# The Value of Online Privacy: Evidence from Smartphone Applications[1]

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**Abstract**

We estimate the value of online privacy with a differentiated products model of the demand for Smartphone apps. We study the apps market because it is typically necessary for the consumer to relinquish some personal information through "privacy permissions" to obtain the app and its benefits. Results show that the representative consumer is willing to make a one-time payment for each app of $2.28 to conceal their browser history, $4.05 to conceal their list of contacts, $1.19 to conceal their location, $1.75 to conceal their phone's identification number, and $3.58 to conceal the contents of their text messages. The consumer is also willing to pay $2.12 to eliminate advertising. Valuations for concealing contact lists and text messages for "more experienced" consumers are also larger than those for "less experienced" consumers. Given the typical app in the marketplace has advertising, requires the consumer to reveal their location and their phone's identification number, the benefit from consuming this app must be at least $5.06.

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## 1 Introduction

The concealment of personal information or "privacy" has been the subject of much recent debate. Most discussion has centered on the low-cost collection of large amounts of personally identifiable data in online markets, and the sharing of these data with third-parties such as advertisers, application developers, and government agencies. The policy responses to increased privacy concerns include: industry self-regulation, full disclosure of how personal information is used (i.e., similar to food labels), government laws to restrict the use of personal information, and the assignment of property rights so that market forces will allocate personal information efficiently. Despite several interesting theoretical and empirical contributions from economists, this discussion has largely evolved without relevant measures of consumer preferences for privacy (Hermalin and Katz, 2006; Goldfarb and Tucker, 2010). This is surprising given that estimates of consumer valuations would help policy makers better understand the trade-offs associated with the protection of personal information when evaluating these proposed initiatives.

This paper estimates the value of online privacy with a differentiated products model of the demand for Smartphone applications ("apps"). We study the apps market because it is typically necessary for the consumer to relinquish some personal information through "privacy permissions" to obtain the app and its benefits.[2] For example, when a consumer provides a weather app with information on the location of their phone, they obtain the convenience benefit of receiving weather conditions where they are currently located. Furthermore, there is potential for variation in the required permissions across apps, allowing more accurate estimation of the individual aspects of privacy such as location, online browsing history, etc.

[2] We borrow the term "privacy permission" from Google Play Store terminology. For the purposes of this study, we extend this definition to the Apple, Blackberry and Windows platforms.

This is in contrast to privacy software for computers. A second aspect of the app market is that it is extremely fast growing, coming from literally nowhere to a projected five billion downloads in the next year (Gartner, 2012). This results in a significant and growing percentage of the population sending and receiving information via Smartphones, potentially heightening online privacy concerns. Third, apps are free or relatively inexpensive, making field experiments feasible.

We first present a theoretical framework that considers a household's labor-leisure choice along with choices about their consumption of apps and their privacy. Households use apps to produce savings in time and trade off these time-savings against their privacy forgone from relinquishing permissions to the app developer. Model results show that, all other things held constant, an experienced consumer will produce time savings more efficiently than an inexperienced consumer, which increases their marginal benefit from apps. This relatively high benefit suggests that an experienced consumer may be more willing to give up personal information that is highly valuable to them. The empirical implications are that experienced consumers should download more apps than inexperienced consumers and they should have larger valuations for concealing personal information.

We examine these predictions with data obtained from choice experiments. The experiments were administered in an in-person survey to consumers at their homes or public places during summer, 2013. A total of 1,726 respondents completed surveys in Atlanta, Chicago, Denver, Philadelphia, Portland, Salt Lake City and San Diego. During the experiments, consumers were presented with a choice set containing one app currently traded in the marketplace and five "new" apps that were purported to have identical functionality to the market app, but varied in their levels of price, advertising and five privacy permissions.

Consumers were informed that the new apps would soon be available in the marketplace and that they must commit to buying one app from the six alternatives or opt out and not make a purchase. The five permissions describe the personal information a consumer must relinquish to the app developer when they download and use the app. They are: the location of the consumer while carrying their phone (*LOCATION*), the websites the consumer has browsed on their phone (*BROWSER HISTORY*), the contacts in the address book on the consumer's phone (*CONTACTS*), the unique identification number of the consumer's phone (*PHONE ID*), and the text messages the consumer has written and received on their phone (*READ TEXTS*).

Our empirical results show that price, advertising and the five privacy permissions are all important characteristics a consumer considers when purchasing a smartphone app. The representative consumer is willing to make a one-time payment of $2.28 to conceal their online browser history, $4.05 to conceal their list of contacts, $1.19 to conceal their location, $1.75 to conceal their phone's identification number, and $3.58 to conceal the contents of their text messages. The representative consumer is also willing to pay $2.12 for not having advertising interfere or distract from their use of the app. Given the typical app in the marketplace has advertising, requires location and at least one other type of personal information, the benefit from consuming this app must be at least $5.06. Our results also show that the willingness-to-pay (WTP) for concealing contact lists and text messages for "more experienced" consumers are larger than those for "less experienced" consumers. This finding is robust to a specification that holds preferences constant across respondents and suggests that we are indeed largely measuring an experience effect and not simply a stronger preference for privacy.

Other recent studies have used experiments to quantify the value of online privacy and security.[3] For example, Hann et. al. (2007) find that protection against errors, improper access, and secondary use of personal information on financial portals is worth about $30 to $45 to consumers. Egelman et. al. (2012) report that about a quarter of their 368 sample respondents were willing to pay a $1.50 premium for the smartphone app that did not require the location and record audio permissions. Grossklags and Acquisti (2007) find that students value privacy differently when asked to pay to protect rather than accept payment for personal information on quiz performance, and that the dollar value on this type of privacy is low in both cases. Our paper contributes to this literature by using a large national sample, and in-person surveys of all types of smartphone users, e.g., Android, iPhone, Windows, etc., to offer new evidence on online privacy from the apps market. Furthermore, we examine valuations for concealing several different types of personal information, and show that these valuations vary systematically with online experience.

Section 2 presents a theoretical framework of the demand for apps or, alternatively, the supply of personal information. The choice experiments and administration of the survey are described in Section 3. Section 4 outlines the empirical model and econometric method used to estimate consumer preferences for online privacy. Empirical results are presented in Section 5, and Section 6 provides concluding remarks.

## 2 Theoretical Background

Privacy is often defined in three contexts; the concealment of information, the right to peace and quiet, and the right for freedom and autonomy (Posner, 1980). We are interested in the

[3] This paper focuses on *privacy* or how much a consumer is willing to pay to control their personal information. We do not directly measure *security* – the malicious use of one's personal information by unauthorized third-parties (e.g., identify theft) – but recognize this is also a major concern of many consumers.

first definition and, more specifically, we want to estimate the value consumer's place on giving up their personal information online net of the benefits received. We are also interested in how consumer valuations vary with their experience. Below, we outline a theory of the optimal choice for smartphone apps. The theory explains the tradeoff between savings in time and privacy foregone and suggests that proxies for experience should be included in empirical specifications of app demand to correctly model this tradeoff.

The labor-leisure choice model is extended to include the costs and benefits from consuming apps. We assume that the representative consumer has a stock of privacy ($P$), and this stock has a value in a manner similar to the existence value of Antarctica or Tasmanian rain forests in the environmental economics literature. Under this assumption, consumers do not require that utility (or disutility) be derived from the direct or third-party use of their privacy. Rather, utility is derived from simply knowing that their stock of privacy exists and that the individual is able to conceal their personal information in order to withdraw from the public spotlight. Even if there is no direct cost from others knowing one's location or the contents of one's address book, individuals value the confidentiality of this information and will not relinquish it without compensation.

Because they typically relinquish personal information to the app developer when purchasing an app, one of the predominant indirect costs of an app to consumers is the diminishment of their privacy stock.[4] Moreover, because multiple sources of information will magnify the uniqueness of individuals, the marginal diminishment of privacy stock likely increases, in absolute terms, with the number of permissions relinquished (Montijoye et. al., 2013). Accordingly, the consumer's stock of privacy is represented by $P(a)$, where $a$ is the

[4] The other is advertising, which we abstract away from in our theory, but include in our empirical model.

number of apps consumed, and we assume $P_a$ and $P_{aa}$ are negative (subscripts indicate partial derivatives). For ease of exposition, we assume a monotonic relationship between the number of apps consumed and the amount of personal information relinquished.[5] This permits the consumer's optimal choice of apps, $a^*$, to simultaneously represent both the demand for apps and the supply of personal information.

