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**Economic Value of Data:
Quantification Using Online Experiments**

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Economic Value of Data: Quantification Using Online Experiments

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PRELIMINARY DRAFT

Abstract

We conduct incentive compatible choice experiments to measure the economic value of social media data. We focus on the value that users place on their personal data related to the three biggest social media platforms: Facebook, Instagram and Twitter. We find that the median Willingness to Accept (WTA) of users for the entire “stock” of data for Facebook and Instagram is \$300 each which is 20% higher than Twitter valued at \$250. We use data valuations from a recent data breach settlement by Facebook to provide information interventions. We find that reducing these information frictions about the value of data can make users revise their valuations upwards. They do not

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reduce their valuation if the amount is less than their initial WTA. Finally, a framing which makes the users think about giving their data up immediately makes them value it much higher. We do not find a significant impact of a potential ‘present bias’ in users’ decisions, especially relative to the immediate data sharing intervention.

1 Introduction

Personal data is increasingly deemed to be a source of great value to firms in general and digital platforms such as Facebook and Instagram in particular. It is conjectured to be extremely important as a tool for targeting, an input for algorithms, and as a general source of revenue. On the other hand, consumers on these digital platforms, who provide these data do not seem to value it adequately (Athey et al., 2017). This is surprising since these data traces often contain sensitive personal information apart from being an important resource for firms. It has increasingly been demonstrated that the value consumers put on their data is affected by different framing and contexts Adjerid et al. (2013). This makes it difficult to put a value on this entity which plays a central role in daily transactions. Debates around the GDPR and California Privacy Act have highlighted this grey area related to privacy and data valuations. Additionally, policy makers are also debating whether there should be a ‘data dividend’ to compensate the consumers who actually create the online footprints but are not being paid for their ‘labor’ yet (Arrieta-Ibarra et al., 2018).¹ These recent conversations bring to light a need to create consensus about the value of data from a privacy and firm revenue perspective. Moreover, slowly we are getting access to credible estimates of what personal data might be worth from firms perspective and from a societal perspective. There has been an emergence of a variety of lawsuits against some of the largest technology companies such as Facebook and Google due to data breaches. A handful of these legal cases have been settled with a stipulated payout to the consumers whose data was

¹See here for some context related to the data dividend in California for example: <https://www.latimes.com/politics/la-pol-ca-gavin-newsom-california-data-dividend-20190505-story.html>.

compromised. These settlements provide us a sense of the middle ground in terms of firms' willingness to pay, what the consumers might demand and what a judge potentially deems fair taking a variety of dimensions into account.

In this paper, we document how much users value their Facebook, Instagram, and Twitter data through incentive compatible, revealed preference experiments. We then randomly provide information about the payouts to users by Facebook in a recent data breach settlement to understand whether these valuations across users can converge to an equilibrium. Finally, we vary the timing of the payment and when users might have to upload their data, we analyze the trade-off between a heightened privacy prompt and potential present bias to monetary payments.

We have three sets of main findings. First, users value their Facebook and Instagram data 20% more than their Twitter data. The median Willingness to Accept (WTA) is \$300 for both Facebook and Instagram while it is \$ 250 for Twitter. There is substantial heterogeneity in this value based on income as well as intensity of the usage of the platform.

Next, we provide information related to the value of data based on a legal settlement by Facebook. We randomly vary the value that respondents are shown with these being \$10, \$50, \$200, \$400 and \$1000. It is important to note that under the legal settlement, these values were plausible and could have been a realization based on the number of people who claimed it. Hence, it is the reaction to real information that we are studying. We find that these information frictions matter with respondents updating their WTA for Facebook data based on the information. This revision of their WTA is asymmetric with individuals willing to revise their estimates up significantly more than revising

them down.

Finally, we demonstrate that asking respondents to upload their data immediately makes them increase their data valuation relative to a context where we mention a later date. This is driven primarily by the fact that we make the decision to part with sensitive data more salient. This effect counteracts a potential “present bias” in their decisions. In these treatments we also vary the fact that the payment is made only once the data is uploaded. Hence, a behavioral bias such as the present bias would make individuals lower their WTA since they don’t have to wait to get the payment. We show that the saliency effect dominates the potential present bias.

This study contributes to several strands of the academic literature. First, we contribute to the literature on the digital privacy paradox. Athey et al. (2017) show that while individuals state that data privacy is important to them, they are willing to divulge their email addresses and friends’ details in exchange for small amounts of money or even a slice of pizza. Acquisti et al. (2013) analyze preferences of individuals to keep their transactions in a store anonymous. Lin (2020) analyzes the WTA of individuals for different demographic variables with household income and information on children being the variables with the highest WTA while gender has the lowest WTA. Relative to these studies, we contribute to the literature by focusing on the value of data which has been central to managerial strategy and policy discussion: consumer data from the biggest social media platforms in the world. We ask individuals to put a value on the entire stock of data to find significantly higher values. Benndorf and Normann (2018) is the paper which comes closest to ours since they look at the WTA for college students to divulge their

Facebook contacts and timeline details. They find a WTA of 19 Euros which is significantly smaller than ours. This is exactly because we ask for a lot of more data including sensitive information related to private messages. This points to a broader point about the literature finding low values because they don't consider the more sensitive information even though such information is also provided to data brokers to sell.

