.21 premium on mobile broadband relative to fixed-line broadband. Hence, fixed-line broadband providers will need to price their services at a differential larger than the $8.21 premium in order to maintain their subscriber base.

Finally, in analyzing Senator Kohl's investigation of SMS prices, the study has shown that SMS prices might be set in the inelastic region of the demand curve. Such pricing behavior is inconsistent with monopoly or cartel price setting. Furthermore, as is the case in all other investigations, the study clearly shows that SMS pricing is only one attribute of the service bundle. Competition occurs at the service bundle level. Consequently, bundles that include discounted SMS prices directly compete with bundles that charge $0.20 for each additional SMS. Finally, the subscribers' marginal willingness to pay closely mirrors the U.S. service providers' pricing structures.

Conclusions

The U.S. mobile sector is fiercely competitive as four nationwide service providers and approximately 30 regional service providers and mobile virtual network operators compete in a highly saturated market. Despite these conditions, or maybe due to these conditions, a key metric in valuing a mobile service provider is the number of new subscribers that it signs up. However, unlike the last decade when subscribers were just discovering mobile, in today's environment, new subscribers primarily originate from competitive actions, specifically, from innovative and competitive service offerings. This, in turn, requires that mobile service providers have a detailed and sophisticated understanding of mobile demand drivers. Without such an understanding, competitive actions become nothing more than a guessing game.

Success stories, such as Apple's iPhone or RIM's Blackberry, lead the casual observer to believe that subscribers select mobile phone service based on the attractiveness and functionality of the mobile phone with little regard for monthly prices, minutes and data allowances, contract lengths, and other attributes. In fact, smaller U.S. mobile service providers have argued that Apple's refusal to offer the iPhone to them prevents them from competing. However, in the United States, mobile phones are generally not sold separately but as part of a larger mobile service bundle. This raises the question of whether the components of the bundle, other than the mobile phone, actually influence the subscriber's purchase decision and, if so, by how much. With the mobile phone clearly an important aspect of the bundle, what features of the mobile service plan shape the demand for the overall service bundle? Moreover, are subscribers willing to trade a less desirable mobile phone for a better service plan or vice versa? This study attempts to assess empirically the demand determinants for mobile phone service when the components are bundled for sale.

The economic literature is replete with discussions on mobile diffusion and mobile demand determinants. The early literature on mobile demand focused mainly on FMS, the phenomenon that eventually ended fixed-line growth and caused fixed-line service providers to divest their copper-based voice networks. Specifically, in the 1990s when mobile telephony was still in its infancy, researchers focused on the competitive impact that mobile had on fixed-line growth. The central research hypothesis of this stream of work was whether mobile telephony was an economic substitute for POTS. With increasing coverage, free long distance, and decreasing service plan prices, mobile telephony became a commodity around the turn of the century. At that time, it also became clear that mobile services had a direct competitive effect on fixed services. Substitution was found initially in the demand for second lines, but it soon expanded to first lines as subscribers started “cutting the cord” and abandoning their fixed lines altogether. With FMS well established, the literature refocused and concentrated on mobile diffusion instead. This stream of work studied the pace and drivers of mobile technology adoption. A central research question was how to forecast the saturation point of mobile demand. Many research papers attempted to determine mobile demand drivers and saturation points based on socioeconomic and demographic variables. Others looked at why countries differed with respect to mobile penetration. Time-series models, in particular S-curve models (e.g., Gompertz, 1825), feature prominently in this early research of mobile demand.

Today, many nations have achieved 100% mobile penetration, where the number of people with subscriptions to a mobile service plan equals the number of citizens in a country. In fact, many European and Middle Eastern nations have exceeded 100% penetration as individuals with more than one mobile device have subscriptions to more than one mobile service plan. Even some poorer nations have over 75% mobile penetration rates as they “leapfrog” technologies, bypassing a ubiquitous fixed-line network and introducing nationwide mobile networks instead. With mobile penetration approaching saturation, the recent literature examines how mobile service providers can continue to grow revenues in a saturated market. This focus is on the demand attributes of mobile telephony from a consumer perspective, answering the question of what attributes drive consumer demand. Some researchers have examined the interaction of SMS and mobile voice service, whereas others have examined whether the services are substitutes, thereby cannibalizing demand, or complements.

The present study expands on this latest stream of the literature and examines consumer demand determinants for mobile phone service bundles. Specifically, it examines the effects and cross-effects of service bundle attributes on consumer demand. Although others have conducted similar studies using RP or market data for POTS, there does not appear to be any similar published work for mobile telephony. Furthermore, the present study expands on the existing body of literature in that it examines consumer demand in a postpaid-service bundled scenario where mobile phone features and minutes-of-use or call prices are bundled with other service attributes, such as the number of allowed monthly voice minutes and the price of excess data usage. The previous literature focused on overall service demand and its dependency on sociodemographic variables and, at times, a few service attributes in a larger bundle.

From a methodological viewpoint, the study employs a multinomial mixed exploded logit model based on consumer-stated-preference data obtained through an online survey. The design of this survey further expands the literature in that it employs efficient design, in particular D-efficient design. This is in contrast to the full factorial and fractional factorial (and mostly orthogonal) design used by the previous literature. The present study seems to be the first of its kind to apply efficient design to a mobile demand survey and possibly the first large scale application of D-optimal design.

The objective of the D-optimal design is to minimize the determinant of the AVC matrix of the service bundle attributes. Practically, this method promises to yield a higher level of accuracy by producing a smaller standard error of the coefficient relative to nonefficient design methods with the same number of observations. Alternatively, D-optimal design stands to minimize the number of required observations to achieve a predetermined level of accuracy. The literature on efficient design offers a limited amount of studies that demonstrate the superiority of the efficient design method over traditional orthogonal methods and chance method, where design matrices are created at random. Efficient design optimizes the survey design matrix based on this perception. None of these studies addresses that final model specifications are likely to differ, possibly significantly, from pre-study perceptions. The present study offers a method by which researchers can evaluate whether deviations from the ex-ante model cancel the promised benefits of efficient design.

A professional market research firm administered the resulting survey to a multimillion-member omnibus panel. Each survey respondent completed six trade-off (conjoint) exercises representing six independent choice situations of three mobile service plan alternatives each. In each choice situation, the survey respondent indicated the most preferred and least preferred mobile service plan. In addition, the survey asked for demographic and socioeconomic data including, age and gender. Four hundred and eighty-nine panel members validly completed the survey. In responding to the question of the most preferred plan, the survey respondents created three observations. One observation indicated which plan was most preferred. The other two observations were for the two plans not most preferred. In responding to the question of the least preferred plan, the survey respondents created two observations. One indicated which plan was least preferred and one for the plan that was not preferred the least. This resulted in five observations per choice situation per respondent. With six choice situations and 489 respondents, the resulting database consisted of 14,670 observations.

Prior to fitting a model to the data, the data were examined for potential biases and other inaccuracies. This review revealed respondent fatigue in the form of biased responses in the last two choice situations. In these choice situations, the respondents' plan selections were a function of the presented sequence of choice alternatives. The data were fitted to several logit models. LR indices and LR hypothesis tests yielded a multinomial mixed exploded logit model with ten variables describing the mobile service plan attributes and two sociodemographic variables. The coefficients for the mobile service plan attributes are distributed lognormal. The coefficients for the sociodemographic variables are fixed parameters. A Hausman specification test accepted the null hypothesis of including the last two choice situations, despite its initial evidence of respondent fatigue. Testing for D-optimality revealed that the fitted model retained no benefits of D-optimization. This finding illustrates that D-optimization requires highly accurate a priori information of the model specification and its coefficients. However, if such information is available, it might question the need for conducting the study. Notwithstanding, with perfect a priori information, the underlying D-error of the design matrix could have been improved by over 80%.