Smartphone apps benefit consumers by producing reductions in "essential time" defined as the non-remunerated time lost when doing fundamental living activities such as banking, driving, playing games, shopping, travelling, watching movies, etc. (Savage and Waldman, 2009). For example, a weather app produces a time-saving benefit by providing detailed information on conditions anywhere, at any time, without the need to consult traditional news media or a telephone hotline. Essential time is represented by the production function $\bar{T}(a, e)$, where $e$ is the experience of the individual. The essential time function is convex in $a$ reflecting diminishing marginal returns from additional consumption of apps. However, because experience also measures one's technical ability, the parameter $e$ augments consumer production of essential time so that increasing $e$ will raise the marginal productivity of $a$. As such, $\bar{T}_a$, $\bar{T}_e$, $\bar{T}_{ae}$ are negative and $\bar{T}_{aa}$ is positive.

The consumer is assumed to maximize a utility function of consumption ($c$), leisure ($L$) and privacy, subject to monetary and time constraints:

$$\begin{aligned} &\max_{h,\,a}\ U(c, L, P(a)) \\ s.t.\ & c = y + wh - pa \qquad\qquad (1) \\ & L = T - h - \bar{T}(a, e) \end{aligned}$$

[5] The model disregards apps that ask for multiple permissions. While more realistic, explicit consideration of the benefits and costs from these apps unnecessarily complicates the results without changing key economic insights.

where $U$ is utility, $y$ is non-wage income, $w$ is the wage rate, $p$ is the per-unit price of an app and $T$ is total time available. Utility is concave in $c$, $L$ and $P$ so that $U_c$, $U_L$, and $U_P$ are positive and $U_{cc}$, $U_{LL}$, and $U_{PP}$ are negative. First-order conditions with respect to the choice variables $h$ and $a$ are:

$$\begin{aligned} h &: 0 = U_c w - U_L \\ a &: 0 = -U_c p - U_L \bar{T}_a - U_P P_a \end{aligned} \qquad (2)$$

The first condition in equation 2 equates the wage with the marginal rate of substitution of leisure for consumption. Substituting the first condition, $U_L/U_c = w$, into the second condition gives:

$$-w\bar{T}_a = p + (-(U_P / U_c) P_a) \qquad (3)$$

where $U_P/U_c$ is the marginal rate of substitution of privacy for consumption. Equation 3 has a familiar interpretation; the consumer maximizes utility by choosing the number of apps such that the marginal benefit equals the marginal cost. In this case, the marginal benefit is the dollar value of the time-savings produced by the app, $-w\bar{T}_a$. The marginal cost is the price of the app, $p$, plus the dollar value of the privacy forgone from relinquishing permissions to the app developer, $-(U_P / U_c) P_a$.

Equation 3 provides useful information about the first-order effects of experience on the demand for apps or, alternatively, the supply of personal information $\frac{\partial a^*}{\partial e}$. Because experience also captures one's technical ability, all other things held constant, an experienced consumer will produce time savings more efficiently through $\bar{T}_{ae} < 0$ than an inexperienced consumer, which increases their marginal benefit from apps. As a result, the consumer can afford to give up more personal information at the margin, and as such, part of the total effect of an increase in experience will always be an increase in the demand for apps or the supply of personal information so that $\frac{\partial a^*}{\partial e} > 0$.[6] Moreover, because their marginal disutility of privacy forgone decreases with the number of apps consumed, the experienced consumer must give up personal information that is more valuable to them. The empirical implications are that experienced consumers should download more apps than inexperienced consumers and they should also have larger valuations for concealing personal information.[7] We test these implications below by estimating consumer demand for smartphone apps.

# 3. Data

## 3.1 Experimental Design

There are two key problems when estimating the demand for apps with market data alone. First, market data are unlikely to exhibit sufficient variation for the precise estimation of demand parameters. For example, the levels for the price and advertising characteristics are often highly, negatively correlated, while personal information on the location of the consumer while carrying their phone and their phone's unique identification number are positively correlated. Second, because consumers often make no payment for consumption, market data contain many zero cost apps, which makes identification of the marginal disutility of price problematic.

[6] This relatively simple analysis does not consider the second-order effects contained in formal comparative static results. When second-order effects run opposite to the effect described above, and have relatively large magnitudes, it is possible that $\frac{\partial a^*}{\partial e} \leq 0$.

[7] It is possible that privacy could be convex for some consumers so that $P_{aa}$ is positive. The empirical implications would be that experienced consumers should still have larger valuations for concealing personal information than inexperienced consumers, but will download fewer apps. Ultimately, the effect of experience on the demand for apps and the supply of personal information is an empirical question and the subject of the remainder of this paper.

We overcome these problems by using an indirect valuation method similar to that used in the environmental economics and transportation choice literature that employs market and experimental data. We use this method to measure consumers' propensity to supply personal information online by the dollar value they place on this information when it is relinquished to the app developer in exchange for the app. The willingness-to-pay for five specific types of personal information, *LOCATION*, *BROWSER HISTORY*, *CONTACTS*, *PHONE ID*, and *READ TEXTS*, and *ADVERTISING*, is estimated with data obtained from an in-person survey employing repeated discrete-choice experiments. Table 1 displays the descriptions of the privacy permissions and other characteristics presented to respondents during the survey.

The survey begins with a cognitive build up section where the interviewer asks the respondent about the type of phone they own, how frequently they use it, their familiarity and use of apps, and their knowledge of the personal information that must be relinquished to download certain apps. Cognitive build up is an important precursor to the choice experiment section. Here, respondents are carefully informed about the functionality of game, shopping, social, travel, TV/movie, and utility apps, their costs, extent of advertising, and the types of personal information requested by app developers. Respondents also indicate the types of activities they like to do with their smartphones. This information permits the interviewer to dynamically select apps in categories of potential interest to the respondent for the choice experiment that follows. The categories and description of the apps in these categories are presented in Table 2. The cognitive buildup section is followed by a series of choice questions where respondents compare similar apps and indicate their preferences.

The interviewer first opens an app currently available on their own smartphone (the "market app") and asks the respondent if they have this app. If the answer is "no", the interviewer continues.  If the answer is "yes", the interviewer chooses another app category.[8] The market app is briefly demonstrated and the interviewer discusses its price, whether or not it has advertising, and the personal information that must be relinquished to the app developer if it is used.  The respondent is then presented with a "show card" that displays the market app and an alternative app (the "new app") that differs in price, level of advertising, and required information.  See Figure 1 for an example for the social app category.  The interviewer informs the respondents that the new app will soon be available in the marketplace, and will have exactly the same functionality and potential benefits as the market app but will do so at a different price and with a different combination of advertising and privacy permissions.  After comparing the benefits and costs of the market app and the new app, the respondent indicates which of the two apps she or he prefers.

Next, the respondent is informed that the developer of the new app is considering several alternative versions, labeled A and B in Figure 2.  It is explained that these versions have the same functionality as the market app and the new app, but again differ by price, advertising and the required personal information.  The two versions are displayed on a card and the respondent indicates her or his preference.  This is repeated once more with two additional versions, labeled C and D in Figure 3.  So at this point in the interview, the respondent has made three, binary choices.

The respondent is now very familiar with the app, its characteristics, and the cognitive task of comparing characteristics and indicating preferences.  He or she is next presented with a show card that lists the market app and all five versions of the new app, in the same, easy to compare format where the rows in Figure 4 are the app characteristics and the columns are the

[8] Because they do not have a smartphone and do not use apps, this question is skipped for 17 percent of respondents in our sample who are not currently smartphone users.

different app versions. Again, the respondent is asked to indicate which of the (now six) alternatives she or he prefers. Say, for example, that the respondent answers that he or she likes "new app D" best. The interviewer then informs the respondent that this app will be available in the market " . . . in about a month," and asks the respondent if she or he would actually purchase, download, and use this app. The respondent answers yes or no and the choice occasion ends.

This series of choice questions is repeated, but with a different app from a different category, and with different levels of the characteristics of the app alternatives.[9] To summarize, each respondent answers three, binary choice questions and one multiple choice question, for each of two apps. We analyze the multiple choice data below.

The experimental design has several important advantages. We design a choice set that manipulates the levels of the app characteristics to obtain the optimal variation in the data needed to estimate the demand parameters precisely. The choice alternatives are believable to consumers because they could conceivably be provided by app developers in the marketplace. This is in contrast to different privacy software for computers, where all brands typically provide protection against identity theft and revelation of browser history and, as such, it is difficult to construct believable alternatives. Moreover, because cookie blockers conceal the websites a person has visited on a computer, computers are becoming increasingly less attractive to app developers and advertisers for collecting personal information. Because our design exogenously determines the levels of the characteristics of each app alternative, and randomly assigns the levels across respondents, we limit measurement and collinearity

[9] 1,444 of 1,713 sample respondents completed two choice occasions. In some cases, where the interviewer deemed it was necessary, the survey was politely cut short after occasion one.

problems.[10] By asking respondents to complete two choice occasions, we increase parameter estimation precision, and reduce sampling costs by obtaining more information on preferences for each respondent. Since the experiments are implemented by in-person survey, the interviewer can explain and demonstrate the functionality of the apps, their privacy permissions and type of advertising, and directly answer respondent's questions. This results in less noise in respondent's choices, relative to mail and online survey modes, and improves the efficiency of our estimator.[11]

A potential disadvantage of the experimental design is hypothetical bias. This arises when the behavior of the respondent is different when making choices in an experimental versus a real market. For example, if the respondent does not fully consider her budget constraint when making choices, WTP may be overestimated, because the cost parameter in the denominator of the WTP calculation (see section 4) will be biased toward zero. We minimize this source of bias with a sequence of "cheap talk" protocols intended to assure respondents that the apps are real, are traded in markets, and that they will be making (or, not making) an actual purchase (List, 2001; Aadland and Caplan, 2006). For example, the interviewer demonstrates an actual app at the beginning of each experiment, informs the respondent that they will have to purchase the market app after the experiment is over, or purchase the new app when it is available in a month, and seeks a commitment from the respondent to follow through on their purchase. The focus groups and random exit interviews in the field indicate that most survey participants were committed to purchasing the app they chose in the experiment.

