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The Value of Online Privacy

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Abstract

We estimate the value of online privacy with a differentiated products model of the

Executive Summary

What is the value of online privacy for US adults and how do these valuations vary with experience?
much recent debate. Most discussion has centered on the collection of large amounts of personally identifiable data in online markets, and the sharing of these data with third-parties.

is growing substantially. This results in a significant and growing percentage of the population sending and receiving information via smartphones, potentially heightening online privacy concerns. Our research puts some numbers behind these concerns. We estimated consumer willingness-to-pay (WTP) for smartphone apps in 2013. Our WTP estimates show that the representative consumer is willing to make a one-time payment to each app to conceal their browser history, list of contacts, location, phone ID, and text messages. Payments to conceal contacts and texts are higher for experienced consumers.

There are many proposals 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. Formal evaluation of these proposals requires industry players to have some understanding of the trade-offs associated with the protection of personal information. Our research provides more understanding of the value consumers place on the personal information they give up in app markets.

Choice experiments were used to estimate consumer preferences for the different characteristics that comprise an app (see Figure 4). During the experiments, consumers were presented with a choice set containing one app currently traded in the marketplace and five new

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 -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

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 phone (*CONTACTS*), *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 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)

are larger than those for nsumers. This finding is robust to a specification

that holds preferences cons 0 0 1 169.58 212.33 Tm[ )]TJat73]TJETBT1 0 0 1 310dosTJt73]TJpond[.)]Tm[c)4(or

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 first definition and, more specifically, we

[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 unauthorized third-parties (e.g., identify theft) but recognize this is also a major concern of many consumers.

of apps consumed and the amount of personal information relinquished.[5] This permits the

a^*, to simultaneously represent both the demand for apps

and the supply of personal information.

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 $\bar{T}$

information so that $\frac{a^*}{e} > 0$.[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 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.

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

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information online by the dollar value they place on this information when it is relinquished to the app developer in exchange for the app 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

and an 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 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

nterviewer then informs the respondent that this app will be available in about a month ould 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 problems.[11] 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 This results in less noise in choices, relative to mail and online survey modes, and improves the efficiency of our estimator.[12]

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 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.

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

[12] 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.

industry journals, two focus groups and a pilot study to develop, test and refine our descriptions of the app characteristics.[13] Measures developed by Huber and Zwerina (1996) were used to generate an efficient, linear design for the levels of the app characteristics.[14] 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.

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 from app alternative j on choice occasion t = 1, 2 is assumed to be[16]:

$$U^{*}_{njt} \qquad {}' x_{njt} \qquad {}_{njt} \qquad (4)$$

where β is a vector of marginal utility coefficients that are common to all individuals, x_{njt} is a vector of observed app characteristics, and ε_{njt} is an unobserved random error term that is where β_n is a vector of consumer-

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 (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) 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 $WTP_L \quad \frac{_L}{_p}$, where β_L is the mean marginal utility of *LOCATION* and β_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.[17] 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 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*,

[17] 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).

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

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 α_{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 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 (

$25,000 and less than $50,000, and zero otherwise. The variable *HIGH INCOME* equals one when 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*

5.2 Heterogeneous preferences

Because they do not have identical preferences, it is possible that individual

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, hig75 Tm[(that)]TJETi3 Tm[2T4pp.p69

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number ($2.29 compared to $1.24), and $0.82 more to conceal their online browser history ($2.74 compared to $1.92).[19]

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 valuations to their less experience counterparts for concealing information on their location and the experienced 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-indicate that the benefit from consuming this typical app must be at least $5.06 ($4.74).[22] 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 (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.[23]

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

e 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 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

[22] 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.

[23] 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.

than inexperienced consumers and that experienced consumers have WTPs for concealing

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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,

Table 3
Determinants of Smartphone Adoption

	Coefficient	s.e.	|t|

Table 6
Weighted Baseline Estimates of Utility

	Weighted by Age		Weighed by Education		Weighted by Age and Education	
	MU	WTP	MU	WTP	MU	WTP

Table 7
Estimates of Utility by Age

	18 to 34		35 to 50		Over 50	
	MU	WTP	MU	WTP	MU	WTP

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.					

Table 10

Table 11

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

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	

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	-0nce	

Figure 3
Binary Choice Question with Alternative Versions of New App

	Social Me C	Social Me D
Contacts		
Phone ID		
Read Texts		
Advertising		