Interpreting the coefficients reveals that consumers consider most, if not all, of the pertinent aspects of the mobile service bundle, including mobile phone price, monthly recurring charge, monthly voice and data minutes included in the plan, mobile upload and download speeds, data overage charges, SMS prices, the type of mobile phone offered, and the length of the term contract. Interestingly, voice overage charges seem not to matter to consumers. A possible explanation of this finding is that consumers select mobile plans that include sufficient voice minutes, thereby making voice overage charges irrelevant. The significance of this first set of findings is that researchers must examine mobile demand as part of a bundle offering, rather than individual bundle attributes, as has been considered in several pieces in the literature. Decision making for mobile phone plans also varies by age and gender. As consumers grow older, their price sensitivity increases by approximately 1% per year. Female consumers are less price sensitive than male consumers by approximately 7%.

Relative interpretation of the coefficients for average consumers finds that:

- Consumers amortize their mobile phones over four months.
- Service providers must recover mobile phone discounts over at least four months.
- Consumers are willing to pay $163 to upgrade from a non-Smartphone to a Smartphone.
- Consumers are willing to forego a mobile phone discount of up to $101 in order to avoid a term contract.
- Consumers are willing to pay approximately $0.06 for each additional voice minute, which is far below current voice overage charges.
- Consumers are willing to pay $0.42 for each additional 100 kilobytes of data transfer or double the current data overage charges.
- Operators with LTE can charge a premium of up to $13.20 per month in the MRC.
- Consumers are willing to pay $13.40 per month for unlimited SMS, consistent with current pricing patterns that offer unlimited SMS plans at $10 per month.

U.S. service providers offer similar and often identical service plans. This study demonstrates how service providers can generate a profit, at least in the short run, by deviating from this apparent market equilibrium. Not all deviations are profitable, and some deviation strategies are better than other strategies. Demand elasticities calculate deviations from the equilibrium and reveal the percentage market shares potentially gained by deviating from the market equilibrium. Specifically:

- Mobile phone price decreases for mobile phones prices above $200 is an effective competitive strategy.
- MRC price decreases are only effective for plans prices above $75.
- Decreasing term lengths is not an effective strategy. However, term lengths changes beyond 24 months still fall in the inelastic range of the demand curve. Hence, increasing terms lengths might be an effective strategy.
- Decreasing SMS rates for subscribers without SMS plan is not an effective strategy.

- Offering free mobile phones, increasing term lengths to 36 months, and increasing MRC by $5 might be an effective strategy. The service provider will gain an additional $80 per subscriber over the term period, in addition to gaining an additional 4.5 points in market share.

The study's findings also provide valuable information on a number of critical policy decisions pending before the U.S. Federal Communications Commission and state regulators. Specifically, state and federal regulators fail to consider mobile phone discounts when reviewing term contracts and their associated ETFs. Instead, regulators consider term contracts in isolation, leading to the incorrect conclusion that they necessarily hurt consumer welfare. This study, however, demonstrates that term contracts represent only one attribute in the service bundle, and the FCC and state regulators must analyze all relevant attributes simultaneously to capture important and complex trade-offs between attributes. For instance, the study finds that subscribers are willing to pay $101 to avoid a term contract. Regional players, MetroPCS in particular, require no term contracts, calling them "stupid term contracts" in their marketing campaigns. However, a closer look at MetroPCS' mobile phone pricing structure finds prices that exceed by more than $101 the prices of other service providers that demand term contracts. For these mobile phones, and possibly others, term contracts are welfare enhancing. Curiously, the FCC does not review MetroPCS as it does not require term contracts.

The study also highlights the importance of offering spectrum that, in turn, will increase mobile upload and download speeds. Finally, SMS prices are subject to a federal investigation and a consumer class action lawsuit where the plaintiffs allege price fixing for SMS. However, as this study demonstrates, subscribers do not consider SMS in isolation. Rather, they trade-off all the attributes of the service bundle. Further, the subscribers' marginal willingness to pay closely mirrors the U.S. service providers' pricing structure.

A fundamental change is occurring in the mobile communications market. While traditionally used for voice communications only, technological evolution has expanded mobile services far beyond simple voice calling. The findings of this study highlight that researchers, service providers, and regulators must adapt to this changing environment by considering mobile communications not as a collection of individual services and service components, but an all-encompassing communications bundle.

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Appendix A
FMS and Mobile Diffusion Literature Summary

Table A1

FMS Literature Summary Overview

Authors	Year	Data	Country	Method	Fixed cross elasticity	FMS finding
Parker & Röller	1997	1984–1988	U.S.	Nash equilibrium index	n/a	Indirect
Sung, Kim, & Lee	2000	1991–1998	South Korea	Cross price elasticity	0.1–0.2	Direct
Barros & Cadima	2001	1981–1999	Portugal	Diffusion curves	n/a	No finding
Rodini, Ward & Woroch	2003	2000–2001	U.S.	Cross price elasticity	0.22–0.26*	Direct
Sung & Lee	2002	1991–1998	South Korea	Cross price elasticity	0.14–0.22	Direct
Ahn, Lee, & Kim	2004	1996–2002	South Korea	Correlation	n/a	Direct
Madden & Coble-Neal	2004	1995–2000	58 countries	Cross price elasticity	0.12	Direct
Ward & Woroch	2004	1999–2001	U.S.	Cross price elasticity	0.13–0.33	Direct
Vagliasindi, Guney, & Taubman	2006	2002	26 countries	Correlation	n/a	Direct

* not statistically significant

Table A2

Mobile Diffusion Literature Summary

Author(s)	Year	Country(ies)	Data	Model	Dependent variable(s)	Independent variable(s)	Key findings
Gruber & Verboven	2001	EU-15 nations	Intro-1997	Logistic diffusion	Mobile subscribers	2G deployment, mobile growth, competition, GDP, teledensity	Transition from 1G to 2G and introduction of competition are key drivers of diffusion.
Gruber & Verboven	2001	140 nations	1981–1998	Logistic diffusion	Mobile subscribers	2G deployment, mobile growth, competition, GDP, teledensity, tech standards	Transition from 1G to 2G, introduction of competition, income, teledensity, and standardization are key drivers of diffusion.
Massini	2002	Italy and UK	1990–2001	Logistic and Gompertz diffusion	Mobile subscribers	Potential adopters, mobile phone price, tariff, consumption expenditure, technological change	Transition to digital and increased competition are key drivers of diffusion in both countries. Lower prices also impact Italy but not UK.
Banerjee & Ros	2004	61 OECD nations	2002	Cluster analysis	Not applicable	Not applicable	Technological and economic substitution explains country differences in fixed and mobile developments.
Wareham, Levy, & Shi	2004	United States	1994–1998	Logistic diffusion; probit model	(1) Mobile subscribers (2G only); (2) mobile diffusion	(1) income, geographic area; (2) income, education, age, household size, own home, married, child, profession	Mobile diffusion is positively correlated with income, geographic size, and occupation. Some ethnic groups adopt faster than others, and family size is negatively correlated.
Koski & Kretschmer	2005	32 industrialized countries	1991–2000	(1) Hazard rate model for competitive entry; (2) logistic diffusion for diffusion; (3) 3SLS IV and Mills ratio for price	Competitive entry dummy; mobile diffusion per capita; price	Regulation; competition, 1G profitability, time, manufacturers, GDP per capita	Technology standardization accelerates 2G entry and diffusion; first mover tends to set monopolistic prices, liberalization accelerates 2G diffusion.