[10] Moreover, by holding all other dimensions of the app alternatives constant, the choice experiment controls for potential correlation between price and quality that is not observed by the researcher.

[11] Feedback from interviewers indicated that respondents were attentive, interested, and engaged in the choice experiment, which is often not the case in a typical mail or online survey.

Data from the various marketplaces for apps were used to choose the six app categories and the market apps used in our experiments. Apps were selected that are relatively easy to explain and understand, can be easily opened and demonstrated at the front door of a house or at a public place, are potentially interesting to a wide audience, and are available on all major platforms, e.g. Google Play, iTunes, Windows Marketplace, etc. We used information from app developer's promotional materials, industry journals, two focus groups and a pilot study to develop, test and refine our descriptions of the app characteristics.[12] Measures developed by Huber and Zwerina (1996) were used to generate an efficient, linear design for the levels of the app characteristics.[13] We created the universe of all reasonable characteristic combinations (ensuring adequate variability on all characteristics) and from this chose 24 app alternatives that were grouped into four choice sets of six alternatives. The alternatives in each choice set are described by *ADVERTISING* and *COST*, and *three* of the five privacy permissions, *LOCATION*, *BROWSER HISTORY*, *CONTACTS*, *PHONE ID* or *READ TEXTS*.[14] The five permissions were distributed across all choice sets so that they were approximately equally represented in the total sample of respondents. Each of the four choice sets were assigned to interviewers so that choice occasions one and two contained a different set of permissions and different levels for all characteristics. This ensured optimal variation in the data across all sample cities.

### 3.2 Survey Administration and Sample Statistics

[12] The focus groups were conducted in Boulder, CO on June 13 at the Department of Economics and on June 27, 2013 at RRC Associates. They involved 13 subjects aged 21 to 65 years. Seven were male, eleven owned a smartphone, and two owned a basic cell phone. The pilot test collected data from 44 subjects at their homes and public places in Boulder from July 2 to July 6, 2013.
[13] See Kuhfeld, 2010.
[14] We want to estimate the WTP for five privacy permissions but do not want to burden the cognitive task for respondents by asking them to evaluate an app with seven characteristics. Therefore, we constrain each choice set to five characteristics; cost, advertising, and three of the five privacy permissions.

The survey was administered to consumers at their home and in public places from July 10 to August 19, 2013. Cluster sampling was used to locate survey participants. A starting location was randomly drawn from a sampling area and a cluster of a maximum of twelve participants were interviewed around this location. All participants had an equal chance of being the starting point. To improve the efficiency of data collection, interviewers visited starting locations where they would find a relatively larger population of smartphone users. We used data from Hiller et. al. (2012) to estimate a probit model of household smartphone adoption as a function of age, education, household size, income, gender and race. Probit model estimates, reported in Table 3, show that smartphone adoption is more likely when the head of the household is young, male and non-white, and has relatively higher education and income. Probit estimates and similar demographics from census block groups (CBGs), were then used to calculate the predicted probability of smartphone adoption for all CBGs in our seven sample cities. We used the predicted probabilities to determine the top ten percent of CBGs in each target city with respect to likelihood of smartphone adoption. Survey locations were randomly drawn from this list for each city and interviews were conducted around these locations. Interviewers offered a cash incentive to respondents for participating in the survey.

Prior to completing the survey, respondents were screened to ensure that they owned a smartphone or owned a basic cellular phone *and* were interested in purchasing a smartphone. A total of 1,726 respondents from Atlanta (306), Chicago (259), Denver (316), Philadelphia (279), Portland (208), Salt Lake City (77) and San Diego (281) completed valid survey questionnaires. Table 4 compares sample demographics with the US population (United States Census Bureau, 2009). Column two shows that 71.9 percent of sample respondents are white and 60.3 percent have at least a four-year college degree. Approximately 50 percent of respondents are female, 52 percent are 18 and 34 years old and 25 percent between 35 and 50 years, while 51 percent earned annual income in 2012 of $50,000 or more. Column four shows relatively large differences between our data and the population with respect to age and education. Specifically, our sample is younger and more educated. We remedy this possible source of bias in our demand results by estimating with weighted maximum likelihood (see Section 5.1).

In our data, about 83 percent of sample respondents own a smartphone and 62 percent of these own an iPhone. The proportion of smartphone users in our sample is high relative to a recent PewInternet (2013) estimate of 61 percent but is expected as we deliberately oversampled locations with a high likelihood of smartphone adoption. About 63 percent of smartphone and basic cell phone users check their phone "frequently" or "all the time." About one-third of smartphone users have been using a smartphone for three or four years, and just over 30 percent have been using a smartphone for five or more years. Almost 60 percent of smartphone users have 20 to 40 apps installed on their smartphone, and about 35 percent have 40 or more apps installed on their smartphone. The average number of apps per smartphone user is 23. About 44 percent of smartphone users indicated that they have never paid money to download an app. For those users that have paid for an app, the median price was $0.99. About 78 percent of respondents indicated that they are knowledgeable about computers and electronics, 45 percent indicated that they have a paper shredder in their home, and 61 percent indicated that they password-protect their cellular phone.

One of the implications of our theoretical framework is that experienced consumers should download more apps than inexperienced consumers. We test this implication with an ordered probit model that relates *APPS* (equals one if respondent has downloaded no apps; two if one to 20 apps; three if 20 to 40 apps; four if 40 to 60 apps; five if 60 to 80 apps; and six if more than 80 apps) to a proxy for online experience. The proxy measures the number of years the consumer has been using a smartphone: three years or fewer, four years, and five or more years. The model is estimated on the 1,431 smartphone users in our sample and shows a strong positive relationship between the number of apps downloaded and experience. The estimated coefficient on experience is 0.198 and is statistically significant at the one percent level ($t$ = 5.91; $P > |t| = 0.00$).

## 4. Empirical Model

The consumer faces seven alternatives; one market app, five new apps, and the option not to purchase. The conditional indirect utility for consumer $n$ = 1, …, N from app alternative $j$ = 0, … 6 on choice occasion $t$ = 1, 2 is assumed to be[15]:

$$U^*_{njt} = \beta' x_{njt} + \varepsilon_{njt} \qquad (4)$$

where $\beta$ is a vector of marginal utility coefficients that are common to all individuals, $x_{njt}$ is a vector of observed app characteristics, and $\varepsilon_{njt}$ is an unobserved random error term that is independently and identically distributed extreme value. Given these assumptions, the probability of consumer $n$ choosing alternative $j$ on choice occasion $t$ is:

$$prob_{nit} = \frac{exp(\beta' x_{nit})}{\sum_j^J exp(\beta' x_{njt})}$$

The probability of each consumer's sequence of choices across choice occasions is:

$$prob_n = \prod_{t=1}^{T} prob_{ni(n,t)t}$$

where $i(n, t)$ is the alternative chosen by consumer $n$ on choice occasion $t$, and the log likelihood is:

[15] Utility for the outside option is normalized to zero and has zero cost, no advertising, and no privacy permissions.

$$LL(\beta) = \sum_{n=1}^{N} \ln prob_n \qquad (5)$$

An alternative model specification recognizes that consumer's preferences may vary across individuals. The conditional indirect utility function with heterogeneous preferences is:

$$U^*_{njt} = \beta_n{}' x_{njt} + \varepsilon_{njt} \qquad (6)$$

where $\beta_n$ is a vector of consumer-specific marginal utility coefficients. The density of the distribution for $\beta_n$ is $f(\beta_n|\theta)$ with the vector $\theta$ containing the mean and covariance parameters of $\beta_n$. The probability of consumer $n$ choosing alternative $j$ on choice occasion $t$ is:

$$prob_{nit}(\beta_n) = \frac{exp(\beta_n{}' x_{nit})}{\sum_j^J exp(\beta_n{}' x_{njt})}$$

The probability of each consumer's sequence of choices across choice occasions is:

$$prob_n(\beta_n) = \prod_{t=1}^{T} prob_{ni(n,t)t}(\beta_n)$$

Given $\varepsilon$ is distributed extreme value, and assuming an appropriate distribution for $\beta_n$, mixed logit estimation of equation 6 is possible by simulated maximum likelihood (Revelt and Train, 1998). The simulated log likelihood is:

$$SLL(\theta) = \sum_{n=1}^{N} \ln\left(\frac{1}{R}\sum_{r=1}^{R} prob_n(\beta^r)\right) \qquad (7)$$

where $R$ is the number of replications and $\beta^r$ is the $r$th draw from $f(\beta_n|\theta)$.