Second, our results are also related to the literature which attempt to provide information treatments to reduce frictions and make individuals take more informed decisions in a variety of contexts ranging from digital privacy to consumer finance. Adjerid et al. (2013) show how different framings and contexts impact an individual's privacy valuations. This point is re-affirmed in the overview of the digital privacy literature by Acquisti et al. (2015). This also implies that such a setting could provide a large payoff to information campaigns by policy makers and advocates. Our results which show that consumers revise their valuations upwards is encouraging in that these valuations are not sticky and can converge to a potential equilibrium value conditional on the reduction in information frictions. This is more broadly related to studies which provide financial information to consumers so that they can make better daily financial decisions (Beshears et al., 2009).

Finally, we design interventions to understand the interaction of a potential present bias with a heightened of privacy is related to behavioral explanations of the privacy paradox (Svirsky, 2019). A behavioral bias arising from time discounting has been explored theoretically by Acquisti (2004). In our experiments, we use a horse-race between heightened privacy and present bias to show that a present bias can be mitigated by priming users about the sensitive

nature of their data. Such interventions can serve as an additional tool to nudge individuals to value their data more.

2 Survey and Experimental Design

We run incentive compatible choice experiments to solicit consumers' willingness to accept (WTA) to give up their data on three major social media platforms: Facebook, Instagram and Twitter. To do so, we recruit 2,500 US based respondents from Prolific² who use each of these platforms at least once a month.

WTA valuations are obtained through a Becker–DeGroot–Marschak (BDM) mechanism (Becker et al., 1964). Respondents are asked to reveal their minimum willingness to accept payments to upload their data from these platforms. To make responses incentive compatible, 1 in 200 respondents are randomly selected to take part in a BDM lottery where a random payment is drawn from a uniform distribution (Ding, 2007; Carson et al., 2014). If the randomly generated payment is greater than the minimum WTA entered by the respondent, they are asked to upload their data in exchange for the randomly generated payment. Each of these platforms offers an easy way to download a copy of users' data.³ If the randomly generated payment is less than the minimum WTA, then the selected respondents do not receive any payment and they

²Prolific (www.prolific.co) is a crowdsourcing platform to hire crowdworkers.

³For Facebook, this data includes posts, photos, messages, likes and comments (<https://www.facebook.com/help/212802592074644>). For Instagram, this data includes photos, direct messages, likes and comments (<https://www.facebook.com/help/instagram/181231772500920>). For Twitter, this data includes tweets, retweets, likes and direct messages (<https://help.twitter.com/en/managing-your-account/accessing-your-twitter-data>).

do not have to upload their data. To mitigate privacy concerns, respondents are told that any personally identifiable data from their uploaded files will be permanently deleted and privacy will be maintained in any published research.

In addition to valuation questions, we obtain demographic information and information related to platform usage. To investigate the impact of present bias on data valuations, we vary the time period after which selected subjects will be contacted to upload their data in exchange for monetary rewards. We randomly assign subjects to one of four time period conditions: immediately, one week, two weeks and one month. To investigate the impact of informing subjects about possible data valuations based on historic legal settlements, we consider the case of Facebook and provide subjects an option to revise their valuations after receiving an informational treatment. More specifically, subjects are informed that Facebook settled a class action lawsuit and agreed to pay a certain amount to every affected user for harvesting user data and violating privacy laws.⁴ Subjects are randomized into one of five settlement amount conditions: \$10, \$50, \$200, \$400 and \$1,000. After providing with this informational treatment, subjects can choose to change their response to their valuation question and provide a new valuation.

⁴We cite the example of a class action lawsuit settlement against in Illinois where Facebook agreed to pay \$550 Million to affected users (<https://www.nytimes.com/2020/01/29/technology/facebook-privacy-lawsuit-earnings.html>).

3 Pilot Results

3.1 Baseline Valuations

First, we present the baseline valuations for each of the platforms. We present median valuations following Brynjolfsson et al. (2019), which allow us to minimize the impact of outlier valuations. In particular, there could be a small fraction of individuals who would not provide their data to researchers at any price. This can impact the mean estimate and provide a skewed view of the valuations. Indeed, we do see that individuals in the 95th percentile of valuations put a value on their data of \$ 1 million. In presenting our median valuations, standard error estimates are heteroskedasticity robust as discussed in Greene (2002) and we plot 95% confidence intervals in all figures. The median WTA for Facebook and Instagram is \$300, \$50 larger than the median for Twitter although the valuations are statistically indistinguishable (Figure 1). This 20% differential between Twitter and Facebook as well as Instagram valuations can simply be explained by the sensitivity of the data involved. Facebook and Instagram involve pictures and posts which are often personal as opposed to Twitter which is by default very public.