Author(s)	Year	Country(ies)	Data	Model	Dependent variable(s)	Independent variable(s)	Key findings
Kauffman & Techatassanasoontorn	2005	46 developed and developing European nations	1992–1999	Non-parametric Kaplan-Meier estimator	Probability of phase end	GNP, teledensity, mobile penetration, analog mobile penetration, number of mobile standards, number of analog standards, number of service providers, standardization policy, licensing policy	Drivers of mobile diffusion differ depending on diffusion phase. Higher digital diffusion and technology standards aide early diffusion; higher analog diffusion and GNP also contributes positively; higher competition increases diffusion during mid-phases; higher number of analog service providers slows diffusion; regional licenses contribute to higher initial diffusion.
Rouvinen	2006	200 developing and developed nations	2002	Gompertz diffusion	Digital mobile subscribers	Population, income, agriculture, illiteracy, credit, trade, freedom, PCs, teledensity, fixed prices, analog penetration, digital users, prepaid, mobile prices, mobile phone prices	Developing and developed nations have different diffusion patterns due to late entry (which contributes positively to diffusion), large customer bases, and different network effects. Income does not explain differences in adoption and diffusion speeds are not significantly different.
Dippon	2010	47 developed and developing nations	2000–2009	Linear probability and binary logit models; logistic and Gompertz diffusion	3G subscribers	MNP, churn, prepaid, GDP, density, population, competition, revenue, penetration, teledensity, time since 3G allocation, MOUs, HHI, others	Time since the allocation of 3G spectrum is most important determinant of 3G take-up; customer characteristics and demographic variable also impact take-up; Gompertz provides superior fit to logistic curve

Appendix B
Study Design Matrix

			Price of mobile phone	Price of mobile phone	Price of mobile phone	Monthly charge	Monthly charge	Monthly charge	Voice allowance per month	Voice allowance per month	Voice allowance per month	Data allowance per month (kilobytes)	Data allowance per month (kilobytes)	Data allowance per month (kilobytes)	Data download speed (kilobits per second)	Data download speed (kilobits per second)	Data download speed (kilobits per second)
Survey	Game	Choice situation	plan1 phone price	plan2 phone price	plan3 phone price	plan1 mrc	plan2 mrc	plan3 mrc	plan1 v_allow-ance	plan2 v_allow-ance	plan3 v_allow-ance	plan1 d_allow-ance	plan2 d_allow-ance	plan3 d_allow-ance	plan1 download	plan2 download	plan3 download
1	1	9	$50	$500	$0	$120	$80	$160	50	500	500	1000	200	200	2000	1500	2000
1	2	11	$300	$100	$200	$20	$40	$80	200	200	100	1000	50	1000	3000	1500	1000
1	3	15	$400	$0	$500	$20	$20	$80	500	2000	1000	500	200	500	1500	1000	2000
1	4	25	$500	$0	$400	$120	$80	$80	1000	1000	unlim.	500	0	unlim.	6000	500	250
1	5	33	$400	$100	$200	$80	$160	$80	50	200	500	200	50	5000	6000	250	250
1	6	40	$0	$300	$300	$40	$160	$20	2000	100	100	5000	5000	0	1500	2000	3000
2	1	6	$100	$400	$100	$60	$120	$120	2000	200	200	50	5000	50	500	3000	250
2	2	13	$0	$50	$400	$80	$120	$20	50	1000	2000	0	1000	200	1000	1000	3000
2	3	20	$200	$400	$100	$120	$60	$20	2000	500	100	200	200	200	500	1500	2000
2	4	27	$400	$100	$50	$80	$100	$100	200	50	2000	5000	1000	1000	1500	1000	1500
2	5	30	$0	$500	$50	$100	$40	$20	50	2000	50	500	5000	200	250	6000	500
2	6	34	$300	$50	$500	$100	$80	$60	unlim.	50	50	unlim.	50	50	2000	500	3000
3	1	2	$100	$200	$200	$60	$100	$160	1000	2000	50	500	0	500	3000	250	250
3	2	4	$50	$400	$100	$120	$20	$120	1000	50	200	500	1000	1000	1500	250	1500
3	3	14	$0	$300	$400	$80	$60	$60	100	1000	50	200	5000	0	3000	250	1500
3	4	19	$50	$400	$100	$80	$40	$40	200	100	1000	0	50	5000	250	500	6000
3	5	21	$300	$400	$50	$100	$40	$120	200	2000	100	500	200	500	2000	500	6000
3	6	42	$100	$200	$400	$160	$60	$120	1000	100	500	50	500	5000	500	3000	500
4	1	3	$100	$500	$400	$40	$100	$40	500	1000	2000	50	200	200	3000	2000	3000
4	2	5	$300	$300	$0	$100	$20	$100	100	2000	200	50	0	200	1500	3000	1000
4	3	7	$50	$100	$300	$160	$80	$20	2000	500	100	5000	0	50	1000	1500	6000
4	4	8	$500	$0	$300	$60	$80	$60	500	500	2000	1000	500	500	500	3000	1500
4	5	10	$200	$50	$50	$40	$60	$120	100	unlim.	50	500	200	50	6000	250	500
4	6	16	$0	$50	$300	$40	$120	$120	500	100	200	50	5000	0	1000	3000	1000
5	1	17	$50	$200	$200	$160	$120	$40	200	500	100	200	50	1000	1500	1000	2000
5	2	22	$500	$0	$100	$20	$100	$100	2000	50	200	200	5000	0	500	6000	500
5	3	29	$100	$500	$500	$20	$60	$60	50	50	1000	0	unlim.	0	6000	500	250
5	4	32	$400	$400	$100	$60	$160	$60	100	50	unlim.	unlim.	500	50	250	6000	6000
5	5	36	$500	$100	$300	$80	$160	$160	500	200	1000	50	500	5000	3000	1000	1000
5	6	37	$200	$0	$0	$20	$120	$60	50	100	1000	200	500	200	1000	2000	250
6	1	18	$500	$500	$50	$100	$20	$40	200	200	500	5000	0	500	6000	2000	500
6	2	23	$500	$300	$0	$20	$120	$100	500	1000	200	1000	0	50	2000	1500	1000
6	3	24	$200	$500	$0	$60	$20	$100	1000	50	500	0	200	5000	6000	1000	3000
6	4	28	$300	$200	$500	$40	$100	$160	50	unlim.	200	1000	50	500	1000	2000	6000
6	5	31	$400	$0	$200	$160	$160	$20	1000	100	50	200	unlim.	0	500	6000	500
6	6	41	$200	$50	$50	$60	$100	$80	100	200	500	0	1000	1000	3000	1500	1000
7	1	1	$100	$300	$300	$160	$40	$160	100	200	2000	0	1000	0	2000	250	3000
7	2	12	$0	$200	$500	$160	$160	$40	200	500	50	1000	1000	500	250	3000	1500
7	3	26	$400	$300	$0	$40	$80	$40	unlim.	500	100	0	500	unlim.	1000	2000	6000
7	4	35	$300	$100	$400	$120	$20	$100	2000	100	2000	5000	50	50	2000	500	2000
7	5	38	$200	$50	$500	$120	$60	$80	100	2000	500	50	500	5000	250	6000	1500
7	6	39	$50	$200	$200	$100	$40	$160	500	1000	1000	5000	0	1000	250	6000	2000