The vector $\boldsymbol{x}$ measures the benefit and costs from the app. The elements of this vector are the benefit from the app to the consumer (which includes a constant), *PRICE*, *ADVERTISING*, and the five privacy permissions, *BROWSER HISTORY*, *CONTACTS*, *LOCATION*, *PHONE ID*, and *READ TEXTS*. The privacy permissions are coded as qualitative variables that equal one when the consumer's personal information is revealed to the app developer, and zero when it is not. Similarly, *ADVERTISING* equals one when the app has advertising, and zero when it does not. Given that the privacy permissions and advertising are measured net of the consumer benefit received from the app ($\alpha_{njt}$ on the constant), our *a priori* expectations for the signs of the marginal utility parameters on these variables are negative. A higher priced app will also provide less consumer satisfaction so we expect the sign on *PRICE* to be negative.

Since they do not have an understandable metric, it is convenient to convert the estimated marginal utilities for changes in $x_{njt}$ into WTP. For example, the WTP for preventing the app developer from knowing the consumer's location ($WTP_L$) is defined as how much more the app would have to be priced to make the consumer just indifferent between the old (cheaper but reveals the consumer's location) app and the new (more expensive but does not reveal location) app. Mean WTP for privacy with respect to location can be calculated from our estimates of utility as $WTP_L = \frac{-\beta_L}{\beta_p}$, where $\beta_L$ is the mean marginal utility of *LOCATION* and $\beta_p$ is the mean marginal utility of *PRICE*. This approach to estimating consumer valuations is used for the five other non-price characteristics of apps.

## 5. Results

Data from the conditional logit choice of the six apps are used to estimate consumer utility from smartphone apps and to calculate WTP.[16] Because most respondents face two choice occasions for two different app categories, the starting maximum sample size for econometric estimation is 3,345 observations, obtained from 1,713 respondents. In models where

[16] In 54 percent of the choice occasions, respondents agreed to buy the app, approximately evenly distributed between the market app and the new apps. The distribution of app categories across respondents was: games (18.78 percent), shopping (16.64 percent), social (8.68 percent), travel (20.27 percent), TV and movies (17.21 percent), utility (18.42 percent).

respondent demographic data are used to measure preference heterogeneity the sample size is reduced as made necessary by missing values for demographic variables.

### 5.1 Baseline Estimates

In the columns labeled model (i) of Table 5 we report maximum likelihood estimates of the conditional logit model, where the marginal utility parameters are assumed to be the same for all consumers. The data fit the model well as judged by the sign and statistical significance of most parameter estimates. The marginal utility parameters for *BROWSER HISTORY*, *CONTACTS*, *LOCATION*, *PHONE ID*, and *READ TEXTS*, reported in column two, are negative and significant at the one percent level. These estimates imply that, all other things held constant, the representative consumer will have higher utility when they conceal their browser history, list of contacts, location, phone identification number, and the contents of their text messages. The estimated parameters for *ADVERTISING* and *PRICE* are also negative and imply that consumer utility is higher when the app has no advertising and when the dollar amount paid for their app is lower.

WTP estimates are presented in column three. Here, we observe that the representative consumer is willing to pay \$2.28 to conceal their online browser history, \$4.05 to conceal their list of contacts, \$1.19 to conceal their location, \$1.75 to conceal their phone's identification number, and \$3.58 to conceal the contents of their text messages. The consumer is also willing to pay \$2.12 for no advertising. Because the benefit from each app alternative within the choice occasion is held constant, the parameter $\alpha_{njt}$ cannot be estimated. However, it is possible to use consumer valuations for privacy and advertising to estimate the indirect cost of buying a typical smartphone app and this can be used to calculate a lower-bound estimate of the benefit of an app. Given the typical app in the marketplace has advertising, and requires the consumer to reveal their location and phone's identification number, the benefit from consuming this app must be at least \$5.06 (= \$2.12 + \$1.20 + \$1.74). See Section 5.4 for more detail on how we constructed this typical app.

For robustness, we estimate two alternative specifications of utility. Model specification (ii) permits the marginal utility of *PRICE* to vary with income by adding two interaction terms, *PRICE*×*MEDIUM INCOME* and *PRICE*×*HIGH INCOME*, to equation 4. The variable *MEDIUM INCOME* equals one when the respondent's income is greater than \$25,000 and less than \$50,000, and zero otherwise. The variable *HIGH INCOME* equals one when the respondent's income is greater than \$50,000, and zero otherwise. In this specification, the estimated parameter on *PRICE* measures the marginal utility of price for low-income consumers (i.e., income of \$25,000 or less), the estimated parameter on *PRICE*×*MEDIUM INCOME* measures the marginal utility of price for medium-income consumers, and the estimated parameter on *PRICE*×*HIGH INCOME* measures the marginal utility of price for high-income consumers. Estimates of the non-price marginal utilities, reported in column four of Table 5, are qualitatively similar to those reported for the baseline conditional logit model. The parameter for *PRICE* is negative and the corresponding parameters for *PRICE*×*MEDIUM INCOME* and *PRICE*×*HIGH INCOME* are positive, albeit imprecisely estimated. These estimates imply that consumer utility decreases when the dollar amount paid for their app increases but that the effect diminishes with increases in income, especially at the high income level.

Hiller et. al. (2012) find that consumers tastes for advertising in news media varies across individuals in the population. To examine whether there is a similar effect in app markets, we estimate equation 5 with the marginal utility of *ADVERTISING* assumed to be independently normally distributed. The mixed logit model (ii) estimates, reported in column five of Table 5, are similar to the conditional logit model estimates, although the mean parameter for *ADVERTISING* has decreased from about -0.5 to -0.75.[17] The standard deviation of the random marginal utility parameter of 0.981 is significant at the one percent level, indicating that tastes for advertising vary in the population. Using the normal distribution, the random parameter estimates indicate that, all other things held constant, about three-quarters of the population prefer having less advertising on their smartphone apps.

Table 4 showed some differences in age and education between our sample and the population. We remedy this possible source of bias in our results by estimating the baseline conditional logit model by weighted maximum likelihood, where the contribution to the likelihood is the weight times the log of the choice probability for the individual choice occasion. Since we oversample the young (i.e., 18 to 34 years) and more educated (i.e., bachelor's degree and higher), we employ post-stratification weights designed to return the sample to census proportions. The weights are constructed by dividing the census proportion for any category by the corresponding sample proportion. For example, 30.4 percent of the population is in the age 18 to 34 category according to the census, while in our sample that percentage is 52.2 percent. Therefore the weight for any observation with age 18 to 34 years is calculated as 30.4/52.2 = 0.582.

Weighted maximum likelihood estimates of the baseline model of utility are reported in Table 6. Columns two and three present utility estimates when observations are weighted by age, and columns four and five present estimates when weighted by education. In addition, columns six and seven present results using the product of the age and education weights, in

[17] The mixed logit model was estimated by simulated maximum likelihood using 500 Halton draws.

lieu of weights constructed from a full age-education cross tabulation, which was not available. Although normally problematic, these results should be meaningful in our case as the correlation between age and education is only approximately 0.02 in our data. Focusing on columns six and seven, we observe that the ranking of consumer valuations for the five privacy permissions are unchanged between the weighted and un-weighted estimates. Consumer's WTPs to conceal their lists of contacts, text messages and location are somewhat lower when calculated from the weighted estimates.

### 5.2 Heterogeneous preferences

Because they do not have identical preferences, it is possible that individual's valuations for online privacy varies with observable characteristics such as age, education, gender, and income. Table 7 reports conditional logit model (i) estimates for subsamples of respondents aged from 18 to 34 years, 35 to 50 years and over 50 years. Younger consumers, aged 18 to 34, appear to be less concerned about advertising on their apps, and also less concerned about their privacy. Their valuations for concealing personal information about their browser history, contacts, location, phone identification number, and text messages are about 34 to 63 percent lower than consumers over 50 years of age.

The possibility that valuations of privacy vary with education is examined in Table 8, which reports estimates for subsamples of respondents with no college education, with a four-year college education, and with a graduate-level college education. Valuations for all five privacy permissions increase with years of education. Consumers with a graduate degree have WTPs for personal information that are substantially larger than consumers with no college degree. Qualitatively similar results are obtained when examining differences in income, which is typically highly correlated with education. Table 9 shows that low- and medium-income consumers have similar valuations for online privacy. However, high-income consumers have WTPs for all five privacy permissions that are about two to three times larger than low- and middle-income consumers.

Estimates for females and males are reported in Table 10. The WTP for concealing personal information on contacts and text messages, and for no advertising, are very similar across these two groups. However, females are willing to pay $1.42 more to conceal their location ($1.99 compared to $0.57), $1.05 more to conceal their phone's unique identification number ($2.29 compared to $1.24), and $0.82 more to conceal their online browser history ($2.74 compared to $1.92).[18]

### 5.3 Experience

Our theoretical framework implies that consumer valuations for online privacy are a function of experience. All other things held constant, an experienced consumer can produce time savings more efficiently than an inexperienced consumer, which increases their marginal benefit from apps. This higher benefit suggests that an experienced consumer would be willing to give up personal information that is more valuable to them. The empirical implication is that the valuations for concealing personal information for experienced consumers should be larger than valuations for inexperienced consumers. We examine this relationship empirically with two proxies for online experience. The first, defined in Section 3.2, measures the number of years the consumer has been using a smartphone: three years or fewer, four years, and five or more years. The second measures intensity of smartphone activity. Specifically, we formed a composite measure of smartphone activity by combining several question responses.

[18] We also estimated utility on subsamples for each city in the sample. The results, not reported, show similar rankings of privacy valuations across all cities although Portland respondents do not value the concealment of their online browser history.

Respondents are “more experienced” if they use their smartphone in four or more ways, either for games, shopping, social media, travel, TV and movies, and utilities, have downloaded 20 or more apps, *and* check their smartphones “frequently or “all the time.” Respondents who are not more experienced are “less experienced.”

Table 11 presents estimates of the marginal utilities and WTPs for three subsamples of respondents based on the number of years they have been using a smartphone. The “three years or fewer” and “four years” groups have relatively similar valuations for all measured aspects of online privacy. Respondents with five years or more experience also have similar valuations to their less experience counterparts for concealing information on their location and their phone’s identification number. However, the experienced consumer’s valuations for concealing personal information on their browser history, contacts and text messages are substantially higher. Specifically, their valuations for concealing personal information on browser history is 48 percent higher than consumers who have owned a smartphone for three or fewer years. Valuations for concealing information in contacts and text messages are 87 and 65 percent higher, respectively. A similar finding arises when “more” and “less” experienced smartphone users are compared on the basis of their intensity of activity. Table 12 shows that valuations for concealing personal information on contacts and text messages are about 48 percent higher for more experienced consumers.

It is possible that the estimates in Table 12 are actually measuring a preference effect and not an increase in efficiency due to more experience. That is, the higher consumer valuations for concealing personal information in column three could be observed because this subsample of respondents have a relatively stronger preference for privacy. One way to control for this potentially confounding effect is to split the sample into respondents with “weak” and "strong" preferences for privacy so that preferences are held reasonably constant within each group. The model can then be estimated on each subsample to see if the relationship between valuations for online privacy and experience hold.

We explore this possibility by defining a strong preference consumer as a respondent who owns a paper shredder and who password protects her or his phone. A weak preference consumer does neither. The estimates in Table 13 show that consumers with a strong preference for privacy have valuations for personal information that are two to three times higher than consumers with weak preferences for privacy. Table 14 reports estimates for subsamples of strong preference-more experience, strong preference-less experience, weak preference-more experience, and weak preference-less experience respondents. The subsamples are not well balanced in terms of number of observations so the results should be treated somewhat cautiously. Nevertheless, similar to Table 12, the estimates continue to show that experienced consumers have much higher valuations for concealing personal information on contacts and text messages. By holding preferences for privacy constant, the evidence suggests that we are indeed largely measuring an experience effect.

### 5.4 Self Selection

### 5.5 External Verification

### 5.6 The Benefits of Smartphone Apps

Finally, we use our estimates of utility to make a rough calculation of the benefits of smartphone apps to the US population. For this calculation, we first construct a typical app with data from the Google Play Store. During April, 2013 we used a web crawler to download a sample of 15,107 apps which comprised about two percent of the total population of apps available on the store. About 84 percent of the apps in the sample are actual applications and

16 percent are games. The average price for an app is $1.35, ranging from $0.00 to $193.14[19] Almost 74 percent of the sample apps are free, about eight percent are less than a dollar, and about eight percent are more than $0.99 but fewer than two dollars.

Based on this information, we describe the typical app in the market as being free, with advertising, and requiring personal information on a consumer's location and their phone's identification number.[20] Our un-weighted (weighted) estimates of utility in Table 5 (Table 6) indicate that the benefit from consuming this typical app must be at least $5.06 ($4.74).[21] Given the number of apps per smartphone user in our sample is 23, we calculate a lower-bound benefit of $116.63 ($109.25) per user. Multiplying this benefit by PewInternet's (2013) estimate of the number of adults using a smartphone in the US of 146,487,987 gives an estimated aggregate lower-bound benefit of 17.08 (16.00) billion dollars.[22]

## 6. Conclusions

Choice experiments were used to estimate consumer preferences for the different price, advertising, and privacy characteristics of apps. The five privacy permissions described the personal information a consumer must relinquish to the app developer when they download and use the app. They are: the location of the consumer while carrying their phone, the websites the consumer has browsed on their phone, the contacts in the address book on the consumer's

[19] This business app *ShopManager:POS,Buy-Sell-StockBoss,* which is a point-of-sale, buy-and-sell shop mobile management system, retails at $193.14.

[20] Although our sample identified about 400 individual permissions, many of these are similar, and many do not impinge on consumer's privacy. The five most commonly requested permissions by app developers are: (1) "INTERNET", (2) "WRITE EXTERNAL STORAGE", (3) "READ EXTERNAL STORAGE", (4) "READ PHONE STATE", and (5) "ACCESS LOCATION." Permission (1) determines if Internet connectivity is available and is used largely to request an advertisement. Permissions (2) and (3) permit the app to read, write and delete data stored on the consumer's phone SD card. Permissions (4) and (5) are the same as *PHONE ID* and *LOCATION* in our model of utility.

[21] The un-weighted benefit is $5.06 = $2.12 + $1.20 + $1.74. The weighted benefit is $4.74 = $2.28 + $0.81 + $1.65.

[22] For context, Rubinson Partners (2011) estimated that the app economy generated $20 billion in revenue in 2011. This includes downloads, in-app revenues, sales of virtual goods, and sales of physical goods and services.

phone, the unique identification number of the consumer’s phone, and the text messages the consumer has written and received on their phone.

Results show that price, advertising and the five privacy permissions are all important characteristics a consumer considers when purchasing a smartphone app. The representative consumer is willing to make a one-time payment of $2.28 to conceal their online browser history, $4.05 to conceal their list of contacts, $1.19 to conceal their location, $1.75 to conceal their phone’s identification number, and $3.58 to conceal the contents of their text messages. The consumer is willing to pay $2.12 for not having advertising interfere or distract them from their use of the app. Our results also show that experienced consumers download more apps than inexperienced consumers and that experienced consumers have WTPs for concealing contact lists and text messages that are much higher than those with less experience.

The concealment of personal information has been the subject of much recent debate and many initiatives have been proposed for alleviating privacy concerns. These include industry self-regulation, full disclosure of how personal information is used, laws that restrict the use of personal information, and the assignment of property rights so that market forces will allocate information efficiently. Our research provides more understanding of the value consumers place on the personal information they give up in app markets. We find that when they are informed about privacy permissions and how their personal information is used, consumers have a very clear understanding of their preferences for privacy. This suggests that full disclosure of how apps use personal information, similar to the labeling of food contents in grocery stores, could be mutually beneficial to consumers and app developers. Here, app developers could design a variety of apps with varying prices, levels of advertising and privacy permissions to better match the heterogeneous preferences of well-informed consumer groups.

For example, a consumer with high value of privacy could buy a relatively expensive app that places a premium on not using and/or protecting personal information.

Your focused on how much consumers value privacy. For this purpose you abstracted from the possibility that the collected information could benefit consumers. For instance, the consumer location information may enable the apps to help the consumer find restaurants, shops, or weather information; the phone identity may enable the apps to help the consumer find the phone if it gets lost; etc. If consumers are presented with such potential benefits when asked for the respective permission to disclose private information, some of them may be willing to provide the information freely. It might be interesting for future research to introduce such potential benefit/cost trade off, which I think will be relevant for policy considerations. In other words, what should be the optimal privacy policy/regulation in an environment in which consumers value privacy but consumer information may also enable the firms to provide better service/products to consumers?