			Fee for excess minutes	Fee for excess data usage	Fee for excess data usage	Fee for excess data usage	SMS fee (per message sent and received)	SMS fee (per message sent and received)	SMS fee (per message sent and received)	Type of phone	Type of phone	Type of phone	Length of contract	Length of contract	Length of contract
Survey	Game	Choice situation	plan3 v_over	plan1 d_over	plan2 d_over	plan3 d_over	plan1 text	plan2 text	plan3 text	plan1 phone type	plan2 phone type	plan3 phone type	plan1 term length	plan2 term length	plan3 term length
1	1	9	$0.30	$0.30	$0.10	$0.30	$0.25	$0.40	$0.00	NS	S	S	12	18	36
1	2	11	$0.20	$0.40	$0.10	$0.20	$0.40	$0.00	$0.20	S	NS	NS	12	12	30
1	3	15	$0.20	$0.25	$0.10	$0.25	$0.30	$0.30	$0.00	S	NS	NS	36	12	12
1	4	25	$0.00	$0.20	$0.40	$0.00	$0.05	$0.10	$0.25	S	S	NS	6	24	6
1	5	33	$0.30	$0.10	$0.25	$0.20	$0.05	$0.10	$0.30	S	NS	S	12	24	30
1	6	40	$0.40	$0.10	$0.30	$0.40	$0.25	$0.10	$0.05	NS	S	S	36	30	6
2	1	6	$0.10	$0.15	$0.25	$0.15	$0.25	$0.00	$0.40	S	S	S	36	12	0
2	2	13	$0.40	$0.30	$0.20	$0.20	$0.00	$0.10	$0.40	S	NS	S	36	0	6
2	3	20	$0.40	$0.20	$0.30	$0.15	$0.30	$0.05	$0.20	S	S	NS	12	12	30
2	4	27	$0.25	$0.30	$0.30	$0.10	$0.20	$0.25	$0.10	NS	NS	S	18	18	18
2	5	30	$0.15	$0.30	$0.40	$0.10	$0.30	$0.05	$0.40	NS	NS	NS	30	36	0
2	6	34	$0.30	$0.00	$0.30	$0.10	$0.10	$0.25	$0.10	NS	S	NS	24	6	12
3	1	2	$0.25	$0.40	$0.10	$0.30	$0.10	$0.25	$0.30	NS	S	NS	0	36	18
3	2	4	$0.20	$0.30	$0.15	$0.25	$0.00	$0.20	$0.00	NS	S	NS	24	6	12
3	3	14	$0.20	$0.15	$0.15	$0.30	$0.00	$0.40	$0.00	NS	S	NS	18	30	18
3	4	19	$0.40	$0.10	$0.20	$0.25	$0.05	$0.25	$0.10	S	NS	NS	24	12	24
3	5	21	$0.15	$0.15	$0.15	$0.40	$0.20	$0.20	$0.25	NS	NS	S	6	18	24
3	6	42	$0.10	$0.30	$0.10	$0.30	$0.20	$0.00	$0.30	NS	NS	S	6	36	24
4	1	3	$0.20	$0.40	$0.20	$0.15	$0.10	$0.30	$0.40	S	S	NS	12	12	18
4	2	5	$0.15	$0.10	$0.15	$0.40	$0.05	$0.40	$0.05	S	NS	S	0	18	24
4	3	7	$0.10	$0.20	$0.30	$0.25	$0.25	$0.30	$0.05	S	NS	NS	36	0	30
4	4	8	$0.30	$0.25	$0.40	$0.10	$0.25	$0.05	$0.25	NS	S	S	30	0	36
4	5	10	$0.40	$0.10	$0.25	$0.40	$0.40	$0.00	$0.05	S	NS	S	24	6	0
4	6	16	$0.25	$0.40	$0.10	$0.25	$0.20	$0.30	$0.20	S	S	S	0	36	36
5	1	17	$0.25	$0.30	$0.15	$0.40	$0.30	$0.00	$0.30	NS	S	NS	24	18	0
5	2	22	$0.30	$0.40	$0.20	$0.10	$0.00	$0.40	$0.10	NS	NS	S	24	24	6
5	3	29	$0.30	$0.30	$0.00	$0.15	$0.40	$0.05	$0.25	NS	NS	NS	6	36	6
5	4	32	$0.00	$0.00	$0.20	$0.40	$0.05	$0.10	$0.30	NS	NS	NS	0	24	36
5	5	36	$0.15	$0.20	$0.15	$0.40	$0.10	$0.30	$0.00	NS	S	NS	30	6	30
5	6	37	$0.25	$0.15	$0.25	$0.25	$0.30	$0.20	$0.25	S	S	NS	0	24	24
6	1	18	$0.25	$0.15	$0.20	$0.15	$0.20	$0.10	$0.05	S	NS	S	12	6	12
6	2	23	$0.40	$0.10	$0.25	$0.30	$0.25	$0.25	$0.10	S	S	S	30	30	6
6	3	24	$0.15	$0.20	$0.40	$0.15	$0.40	$0.05	$0.05	S	S	NS	18	18	0
6	4	28	$0.30	$0.15	$0.40	$0.20	$0.00	$0.40	$0.20	NS	S	S	36	0	30
6	5	31	$0.20	$0.25	$0.00	$0.40	$0.30	$0.20	$0.20	NS	S	S	18	0	36
6	6	41	$0.20	$0.15	$0.25	$0.30	$0.00	$0.20	$0.30	S	NS	NS	18	30	24
7	1	1	$0.10	$0.25	$0.40	$0.20	$0.40	$0.40	$0.00	NS	NS	S	18	30	0
7	2	12	$0.10	$0.20	$0.10	$0.40	$0.20	$0.00	$0.40	NS	S	S	6	6	18
7	3	26	$0.30	$0.40	$0.30	$0.00	$0.10	$0.25	$0.20	S	NS	NS	0	24	36
7	4	35	$0.15	$0.25	$0.10	$0.20	$0.40	$0.05	$0.40	S	NS	NS	30	30	12
7	5	38	$0.40	$0.25	$0.40	$0.10	$0.10	$0.20	$0.10	NS	NS	S	6	36	18
7	6	39	$0.10	$0.40	$0.10	$0.15	$0.05	$0.30	$0.25	S	S	S	30	0	12

Appendix C
Orthogonal Design Example

Fractional factorial designs, orthogonal designs in particular, become more evident when demonstrated with an example. Following Louviere et al. (2000), consider an example with three attributes, Attribute A, B, and C. Each attribute is either zero or one. To measure the impact that the three attributes have independently or in combination, an analyst could simply run the full factorial design. Per equation (21), the full factorial design has $2^3 = 8$ possible combinations. Table C1 presents the full factorial design for these three attributes, presenting all possible attribute combinations. Each unique combination is labeled. In addition, the last column in Table C1 lists the change from one combination to another, the simple effects. The use of the simple effects becomes clearer in the example provided below.

Table C1
Full Factorial Design Matrix

Attribute A	Attribute B	Attribute C	Notation	Simple Effects
0	0	0	(1)	
1	0	0	A	A-(1)
0	1	0	B	
1	1	0	AB	AB-B
0	0	1	C	
1	0	1	AC	AC-C
0	1	1	BC	
1	1	1	ABC	ABC-BC

Although there are eight possible attribute combinations, there are seven effects in this example. Specifically, each attribute has a main effect, ME(A), ME(B), and ME(C). There are three two-way interactions, INT(AB), INT(AC), and INT(BC), and one three-way interaction, INT(ABC). To arrive at a fractional factorial design, the analyst draws from this list of effects (instead of attribute combinations), thereby ensuring the representation of all effects.

Main effects are measured by subtracting the average value of the dependent variable, evaluated with the attribute of interest on the high (+) side, from the average value of the dependent variable, evaluated with the attribute of interest on the low (−) side (DeVeaux, 2001). Specifically, the main effect of A, ME(A), equals:

(C1) $$ME(A) = \frac{A-(1)+AB-B+AC-C+ABC-BC}{4}.$$

Substituting the simple effects from Table C1 into equation (C1) yields:

(C2) $$ME(A) = \frac{(A-1)(B+1)(C+1)}{4}.$$

The main effects for Attribute B and Attribute C are derived in a similar fashion:

(C3) $$ME(B) = \frac{(A+1)(B-1)(C+1)}{4},$$

and

(C4) $$ME(C) = \frac{(A+1)(B+1)(C-1)}{4}.$$

Interaction effects also are derived in a similar fashion. However, instead of examining the impact of one attribute, the interaction effect examines the combined impact of two or more attributes. Specifically, interaction effects are measured by the difference of the average value of the dependent variable with the combined attributes of interest on the high (+) side and the average value of the dependent variable with the combined attributes of interest on the low (−) side (DeVeaux, 2001).