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**Table 1**
**App Characteristics as Described in the Survey**

| Characteristic | Survey Description |
| --- | --- |
| *LOCATION* | The *Location* permission allows the app to know where you are at all times. For example, a weather app with the *Location* permission will save you time by displaying the conditions where you are currently located. |
| *BROWSER HISTORY* | The *Browser History* permission allows the app to know all the websites you have visited on your smartphone. This permission can speed up website logins and Internet searches. |
| *CONTACTS* | The *Contacts* permission allows an app to read your address book on your phone. With this permission an app can speed dial, easily share your contact information with others, and make video calls (e.g., Skype, Facetime) from your phone. |
| *PHONE ID* | The *Phone ID* permission allows an app to find your phone if lost or stolen. However, with this information, a third party can obtain a list of all the apps on your smartphone, and when you use them. |
| *READ TEXTS* | The *Read Texts* permission allows an app to know what you have received or written in your text messages. Some apps require this permission to provide enhanced texting, such as spell check, and speech-to-text messaging. |
| *ADVERTISING* | Many apps contain *Advertisements* ("Ads"). This could be a small banner that is stationary, or moves across your cell phone screen. |
| *COST* | Many apps are free. Others have a one-time *Cost* for unlimited usage, ranging from $0.99 to about $9.99. |

**Table 2**
**App Descriptions**

| Category | App |
|---|---|
| Shopping | *Barcode Shopper* is useful when shopping. With your smartphone you scan the bar code of an item at the store, and do comparison shopping. Barcode Shopper requires the Contacts and Phone ID permissions. |
| TV & Movies | *Crackle* lets you watch thousands of free Hollywood movies and TV shows anywhere, any time. You can watch instantly, or download and watch later when you're not connected. Crackle's content is updated monthly and current titles include Pineapple Express, Big Daddy, Joe Dirt, Seinfeld, Spiderman, and Rescue Me. Crackle requires the Location and Phone ID permissions. |
| Games | *CSR Racing* is a free racing app that allows you to customize your dream car from Audi, BMW, Ford, and Nissan, and drag race along deserted city streets. It's you versus your rivals, and you will need all your power, skill and tactics to race in a straight line. Hit the right revs and let the turbo work. However, deploy the nitrous oxide at the wrong time, and you're doomed. This app requires the Location and Phone ID permissions. |
| Games | *Doodle Jump* is an arcade game where you travel up a sheet of graph paper, jumping from one platform to the next, picking up jet packs, avoiding black holes, and blasting baddies with nose balls. You can play alone and compare your score with other players' scores scribbled in the margins. This app requires the Phone ID permission. |
| Social | *HootSuite* allows you to view and update all your social media accounts at the same time, and to easily share photos and videos. It supports Facebook, FourSquare, LinkedIn, and Twitter and may offer services. HootSuite requires the Location and Phone ID permissions. |
| Utilities | *Life360* will locate your lost or stolen phone. By giving up the location permission, you can use your tablet/PC, or a friend's phone, to find your misplaced phone. The app can also locate family members at parks, concerts, sporting events, etc. |
| Games | *Solitaire* allows you to solve your favorite card puzzles, such as Solitaire and Free Cell, anytime, anywhere. Solitaire requires the Location and Phone ID permissions. |
| Travel | An app that is useful when traveling is the smartphone form of the popular website TripAdvisor.com. By giving it the location permission, *TripAdvisor* finds restaurants, hotels, and things to do wherever you go. You can read reviews, look at pictures and menus, and get directions. TripAdvisor also requires the Phone ID and Browser History permissions. |

**Table 3**
**Determinants of Smartphone Adoption**

| | Coefficient | s.e. | \|t\| |
|---|---|---|---|
| HOUSEHOLD SIZE (number of persons) | -0.0316$^{**}$ | 0.0150 | 2.11 |
| WHITE | -0.2214$^{***}$ | 0.0445 | 4.98 |
| FEMALE | -0.1064$^{***}$ | 0.0393 | 2.71 |
| AGE (number of years) | -0.0279$^{***}$ | 0.0014 | 19.91 |
| EDUCATION (number of years of schooling) | 0.0416$^{***}$ | 0.0081 | 5.16 |
| HOUSEHOLD INCOME ($ per annum) | 6.73e-06$^{***}$ | 4.63e-07 | 14.52 |
| CONSTANT | -0.1016$^{*}$ | 0.1451 | 0.70 |
| Likelihood | -2,698.2 | | |
| Observations | 5,535 | | |

*NOTES*. Sample of 5,535 households obtained from Hiller et. al. (2012). Dependent variable equals one if the household owns a Smartphone at March, 2011, and zero otherwise. 25.4 percent of sample households have a smartphone. s.e. denotes robust standard errors. $^{***}$denotes significant at the one percent level. $^{**}$denotes significant at the five percent level. $^{*}$denotes significant at the ten percent level. t denotes the t value.

**Table 4**
**Sample Demographics (%)**

| | Sample | | Census |
|---|---|---|---|
| Region | | Region | |
| Northeast | 16.2 | Northeast | 18.4 |
| Midwest | 15.0 | Midwest | 21.8 |
| South | 17.7 | South | 36.5 |
| West | 51.1 | West | 23.2 |
| Age | | Age | |
| 18-34 years | 52.2 | 18-34 years | 30.4 |
| | | 35-44 years | 17.8 |
| 35-50 years | 25.3 | | |
| | | 45-54 years | 19.5 |
| 50-64 years | 13.4 | 55-64 years | 15.5 |
| 65 years or over | 9.10 | 65 years or over | 16.8 |
| Race | | Race | |
| Non-white | 28.1 | Non-white | 18.9 |
| White | 71.9 | White | 81.1 |
| Gender | | Gender | |
| Female | 49.7 | Female | 51.7 |
| Male | 50.3 | Male | 48.3 |
| Education | | Education | |
| < High school | 2.57 | < High school | 13.8 |
| High school | 11.0 | High school | 30.7 |
| Some college | 26.1 | Some college | 28.2 |
| Bachelor's degree or higher | 60.3 | Bachelor's degree or higher | 27.4 |
| Household income | | Household income | |
| < $25,000 | 28.7 | < $25,000 | 23.4 |
| $25,000-$49,999 | 19.9 | $25,000-$49,999 | 26.2 |
| $50,000-$74,999 | 16.8 | $50,000-$74,999 | 19.5 |
| > $75,000 | 34.5 | > $75,000 | 30.8 |

*NOTES.* Census data are from December, 2009. Sample data are from July and August, 2013.

*SOURCE*. United States Census Bureau (2009).

**Table 5**
**Baseline Estimates of Utility**

| | Conditional Logit | | | Mixed Logit |
|---|---|---|---|---|
| | Model (i) | | Model (ii) | Model (iii) |
| | MU | WTP | MU | MU |
| BROWSER HISTORY | -0.607*** | $2.28 | -0.578*** | -0.566*** |
| | (0.064) | (0.26) | (0.069) | (0.070) |
| CONTACTS | -1.078*** | $4.05 | -1.074*** | -1.095*** |
| | (0.073) | (0.32) | (0.078) | (0.080) |
| LOCATION | -0.317*** | $1.19 | -0.294*** | -0.287*** |
| | (0.056) | (0.21) | (0.060) | (0.060) |
| PHONE ID | -0.465*** | $1.75 | -0.434*** | -0.434*** |
| | (0.066) | (0.28) | (0.071) | (0.071) |
| READ TEXTS | -0.952*** | $3.58 | -0.967*** | -0.988*** |
| | (0.086) | (0.35) | (0.090) | (0.092) |
| ADVERTISING | -0.565*** | $2.12 | -0.520*** | -0.753*** |
| | (0.050) | (0.22) | (0.053) | (0.082) |
| ADVERTSING STD. DEV. | | | | 0.981*** |
| | | | | (0.129) |
| PRICE | -0.266*** | | -0.286*** | -0.291*** |
| | (0.010) | | (0.020) | (0.020) |
| PRICE×MEDIUM INCOME | | | 0.017 | 0.021 |
| | | | (0.030) | (0.031) |
| PRICE×HIGH INCOME | | | 0.035 | 0.042* |
| | | | (0.024) | (0.025) |
| Log likelihood | -4,884 | - | -4,284 | -4,272 |
| Respondents | 1,713 | | 1,444 | 1,444 |
| Observations | 3,345 | | 2,888 | 2,888 |

*NOTES*. MU is marginal utility. WTP is willingness to pay. STD. DEV. is the standard deviation of the random MU parameter for ADVERTISING. Standard errors in parenthesis. ***denotes significant at the one percent level. **denotes significant at the five percent level. *denotes significant at the ten percent level.

**Table 6**
**Weighted Baseline Estimates of Utility**

| | Weighted by Age | | Weighed by Education | | Weighted by Age and Education | |
|---|---|---|---|---|---|---|
| | MU | WTP | MU | WTP | MU | WTP |
| BROWSER HISTORY | -0.597 | $2.43 | -0.536 | $2.15 | -0.529 | $2.21 |
| | (0.039) | (0.28) | (0.033) | (0.26) | (0.033) | (0.28) |
| CONTACTS | -1.123 | $4.57 | -0.939 | $3.76 | -0.810 | $3.38 |
| | (0.083) | (0.35) | (0.063) | (0.31) | (0.054) | (0.31) |
| LOCATION | -0.322 | $1.31 | -0.223 | $0.89 | -0.195 | $0.81 |
| | (0.018) | (0.24) | (0.012) | (0.22) | (0.011) | (0.23) |
| PHONE ID | -0.484 | $1.97 | -0.361 | $1.45 | -0.397 | $1.65 |
| | (0.032) | (0.30) | (0.023) | (0.28) | (0.026) | (0.30) |
| READ TEXTS | -0.979 | $3.99 | -0.761 | $3.05 | -0.720 | $3.00 |
| | (0.085) | (0.39) | (0.058) | (0.33) | (0.056) | (0.34) |
| ADVERTISING | -0.604 | $2.46 | -0.526 | $2.11 | -0.548 | $2.28 |
| | (0.030) | (0.25) | (0.025) | (0.22) | (0.026) | (0.24) |
| PRICE | -0.246 | | -0.250 | | -0.240 | |
| | (0.003) | | (0.003) | | (0.003) | |
| Log likelihood | -4848.4 | | -5,221 | | -4,987 | |
| Respondents | 3,333 | | 3,342 | | 3,324 | |
| Observations | 1,715 | | 1,716 | | 1,699 | |

*NOTES*. Conditional logit model. MU is marginal utility. WTP is willingness to pay. Standard errors in parenthesis.

**Table 7**
**Estimates of Utility by Age**

| | 18 to 34 | | 35 to 50 | | Over 50 | |
|---|---|---|---|---|---|---|
| | MU | WTP | MU | WTP | MU | WTP |
| BROWSER HISTORY | -0.636 | $2.02 | -0.525 | $2.34 | -0.636 | $3.10 |
| | (0.090) | (0.30) | (0.123) | (0.58) | (0.142) | (0.77) |
| CONTACTS | -1.007 | $3.19 | -1.179 | $5.25 | -1.101 | $5.37 |
| | (0.100) | (0.35) | (0.149) | (0.81) | (0.152) | (0.92) |
| LOCATION | -0.324 | $1.03 | -0.218 | $0.97 | -0.441 | $2.15 |
| | (0.078) | (0.25) | (0.106) | (0.48) | (0.130) | (0.66) |
| PHONE ID | -0.408 | $1.29 | -0.458 | $2.04 | -0.652 | $3.18 |
| | (0.093) | (0.31) | (0.128) | (0.64) | (0.143) | (0.88) |
| READ TEXTS | -0.886 | $2.81 | -1.141 | $5.08 | -0.874 | $4.26 |
| | (0.114) | (0.38) | (0.174) | (0.89) | (0.195) | (1.03) |
| ADVERTISING | -0.463 | $1.47 | -0.564 | $2.51 | -0.817 | $3.99 |
| | (0.069) | (0.24) | (0.097) | (0.52) | (0.109) | (0.73) |
| PRICE | -0.316 | | -0.225 | | -0.205 | |
| | (0.015) | | (0.020) | | (0.021) | |
| Log likelihood | -2542.7 | | -1275.8 | | -1056.4 | |
| Respondents | 897 | | 434 | | 395 | |
| Observations | 1,755 | | 842 | | 754 | |

*NOTES*. Conditional logit model. MU is marginal utility. WTP is willingness to pay. Standard errors in parenthesis.

**Table 8**
**Estimates of Utility by Education**

| | Less than college | | Four-year college | | Advanced degree | |
|---|---|---|---|---|---|---|
| | MU | WTP | MU | WTP | MU | WTP |
| BROWSER HISTORY | -0.475 | $1.85 | -0.578 | $2.02 | -0.827 | $3.36 |
| | (0.10) | (0.42) | (0.11) | (0.40) | (0.13) | (0.59) |
| CONTACTS | -0.863 | $3.35 | -1.201 | $4.21 | -1.255 | $5.10 |
| | (0.11) | (0.49) | (0.13) | (0.53) | (0.15) | (0.71) |
| LOCATION | -0.167 | $0.65 | -0.344 | $1.20 | -0.491 | $2.00 |
| | (0.09) | (0.35) | (0.09) | (0.34) | (0.11) | (0.49) |
| PHONE ID | -0.374 | $1.45 | -0.494 | $1.73 | -0.554 | $2.25 |
| | (0.11) | (0.46) | (0.11) | (0.44) | (0.12) | (0.59) |
| READ TEXTS | -0.791 | $3.08 | -1.149 | $4.02 | -0.991 | $4.03 |
| | (0.114) | (0.53) | (0.15) | (0.60) | (0.18) | (0.78) |
| ADVERTISING | -0.433 | $1.68 | -0.562 | $1.97 | -0.760 | $3.09 |
| | (0.08) | (0.34) | (0.09) | (0.35) | (0.10) | (0.51) |
| PRICE | -0.257 | | -0.286 | | -0.246 | |
| | (0.017) | | (0.02) | | (0.02) | |
| Log likelihood | -1846.1 | | -1925.7 | | -1313.0 | |
| Respondents | 594 | | 615 | | 517 | |
| Observations | 1,156 | | 1,204 | | 991 | |

*NOTES*. Conditional logit model. MU is marginal utility. WTP is willingness to pay. Standard errors in parenthesis.

**Table 9**
**Estimates of Utility by Income**

| | Less than $25,000 | | $25,000 to $50,000 | | Greater than $50,000 | |
|---|---|---|---|---|---|---|
| | MU | WTP | MU | WTP | MU | WTP |
| BROWSER HISTORY | -0.517 | $1.63 | -0.544 | $2.01 | -0.660 | $2.77 |
| | (0.13) | (0.41) | (0.14) | (0.55) | (0.10) | (0.46) |
| CONTACTS | -0.851 | $2.68 | -0.833 | $3.07 | -1.360 | $5.71 |
| | (0.13) | (0.45) | (0.17) | (0.68) | (0.12) | (0.61) |
| LOCATION | -0.188 | $0.59 | -0.196 | $0.72 | -0.422 | $1.77 |
| | (0.11) | (0.34) | (0.12) | (0.46) | (0.09) | (0.38) |
| PHONE ID | -0.277 | $0.87 | -0.492 | $1.82 | -0.509 | $2.14 |
| | (0.13) | (0.44) | (0.15) | (0.63) | (0.10) | (0.48) |
| READ TEXTS | -0.868 | $2.74 | -0.691 | $2.55 | -1.189 | $4.99 |
| | (0.15) | (0.50) | (0.18) | (0.70) | (0.15) | (0.68) |
| ADVERTISING | -0.332 | $1.05 | -0.558 | $2.06 | -0.633 | $2.66 |
| | (0.09) | (0.32) | (0.11) | (0.49) | (0.08) | (0.40) |
| PRICE | -0.317 | | -0.271 | | -0.238 | |
| | (0.02) | | (0.02) | | (0.02) | |
| Log likelihood | -1316.2 | | -917.78 | | -2092.0 | |
| Respondents | 434 | | 300 | | 775 | |
| Observations | 847 | | 592 | | 1,512 | |

*NOTES*. Conditional logit model. MU is marginal utility. WTP is willingness to pay. Standard errors in parenthesis.

**Table 10**
**Estimates of Utility by Gender**

| | Men | | Women | |
|---|---|---|---|---|
| | MU | WTP | MU | WTP |
| BROWSER HISTORY | -0.52 | $1.92 | -0.714 | $2.74 |
| | (0.09) | (0.34) | (0.09) | (0.40) |
| CONTACTS | -1.012 | $3.75 | -1.162 | $4.46 |
| | (0.10) | (0.42) | (0.11) | (0.49) |
| LOCATION | -0.153 | $0.57 | -0.518 | $1.99 |
| | (0.08) | (0.28) | (0.08) | (0.34) |
| PHONE ID | -0.334 | $1.24 | -0.596 | $2.29 |
| | (0.09) | (0.37) | (0.10) | (0.42) |
| READ TEXTS | -0.948 | $3.51 | -0.955 | $3.66 |
| | (0.11) | (0.46) | (0.13) | (0.53) |
| ADVERTISING | -0.563 | $2.08 | -0.559 | $2.15 |
| | (0.07) | (0.30) | (0.07) | (0.33) |
| PRICE | -0.27 | | -0.26 | |
| | (0.01) | | (0.01) | |
| Log likelihood | -2559.9 | | -2298.5 | |
| Respondents | 862 | | 855 | |
| Observations | 1,678 | | 1,659 | |

*NOTES*. Conditional logit model. MU is marginal utility. WTP is willingness to pay. Standard errors in parenthesis.