In the example mentioned at the beginning of this appendix, the interaction effect of Attribute A and Attribute B, INT(AB), is measured as follows:

(C5) $$INT(AB) = (AB-B+ABC-BC)-(A-(1))+(AC-C).$$

Substituting the single effects from Table C1 into equation (C5) yields:

(C6) $$INT(AB) = (A-1)(B-1)(C+1).$$

The remaining two two-way interactions and the one three-way interaction are derived in a similar fashion and are shown below for completeness:

(C7) $$INT(AC) = (A-1)(B+1)(C-1),$$

(C8) $INT(BC) = (A+1)(B-1)(C-1)$,

(C9) $INT(ABC) = (A-1)(B-1)(C-1)$.

With the main and interaction effects defined, the effect matrix simply summarizes the attribute combinations from Table C1 that are required to be measured for each of the effects. A plus sign symbolizes that the level of the attribute is set at "high," whereas a negative sign represent the lower setting. For instance, if Attribute A was the price of a mobile phone and had two levels, $50 and $150, the plus sign would symbolize the $150 and the negative sign the $50. Table C2 presents the effect matrix for this example.

Table C2
Full Factorial Effect Matrix

(1)	A	B	AB	C	AC	BC	ABC	Effect
-	+	-	+	-	+	-	+	ME(A)
-	-	+	+	-	-	+	+	ME(B)
+	-	-	+	+	-	-	+	INT(AB)
-	-	-	-	+	+	+	+	ME(C)
+	-	+	-	-	+	-	+	INT(AC)
+	+	-	-	-	-	+	+	INT(BC)
-	+	+	-	+	-	-	+	INT(ABC)

To arrive at the fractional factorial design, the analyst defines the size of a matrix that reasonably can be administered in a survey. For instance, the analyst can elect to present the survey respondent with four combinations only, such as A, B, C, and ABC. Table C3 shows this.

Table C3
Fractional Factorial Matrix

A	B	C	ABC
1	-1	-1	1
-1	1	-1	1
-1	-1	1	1
-1	-1	1	1
-1	1	-1	1
1	-1	-1	1
1	1	1	1

Scaling each of these four vectors by ABC demonstrates that each main effect is a transformation of a two-way interaction. Specifically:

(C10) $A = A \times ABC = A^2BC = BC$,

(C11) $B = B \times ABC = AB^2C = AC$,

(C12) $C = C \times ABC = ABC^2 = AB$,

(C13) $ABC = ABC \times ABC = A^2B^2C^2 = 1$.

Thus, in this particular design, the main effects are "aliased" with each two-way interaction. The three-way interaction is one and thus can be ignored (Louviere et al., 2000). Importantly, the effect matrix sheds light on causation. It illustrates that if an effect of A is observed it is unclear whether this is truly an effect of A or an effect of BC. Hence, unless BC is insignificant, the causation of effect remains unclear.

Alternatively, the analyst also can select a combination of attributes from Table C1 in such a way that the orthogonal codes within each of the vectors of the design sum to zero and the inner products of each column are also zero (i.e., $A^TB = 0,\ A^TC = 0,\ B^TC = 0$). For instance, from Table C1, the following combination could be drawn:

Table C4
Fractional Factorial Matrix

Attribute A	Attribute B	Attribute C	Notation
0	0	0	(1)
0	1	1	BC
1	0	1	AC
1	1	0	AB

Orthogonal coding transforms zeros to negative ones and leaves ones unchanged. Table C5 shows that the sum of each of the three fractional factorial vectors is zero and so are the inner products of each vector combination. This design is an orthogonal design.

Table C5
Orthogonal Fractional Factorial Matrix

Attribute A	Attribute B	Attribute C	Product AB	Product AC	Product BC	Notation
-1	-1	-1	1	1	1	(1)
-1	1	1	-1	-1	1	BC
1	-1	1	-1	1	-1	AC
1	1	-1	1	-1	-1	AB
0	0	0	0	0	0	

In contrast, the design in Table C6 is not orthogonal even though the individual vectors sum to zero.

Table C6
Nonorthogonal Fractional Factorial Matrix

Attribute A	Attribute B	Attribute C	Product AB	Product AC	Product BC	Notation
-1	1	-1	-1	1	-1	B
-1	-1	1	1	-1	-1	C
1	-1	1	-1	1	-1	AC
1	1	-1	1	-1	-1	AB
0	0	0	0	0	-4	

Appendix D
Design Matrix Optimization Code (*Ngene)*

```
design
;alts = Plan1, Plan2, Plan3
;rows =42
;block=7 ;eff=(mnl,d)
;alg=swap
;cond:
if(Plan1.V_allowance=99999, Plan1.V_over=0),
if(Plan2.V_allowance=99999, Plan2.V_over=0),
if(Plan3.V_allowance=99999, Plan3.V_over=0),
if(Plan1.D_allowance=99999, Plan1.D_over=0),
if(Plan2.D_allowance=99999, Plan2.D_over=0),
if(Plan3.D_allowance=99999, Plan3.D_over=0),
if(Plan1.V_allowance<>99999, Plan1.V_over<>0),
if(Plan2.V_allowance<>99999, Plan2.V_over<>0),
if(Plan3.V_allowance<>99999, Plan3.V_over<>0),
if(Plan1.D_allowance<>99999, Plan1.D_over<>0),
if(Plan2.D_allowance<>99999, Plan2.D_over<>0),
if(Plan3.D_allowance<>99999, Plan3.D_over<>0)
;model:
U(Plan1)=b1[-0.0020992]*Phone_Price[0,50,100,200,300,400,500]+b2[-
0.0166683]*MRC[20,40,60,80,100,120,160]+b3[0.0000659]*V_allowance[50
,100,200,500,1000,2000,9999]+b4[0.0001119]*D_allowance[0,50,200,500,
1000,5000,9999]+b5[0.000034]*Download[250,500,1000,1500,2000,3000,60
00]+b6[-0.0837528]*V_over[0,0.1,0.15,0.2,0.25,0.3,0.4]+b7[-
0.3806611]*D_over[0,0.1,0.15,0.2,0.25,0.3,0.4]+b8[-
1.633345]*Text[0,0.05,0.1,0.2,0.25,0.3,0.4]+b9[1.078538]*Phone_type[
0,1]+b10[-0.0032271]*Term_length[0,6,12,18,24,30,36]/
U(Plan2)=b1*Phone_Price+b2*MRC+b3*V_allowance+b4*D_allowance+b5*Down
load+b6*V_over+b7*D_over+b8*Text+b9*Phone_type+b10*Term_length/
U(Plan3)=b1*Phone_Price+b2*MRC+b3*V_allowance+b4*D_allowance+b5*Down
load+b6*V_over+b7*D_over+b8*Text+b9*Phone_type+b10*Term_length
      $
```

Appendix E
Design Matrix MNL Choice Probabilities (*Ngene)*

Choice Situation	Plan1	Plan2	Plan3
1	0.10	0.44	0.46
2	0.50	0.45	0.05
3	0.79	0.10	0.11
4	0.13	0.75	0.12
5	0.29	0.24	0.47
6	0.55	0.29	0.16
7	0.30	0.18	0.52
8	0.07	0.60	0.33
9	0.20	0.35	0.45
10	0.40	0.40	0.19
11	0.53	0.36	0.11
12	0.11	0.35	0.54
13	0.49	0.09	0.42
14	0.30	0.54	0.16
15	0.47	0.44	0.09
16	0.67	0.24	0.09
17	0.07	0.50	0.43
18	0.16	0.12	0.72
19	0.42	0.10	0.48
20	0.17	0.42	0.40
21	0.15	0.34	0.50
22	0.30	0.23	0.47
23	0.49	0.12	0.39
24	0.32	0.43	0.25
25	0.14	0.48	0.38
26	0.42	0.04	0.54
27	0.17	0.13	0.69
28	0.40	0.52	0.08
29	0.44	0.45	0.11
30	0.13	0.41	0.46
31	0.01	0.41	0.58
32	0.55	0.03	0.41
33	0.41	0.05	0.54
34	0.49	0.40	0.11
35	0.27	0.67	0.06
36	0.32	0.44	0.24
37	0.62	0.21	0.17
38	0.09	0.37	0.54
39	0.43	0.51	0.07
40	0.36	0.08	0.56
41	0.73	0.12	0.15
42	0.09	0.55	0.36

Appendix F
Consumer Survey Mobile Research

Mobile Research

March 2010

Page 1:

You have been selected to participate in a study regarding telecommunications services. We appreciate your participation in this survey and hope that this experience will be a pleasant one. Your information will be kept strictly confidential and only reported in aggregate.

Our survey today is about the choices people make when subscribing to wireless telephone service for their personal use. Wireless service, also known as mobile service or cell phone service, is a telephone service that allows calls to be made and received at any location within the designated network you subscribe to.

To begin the survey, simply click the “Continue” button. While in the survey, click on the arrow at the bottom of the page to go to the next screen.

Page 2:

1. What is your age? (Open numeric response) **[Term if less than 18]**

Page 3:

2. Do you use a wireless/cell phone?

Yes.. ☐
No.. ☐

[Skip to page 7 if answer is “no”]

3. Have you ever been financially responsible for a wireless phone service account?

Yes.. ☐
No.. ☐

[Skip to page 7 if answer is “no”]

Page 4:

4. How many minutes are included in your monthly voice plan?

- Less than 400 minutes .... ☐
- Between 400 minutes and less than 700 minutes .... ☐
- Between 700 minutes and less than 900 minutes .... ☐
- Between 900 minutes and less than 1400 minutes .... ☐
- Between 1400 minutes and less than 2100 minutes .... ☐
- I have unlimited minutes .... ☐
- I have a prepaid plan .... ☐
- I don't know .... ☐

5. Do you subscribe to a monthly data plan, allowing you to access the Internet and send email via your cell phone?

- Yes .... ☐
- No .... ☐

Page 5:

6. Do you subscribe to a plan for small message service (SMS)?

- Yes .... ☐
- No .... ☐

7. Do you use your wireless/cell phone to access the Internet?

- Yes .... ☐
- No .... ☐

8. Do you use your wireless/cell phone to send and receive emails?

- Yes .... ☐
- No .... ☐

Page 6:

9. Approximately how much do you typically spend on wireless phone service per month?

    Less than $50.. ☐
    Between $50 and $99.. ☐
    Between $100 and $149.. ☐
    More than $150.. ☐
    I don't know .... ☐

10. Do you subscribe to a mobile phone pan that is subject to a term contract, requiring you to remain with the mobile phone company for a certain number of months?

    Yes.. ☐
    No... ☐
    I don't know .... ☐

Page 7:

Now, we would like you to imagine that you need to sign up for new wireless telephone service. When answering the next set of questions, please think about all the aspects of your life that would impact or have an effect on what choices you might make when selecting a new wireless telephone service.

In the following, we are going to show you three different wireless telephone service plans, each with different service features and prices. We will then ask you which of the three plans is (1) most attractive and (2) least attractive to you. Even if you feel that there are better plans available in the marketplace, please suppose that the listed plans are the only plans available to you. In making your selection, please assume that you will be responsible for paying the bills.

Please assume that the three plans are identical in all features that are not shown in the plans offered.

Page 8:

The following is a **glossary of terms** that will be used during the following part of the survey:

- **Voice** means common wireless phone calls, where only spoken words are exchanged.
- **Data** means an exchange, upload, or download of data, such as emails, pictures, text messaging, and Internet browsing.
- **Price of mobile phone** which is the price of the wireless mobile phone.
- **Monthly charge** which includes a certain number of voice minutes and data up/downloads per month.
- **Voice minutes allowance** which is the total number of voice minutes included in the monthly charge.
- **Data allowance** which is the total number of kilobytes download and upload included in the monthly charge.
- **Data download speed**, which is the speed in seconds by which a file (i.e., a website) can be downloaded from the Internet. The higher the number, the faster the download. As a reference point, standard dial-up service offers 56 kilobits per second (Kbps). DSL offers speeds between 3000-7,100 Kbps, while a cable Internet access is between 8,000 and 20,000 Kbps.
- **Fee for excess minutes** which is the per-minute charge for each minute in excess of the monthly voice allowance.
- **Fee for excess data usage** which is the per kilobyte charge for each kilobyte of data in excess of the monthly data allowance.
- **SMS fee** which is the charge for each text message sent and received.
- **Type of Phone** which is either a smart phone (i.e., iPhone or Blackberry) or a regular “non-smart” phone (i.e., a basic flip phone).
- **Length of contract** which is the contract length in months. Terminating the contract before its expiration will result in an early termination (ETF) fee of $150.

NOTE: A timer was added to track the amount of time spent on this page.

Page 9:

NOTE: Timers were added to track the amount of time spent on each conjoint page and tooltips were added when rolling over the '?' icons containing the definition of just that specific term.

S1G1	Plan 1	Plan 2	Plan 3
? Price of mobile phone	$ 200	$ 50	$ 400
? Monthly charge	$ 120	$ 60	$ 20
? Voice minutes allowance per month	400	3,000	2,000
? Data allowance per month (kilobytes)	5,000	200	50
? Data download speed (kilobits per second)	3,000	500	2,000
? Fee for excess minutes	$ 0.40	$ 0.10	$ 0.10
? Fee for excess data usage	$ 0.40	$ 0.25	$ 0.10
? SMS fee (per message sent and received)	$ 0.30	$ 0.25	Free
? Type of phone	Smart	Smart	Non-smart
? Length of contract (months)	30	18	12

Assuming that these three plans are the only way you can obtain wireless telephone service, which plan are you most likely to purchase?	○ Plan 1	○ Plan 2	○ Plan 3
Assuming that these three plans are the only way you can obtain wireless telephone service, which plan are you least likely to purchase?	○ Plan 1	○ Plan 2	○ Plan 3

S1G2	Plan 1	Plan 2	Plan 3
?Price of mobile phone	$ 200	$ 50	$ 400
?Monthly charge	$ 120	$ 60	$ 20
?Voice minutes allowance per month	400	3,000	2,000
?Data allowance per month (kilobytes)	5,000	200	50
?Data download speed (kilobits per second)	3,000	500	2,000
?Fee for excess minutes	$ 0.40	$ 0.10	$ 0.10
?Fee for excess data usage	$ 0.40	$ 0.25	$ 0.10
? SMS fee (per message sent and received)	$ 0.30	$ 0.25	Free
?Type of phone	Smart	Smart	Non-smart
?Length of contract (months)	30	18	12

Assuming that these three plans are the only way you can obtain wireless telephone service, which plan are you <u>most likely</u> to purchase?	○ Plan 1	○ Plan 2	○ Plan 3
Assuming that these three plans are the only way you can obtain wireless telephone service, which plan are you <u>least likely</u> to purchase?	○ Plan 1	○ Plan 2	○ Plan 3

S1G3	Plan 1	Plan 2	Plan 3
?Price of mobile phone	$ 200	$ 50	$ 400
?Monthly charge	$ 120	$ 60	$ 20
?Voice minutes allowance per month	400	3,000	2,000
?Data allowance per month (kilobytes)	5,000	200	50
?Data download speed (kilobits per second)	3,000	500	2,000
?Fee for excess minutes	$ 0.40	$ 0.10	$ 0.10
?Fee for excess data usage	$ 0.40	$ 0.25	$ 0.10
? SMS fee (per message sent and received)	$ 0.30	$ 0.25	Free
?Type of phone	Smart	Smart	Non-smart
?Length of contract (months)	30	18	12