**Table 11**
**Estimates of Utility by Years of Smartphone Experience**

| | Three years or fewer | | Four years | | Five years or more | |
|---|---|---|---|---|---|---|
| | MU | WTP | MU | WTP | MU | WTP |
| BROWSER HISTORY | -0.685 | $2.30 | -0.570 | $1.92 | -0.773 | $3.41 |
| | (0.12) | (0.41) | (0.12) | (0.43) | (0.13) | (0.66) |
| CONTACTS | -0.890 | $2.99 | -0.963 | $3.25 | -1.271 | $5.60 |
| | (0.13) | (0.49) | (0.14) | (0.51) | (0.15) | (0.84) |
| LOCATION | -0.356 | $1.19 | -0.453 | $1.53 | -0.291 | $1.28 |
| | (0.10) | (0.35) | (0.11) | (0.37) | (0.12) | (0.52) |
| PHONE ID | -0.719 | $2.41 | -0.450 | $1.51 | -0.516 | $2.27 |
| | (0.13) | (0.48) | (0.13) | (0.47) | (0.13) | (0.66) |
| READ TEXTS | -0.893 | $3.00 | -0.871 | $2.93 | -1.124 | $4.95 |
| | (0.16) | (0.56) | (0.16) | (0.56) | (0.19) | (0.92) |
| ADVERTISING | -0.434 | $1.46 | -0.458 | $1.54 | -0.649 | $2.86 |
| | (0.09) | (0.34) | (0.09) | (0.36) | (0.10) | (0.56) |
| PRICE | -0.298 | | -0.297 | | -0.227 | |
| | (0.02) | | (0.02) | | (0.02) | |
| Log Likelihood | -1460.5 | | -1362.3 | | -1186.3 | |
| Respondents | 519 | | 478 | | 433 | |
| Observations | 1,016 | | 930 | | 843 | |

*NOTES*. Conditional logit model. MU is marginal utility. WTP is willingness to pay. Standard errors in parenthesis.

**Table 12**
**Estimates of Utility by More or Less Experience**

| | More experienced | | Less experienced | |
|---|---|---|---|---|
| | MU | WTP | MU | WTP |
| BROWSER HISTORY | -0.276 | $1.47 | -0.363 | $1.41 |
| | (0.12) | (0.67) | (0.07) | (0.26) |
| CONTACTS | -0.913 | $4.86 | -0.847 | $3.29 |
| | (0.14) | (0.94) | (0.07) | (0.29) |
| LOCATION | 0.093 | -$0.49 | -0.128 | $0.50 |
| | (0.11) | (0.56) | (0.06) | (0.22) |
| PHONE ID | -0.111 | $0.59 | -0.102 | $0.40 |
| | (0.13) | (0.73) | (0.07) | (0.28) |
| READ TEXTS | -0.870 | $4.63 | -0.531 | $2.06 |
| | (0.16) | (0.97) | (0.07) | (0.30) |
| ADVERTISING | -0.262 | $1.39 | -0.273 | $1.06 |
| | (0.09) | (0.55) | (0.05) | (0.20) |
| PRICE | -0.188 | | -0.257 | |
| | (0.02) | | (0.01) | |
| Log likelihood | -1,165.9 | | -4598.5 | |
| Respondents | 336 | | 1390 | |
| Observations | 659 | | 2692 | |

*NOTES*. Conditional logit model. MU is marginal utility. WTP is willingness to pay. Standard errors in parenthesis.

**Table 13**
**Estimates of Utility by Privacy Preferences**

| | Weak Preference | | Strong Preference | |
|---|---|---|---|---|
| | MU | WTP | MU | WTP |
| BROWSER HISTORY | -0.520 | $1.68 | -0.828 | $4.43 |
| | (0.13) | (0.44) | (0.13) | (0.83) |
| CONTACTS | -0.957 | $3.09 | -1.249 | $6.68 |
| | (0.15) | (0.55) | (0.15) | (1.03) |
| LOCATION | -0.096 | $0.31 | -0.658 | $3.52 |
| | (0.11) | (0.37) | (0.12) | (0.71) |
| PHONE ID | -0.347 | $1.12 | -0.767 | $4.10 |
| | (0.14) | (0.49) | (0.13) | (0.89) |
| READ TEXTS | -1.012 | $3.27 | -1.098 | $5.87 |
| | (0.18) | (0.62) | (0.19) | (1.16) |
| ADVERTISING | -0.648 | $2.09 | -0.764 | $4.09 |
| | (0.11) | (0.40) | (0.10) | (0.73) |
| PRICE | -0.310 | | -0.187 | |
| | (0.02) | | (0.02) | |
| Log likelihood | -569.98 | | -665.25 | |
| Respondents | 385 | | 498 | |
| Observations | 748 | | 965 | |

*NOTES*. Conditional logit model. MU is marginal utility. WTP is willingness to pay. Standard errors in parenthesis.

**Table 14**
**Estimates of Utility by Privacy Preferences and Experience**

| | Strong Preference/ More experienced | | Strong Preference/ Less experienced | | Weak Preference/ More experienced | | Weak Preference/ Less experienced | |
|---|---|---|---|---|---|---|---|---|
| | MU | WTP | MU | WTP | MU | WTP | MU | WTP |
| BROWSER HISTORY | -0.234 | $1.57 | -0.962 | $4.85 | -0.421 | $1.26 | -0.533 | $1.74 |
| | (0.26) | (1.81) | (0.15) | (0.94) | (0.32) | (0.95) | (0.15) | (0.50) |
| CONTACTS | -2.250 | $15.09 | -1.073 | $5.40 | -1.615 | $4.83 | -0.898 | $2.92 |
| | (0.45) | (4.65) | (0.16) | (1.00) | (0.56) | (1.93) | (0.16) | (0.58) |
| LOCATION | -0.046 | $0.31 | -0.827 | $4.17 | 0.185 | -$0.55 | -0.155 | $0.51 |
| | (0.23) | (1.55) | (0.14 | (0.84) | (0.26) | (0.78) | (0.13) | (0.42) |
| PHONE ID | -0.607 | $4.07 | -0.813 | $4.10 | -0.672 | $2.01 | -0.279 | $0.91 |
| | (0.27) | (2.36) | (0.14) | (0.96) | (0.36) | (1.18) | (0.16) | (0.53) |
| READ TEXTS | -2.538 | $17.01 | -0.818 | $4.12 | -1.248 | $3.73 | -0.980 | $3.19 |
| | (0.56) | (5.43) | (0.21) | (1.11) | (0.48) | (1.62) | (0.19) | (0.67) |
| ADVERTISING | -1.077 | $7.22 | -0.736 | $3.71 | -0.606 | $1.81 | -0.665 | $2.17 |
| | (0.23) | (2.42) | (0.11) | (0.76) | (0.29) | (0.97) | (0.11) | (0.44) |
| PRICE | -0.149 | | -0.199 | | -0.335 | | -0.307 | |
| | (0.04) | | (0.02) | | (0.06) | | (0.02) | |
| Log Likelihood | -278 | | -999.3 | | -176.4 | | -927.6 | |
| Respondents | 108 | | 390 | | 61 | | 324 | |
| Observations | 208 | | 757 | | 122 | | 626 | |

*NOTES*. Conditional logit model. MU is marginal utility. WTP is willingness to pay. Standard errors in parenthesis.

**Figure 1**
**Binary Choice Question for Social App**

| | HootSuite | Social Me |
|---|---|---|
| Contacts | ✓ | ✓ |
| Phone ID | ✓ | ✓ |
| Read Texts | ✓ | x |
| Advertising | ✓ | ✓ |
| Cost | $0.00 | $1.99 |

**Figure 2**
**Binary Choice Question with New App**

| | Social Me A | Social Me B |
|---|---|---|
| Contacts | ✓ | x |
| Phone ID | ✓ | x |
| Read Texts | X | ✓ |
| Advertising | X | ✓ |
| Cost | $2.99 | $3.99 |

**Figure 3**
**Binary Choice Question with Alternative Versions of New App**

| | Social Me C | Social Me D |
|---|---|---|
| Contacts | X | ✓ |
| Phone ID | ✓ | X |
| Read Texts | X | X |
| Advertising | X | ✓ |
| Cost | $5.99 | $4.99 |

**Figure 4**
**Multiple Choice Question for Social App**

| | HootSuite | Social Me | Social Me A | Social Me B | Social Me C | Social Me D |
|---|---|---|---|---|---|---|
| Contacts | ✓ | ✓ | ✓ | x | x | ✓ |
| Phone ID | ✓ | ✓ | ✓ | x | ✓ | x |
| Read Texts | ✓ | x | x | ✓ | x | x |
| Advertising | ✓ | ✓ | x | ✓ | x | ✓ |
| Cost | $0.00 | $1.99 | $2.99 | $3.99 | $5.99 | $4.99 |