Assuming that these three plans are the only way you can obtain wireless telephone service, which plan are you <u>most likely</u> to purchase?	○ Plan 1	○ Plan 2	○ Plan 3
Assuming that these three plans are the only way you can obtain wireless telephone service, which plan are you <u>least likely</u> to purchase?	○ Plan 1	○ Plan 2	○ Plan 3

S1G4	Plan 1	Plan 2	Plan 3
Price of mobile phone	$ 200	$ 50	$ 400
Monthly charge	$ 120	$ 60	$ 20
Voice minutes allowance per month	400	3,000	2,000
Data allowance per month (kilobytes)	5,000	200	50
Data download speed (kilobits per second)	3,000	500	2,000
Fee for excess minutes	$ 0.40	$ 0.10	$ 0.10
Fee for excess data usage	$ 0.40	$ 0.25	$ 0.10
SMS fee (per message sent and received)	$ 0.30	$ 0.25	Free
Type of phone	Smart	Smart	Non-smart
Length of contract (months)	30	18	12

Assuming that these three plans are the only way you can obtain wireless telephone service, which plan are you <u>most likely</u> to purchase?	○ Plan 1	○ Plan 2	○ Plan 3
Assuming that these three plans are the only way you can obtain wireless telephone service, which plan are you <u>least likely</u> to purchase?	○ Plan 1	○ Plan 2	○ Plan 3

S1G5	Plan 1	Plan 2	Plan 3
Price of mobile phone	$ 200	$ 50	$ 400
Monthly charge	$ 120	$ 60	$ 20
Voice minutes allowance per month	400	3,000	2,000
Data allowance per month (kilobytes)	5,000	200	50
Data download speed (kilobits per second)	3,000	500	2,000
Fee for excess minutes	$ 0.40	$ 0.10	$ 0.10
Fee for excess data usage	$ 0.40	$ 0.25	$ 0.10
SMS fee (per message sent and received)	$ 0.30	$ 0.25	Free
Type of phone	Smart	Smart	Non-smart
Length of contract (months)	30	18	12

Assuming that these three plans are the only way you can obtain wireless telephone service, which plan are you <u>most likely</u> to purchase?	○ Plan 1	○ Plan 2	○ Plan 3
Assuming that these three plans are the only way you can obtain wireless telephone service, which plan are you <u>least likely</u> to purchase?	○ Plan 1	○ Plan 2	○ Plan 3

S1G6	Plan 1	Plan 2	Plan 3
Price of mobile phone	$ 200	$ 50	$ 400
Monthly charge	$ 120	$ 60	$ 20
Voice minutes allowance per month	400	3,000	2,000
Data allowance per month (kilobytes)	5,000	200	50
Data download speed (kilobits per second)	3,000	500	2,000
Fee for excess minutes	$ 0.40	$ 0.10	$ 0.10
Fee for excess data usage	$ 0.40	$ 0.25	$ 0.10
SMS fee (per message sent and received)	$ 0.30	$ 0.25	Free
Type of phone	Smart	Smart	Non-smart
Length of contract (months)	30	18	12

Assuming that these three plans are the only way you can obtain wireless telephone service, which plan are you <u>most likely</u> to purchase?	○ Plan 1	○ Plan 2	○ Plan 3
Assuming that these three plans are the only way you can obtain wireless telephone service, which plan are you <u>least likely</u> to purchase?	○ Plan 1	○ Plan 2	○ Plan 3

Page 10:

Now we would like to ask you a question NOT about wireless phone service but landline (wireline) service.

11. Do you currently have a landline phone number in your main residence?

- Yes.. ☐
- No.. ☐

Page 11:

These last few questions are for classification purposes only.

12. What is the state of your main residence? (Select from pull down menu)

[Pull down menu here]

13. Is your main residence located in a:

- Metropolitan city .... ☐
- Suburban community of a larger city .... ☐
- Small town or rural city... ☐
- Farming area... ☐

Page 12:

14. Which of the following categories best describes the highest level of education you have completed? (Select one)

- Less than High school.. ☐
- High school graduate .... ☐
- Vocational or technical school but no college .... ☐
- College graduate... ☐
- Post-graduate degree... ☐

Page 13:

15. Are you currently employed?

- Yes, full-time .... ☐
- Yes, part-time... ☐
- No... ☐

16. Are you:

- Male... ☐
- Female .... ☐

Page 14:

17. Are you:

- Single .... ☐
- Married .... ☐
- Partnered .... ☐
- Other .... ☐
- Partnered .... ☐
- Other .... ☐

18. How many children under the age of 18 do you have?

- Zero........ ☐
- One .... ☐
- Two........ ☐
- Three or more .... ☐

Page 15:

19. What is your household's total annual income from all sources before taxes? (Select one)

- Less than \$30,000........ ☐
- From 30 to just under \$50,000 .... ☐
- From 50 to just under \$75,000 .... ☐
- From 75 to just under \$150,000, or .... ☐
- \$150,000 or more........ ☐
- Decline to answer .... ☐

Thank you for your participation!

Appendix G
Survey Responses

Survey	Choice situation	Ranking	No. of selections Plan 1	No. of selections Plan 2	No. of selections Plan 3	No. of rejections Plan 1	No. of rejections Plan 2	No. of rejections Plan 3
1	1	1	17	28	27	55	44	45
1	1	2	30	19	23	25	25	22
1	2	1	31	37	4	41	35	68
1	2	2	22	28	22	19	7	46
1	3	1	10	57	5	62	15	67
1	3	2	41	14	17	21	1	50
1	4	1	10	39	23	62	33	49
1	4	2	19	20	33	43	13	16
1	5	1	16	15	41	56	57	31
1	5	2	26	30	16	30	27	15
1	6	1	49	4	19	23	68	53
1	6	2	11	25	36	12	43	17
2	1	1	43	19	9	28	52	62
2	1	2	18	12	41	10	40	21
2	2	1	19	19	33	52	52	38
2	2	2	24	32	15	28	20	23
2	3	1	21	26	24	50	45	47
2	3	2	25	25	21	25	20	26
2	4	1	7	3	61	64	68	10
2	4	2	31	33	7	33	35	3
2	5	1	15	23	33	56	48	38
2	5	2	33	11	27	23	37	11
2	6	1	39	30	2	32	41	69
2	6	2	18	30	23	14	11	46
3	1	1	57	11	0	11	57	68
3	1	2	9	44	15	2	13	53
3	2	1	29	22	17	39	46	51
3	2	2	23	9	36	16	37	15
3	3	1	33	34	1	35	34	67
3	3	2	27	24	17	8	10	50
3	4	1	19	5	44	49	63	24
3	4	2	30	19	19	19	44	5
3	5	1	6	36	26	62	32	42
3	5	2	35	15	18	27	17	24
3	6	1	22	33	13	46	35	55
3	6	2	30	12	26	16	23	29
4	1	1	61	2	7	9	68	63
4	1	2	5	20	45	4	48	18
4	2	1	15	34	21	55	36	49
4	2	2	21	13	36	34	23	13
4	3	1	23	19	28	47	51	42
4	3	2	11	34	25	36	17	17
4	4	1	0	46	24	70	24	46
4	4	2	17	15	38	53	9	8
4	5	1	26	40	4	44	30	66

Survey	Choice situation	Ranking	No. of selections			No. of rejections		
			Plan 1	Plan 2	Plan 3	Plan 1	Plan 2	Plan 3
4	5	2	32	17	21	12	13	45
4	6	1	62	8	0	8	62	70
4	6	2	6	52	12	2	10	58
5	1	1	9	28	33	61	42	37
5	1	2	24	27	19	37	15	18
5	2	1	20	22	28	50	48	42
5	2	2	15	20	35	35	28	7
5	3	1	39	14	17	31	56	53
5	3	2	18	23	29	13	33	24
5	4	1	18	0	52	52	70	18
5	4	2	43	17	10	9	53	8
5	5	1	24	29	17	46	41	53
5	5	2	19	19	32	27	22	21
5	6	1	18	14	38	52	56	32
5	6	2	21	29	20	31	27	12
6	1	1	8	2	59	61	67	10
6	1	2	16	44	9	45	23	1
6	2	1	35	8	26	34	61	43
6	2	2	20	17	32	14	44	11
6	3	1	18	17	34	51	52	35
6	3	2	28	25	16	23	27	19
6	4	1	18	43	8	51	26	61
6	4	2	30	22	17	21	4	44
6	5	1	9	38	22	60	31	47
6	5	2	24	20	25	36	11	22
6	6	1	29	4	36	40	65	33
6	6	2	14	28	27	26	37	6
7	1	1	10	25	34	59	44	35
7	1	2	26	23	20	33	21	15
7	2	1	19	44	6	50	25	63
7	2	2	32	16	21	18	9	42
7	3	1	28	13	28	41	56	41
7	3	2	25	24	20	16	32	21
7	4	1	29	31	9	40	38	60
7	4	2	21	14	34	19	24	26
7	5	1	6	49	14	63	20	55
7	5	2	28	12	29	35	8	26
7	6	1	21	44	4	48	25	65
7	6	2	31	13	25	17	12	40

Appendix H
Model 5-1 Variance-Covariance Matrix

		phone_n m	mrc_n m	v_allow m	d_allow m	download m	text_n m	phone type m	term_n m	dummy high m	phone_n sd	mrc_n sd	v_allow sd	d_allow sd	download sd	text_n sd	phone type sd	term_n sd	dummy high sd	age fx	gender fx	d_over_n fx
phone_n	m	0.0118	0.0032	0.0004	0.0005	0.0003	0.0004	0.0019	-0.0065	0.0002	0.0009	0.0001	-0.0005	-0.0003	0.0002	-0.0002	-0.0014	0.0021	-0.0003	-0.0007	0.0002	0.0004
mrc_n	m	0.0032	1.6118	0.0013	0	0.1118	0.0041	-0.0401	-0.0041	0.0038	-0.0009	0.0135	0.0079	-0.0022	-0.0678	-0.0058	0.0444	0.0064	-0.0017	0.0058	-0.0121	-0.0113
v_allow	m	0.0004	0.0013	0.0384	0.0008	0.0001	0.0028	-0.031	-0.0221	0.0001	-0.0001	-0.0008	-0.0018	-0.0002	-0.0004	-0.0029	0.0205	0.008	0	0.0012	-0.0016	0.002
d_allow	m	0.0005	0	0.0008	0.0045	0.0011	-0.0001	0	-0.0031	-0.0006	0.0013	0.0005	0.0009	-0.0025	-0.0002	0.0005	0.0013	0.0013	0.001	-0.0002	0.0002	-0.0001
download	m	0.0003	0.1118	0.0001	0.0011	0.0159	-0.0033	0.0006	-0.0078	0.0035	0.0013	0.0028	0.0038	-0.0004	-0.0092	0.0016	0.0032	0.0028	-0.001	0.0002	-0.0015	-0.0019
text_n	m	0.0004	0.0041	0.0028	-0.0001	-0.0033	0.272	-0.0411	0.1386	-0.0009	-0.006	0.0038	-0.0736	0.0008	0.0019	-0.1423	0.0232	-0.036	0.0023	0.0049	-0.0034	0.0089
phone type	m	0.0019	-0.0401	-0.031	0	0.0006	-0.0411	0.3111	-0.0112	0.0048	0.0206	-0.0147	0.0085	0.0011	0.0037	0.0295	-0.2305	-0.0173	-0.0026	-0.0208	0.0262	0.0059
term_n	m	-0.0065	-0.0041	-0.0221	-0.0031	-0.0078	0.1386	-0.0112	2.041	0.0287	-0.0375	0.0165	-0.0434	0.0018	-0.0002	-0.0624	-0.009	-0.5845	-0.0094	0.0179	-0.0017	-0.0038
dummy high	m	0.0002	0.0038	0.0001	-0.0006	0.0035	-0.0009	0.0048	0.0287	0.2599	0.0017	0.0073	0.0144	0.0016	-0.0014	0.0002	0.0007	-0.007	-0.1324	0.0001	-0.0072	-0.0033
phone_n	sd	0.0009	-0.0009	-0.0001	0.0013	0.0013	-0.006	0.0206	-0.0375	0.0017	0.0928	0.0046	0.0049	0.0002	0.0008	0.0006	-0.0163	0.0086	-0.0002	-0.0608	-0.0014	0.004
mrc_n	sd	0.0001	0.0135	-0.0008	0.0005	0.0028	0.0038	-0.0147	0.0165	0.0073	0.0046	0.0875	0.0033	0.0003	-0.0019	-0.0063	0.0246	-0.0011	-0.0039	-0.0027	-0.0482	-0.0009
v_allow	sd	-0.0005	0.0079	-0.0018	0.0009	0.0038	-0.0736	0.0085	-0.0434	0.0144	0.0049	0.0033	0.0993	-0.0005	-0.0024	0.0359	0.0009	0.0124	-0.0052	-0.0013	-0.0007	-0.0614
d_allow	sd	-0.0003	-0.0022	-0.0002	-0.0025	-0.0004	0.0008	0.0011	0.0018	0.0016	0.0002	0.0003	-0.0005	0.0051	0.0008	-0.0002	-0.0014	0	-0.0009	-0.0002	0.0001	0.0006
download	sd	0.0002	-0.0678	-0.0004	-0.0002	-0.0092	0.0019	0.0037	-0.0002	-0.0014	0.0008	-0.0019	-0.0024	0.0008	0.0094	-0.0003	-0.0051	-0.0004	0.001	-0.0011	0.0021	0.0023
text_n	sd	-0.0002	-0.0058	-0.0029	0.0005	0.0016	-0.1423	0.0295	-0.0624	0.0002	0.0006	-0.0063	0.0359	-0.0002	-0.0003	0.0926	-0.0198	0.0154	-0.0002	0.0004	0.0075	-0.0068
phone type	sd	-0.0014	0.0444	0.0205	0.0013	0.0032	0.0232	-0.2305	-0.009	0.0007	-0.0163	0.0246	0.0009	-0.0014	-0.0051	-0.0198	0.2018	0.0229	0.0002	0.0185	-0.0294	-0.0084
term_n	sd	0.0021	0.0064	0.008	0.0013	0.0028	-0.036	-0.0173	-0.5845	-0.007	0.0086	-0.0011	0.0124	0	-0.0004	0.0154	0.0229	0.1808	0.0023	-0.003	-0.0029	0
dummy high	sd	-0.0003	-0.0017	0	0.001	-0.001	0.0023	-0.0026	-0.0094	-0.1324	-0.0002	-0.0039	-0.0052	-0.0009	0.001	-0.0002	0.0002	0.0023	0.0799	-0.0003	0.0058	0
age	fx	-0.0007	0.0058	0.0012	-0.0002	0.0002	0.0049	-0.0208	0.0179	0.0001	-0.0608	-0.0027	-0.0013	-0.0002	-0.0011	0.0004	0.0185	-0.003	-0.0003	0.0521	0.0008	-0.0044
gender	fx	0.0002	-0.0121	-0.0016	0.0002	-0.0015	-0.0034	0.0262	-0.0017	-0.0072	-0.0014	-0.0482	-0.0007	0.0001	0.0021	0.0075	-0.0294	-0.0029	0.0058	0.0008	0.0354	-0.0009
d_over_n	fx	0.0004	-0.0113	0.002	-0.0001	-0.0019	0.0089	0.0059	-0.0038	-0.0033	0.004	-0.0009	-0.0614	0.0006	0.0023	-0.0068	-0.0084	0	0	-0.0044	-0.0009	0.0698