During the survey, we collected background demographic and usage information to study heterogeneity in valuations. We discuss differences in the point estimates of median valuations by platform usage, race, income, and political views. Given the sample size in this pilot, the dimensions of heterogeneity we explore do not have sufficient power statistically distinguish between the point estimates. In what follows, we focus on the direction of the magnitudes rather than statistical differences.

The estimates of the median WTA decline with platform usage (Figure 2). The decline is concentrated in users who spend more than an hour per day on the platform. While this may seem counter-intuitive at first, it is in line with the belief that more intensive users might believe that their “data is already” out there online. Since digital data is partially non-rival and non-excludable, it is likely an explanation. Moreover, in some post-survey responses users did seem to imply this while justifying their valuations.

Median valuations for Black or African American subjects are \$50 lower than for any other group as can be seen in Figure 3. Similarly, the median valuations for subjects with income less than \$50,000 are also \$50 lower than for subjects with incomes above \$50,000 (Figure 4). There is, of course, some correlation between race and income, hence it is reassuring to see that the results seem consistent. Finally, we also find that conservative leaning subjects had a median valuation that was \$50 less than moderate or liberal leaning subjects (Figure 5).

Putting these values in the context of the prior literature, and we see our estimates significantly exceed many existing studies (Benndorf and Normann, 2018; Lin, 2020). Existing work has focused on less sensitive data and less data quantity, so the nature of the data we are asking about and the amount of data lead to valuations that are roughly an order of magnitude higher.

Figure 1: Median WTA by platform

(a) Median WTA by Usage

(b) Platform Specific Median WTA by Usage

Figure 2: Heterogeneity by Usage

(a) Median WTA by Race

(b) Platform Specific Median WTA by Race

Figure 3: Heterogeneity by Race

(a) Median WTA by Income

(b) Platform Specific Median WTA by Income

Figure 4: Heterogeneity by Income

(a) Median WTA by Political Views

(b) Platform Specific Median WTA by Political Views

Figure 5: Heterogeneity by Political Views

3.2 Information Intervention

Despite these relatively high baseline valuations, we find evidence of information frictions with consumers revising their valuations higher after learning about past Facebook settlements. A natural follow up question is to understand whether these valuations are sticky or not. If they can be revised based on information provision then going forward, we could arrive at consensus data valuations between the users, the technology firms and policy makers. Moreover, since we find heterogeneity in valuations across demographic groups, it is plausible that such interventions could close a potential inequality in valuations. Hence, to test this we carry out information interventions based on data values we got from a Facebook settlement with users due to a data security breach. In these interventions, we only look at how individuals revise their Facebook data valuations since the lawsuit only featured Facebook.

In the interventions, subjects were randomly shown a Facebook settlement amount ranging from \$10 to \$1,000 and were given the opportunity to revise their Facebook WTA. Figure 6 plots the probability of revising their WTA conditional on the treatment amount. We see that subjects are much more likely to revise their WTA when told about a large settlement than a small settlement. Nearly all revisions are positive, and only 2.5% of respondents revised their WTA lower.

The median revision amount, conditional on revising, is also monotonically increasing in the settlement amount (Figure 7), with the median subject who revised their treatment in the \$1,000 settlement treatment increasing their WTA upward by \$500. Those who revised their WTA had much lower initial

Figure 6: Probability of Revising

WTAs (median of \$55) relative to those who did not revise (median of \$700).

These results are consistent with the hypothesis that a lack of information on the value of consumers' data leads to consumers undervaluing their privacy. The cost of selling one's data is highly uncertain, and we find that consumers respond to suggestions that their data may be worth a substantial amount of money. Moreover, we find that larger settlement amount treatment groups disproportionately impact groups with low baseline valuations, such as those with lower incomes (Figure 8). This provides suggestive evidence that information frictions may contribute to low baseline privacy valuations in addition to inequality in valuations across demographic groups of interest.

Figure 7: Median Revision Amount

3.3 Time Preferences

Finally, in this section we also test for possible behavioral biases in users' valuation decisions. In particular, we test for whether there might be a present bias in these decisions. This is motivated by Acquisti (2004), who suggested that low revealed preference valuations for privacy could be a result of present focused consumers.

In the choice experiments, we also cross-randomized the timing of the follow-up transaction, and found that valuations were substantially higher if the transaction were to occur immediately relative to in the future (Figure 9). As can be seen, this holds for each of the platforms and the difference is statistically significant since we don't see an overlap in confidence intervals.

If consumers were present focused with quasi hyperbolic preferences, we

(a) Revised WTA by Income

(b) Revised WTA by Race

Figure 8: Heterogeneity in Revised WTA

would expect the immediate valuations to be lower than the future valuations. The cost of giving up one's data will be distributed over time and the future is discounted by an additional present bias term relative to the present. Therefore, less compensation would be required immediately in this setting relative to a future transaction.

This intuition can also be seen in a stylized model, where utility over a known stream of income $M = (m_0, m_1, \dots)$ and costs $C = (c_0, c_1, \dots)$ is

$$u(M, C) = m_0 - c_0 + \beta \sum_{t=1}^{\infty} \delta^t (m_t - c_t)$$

with $\beta \leq 1$ and $\delta < 1$. Suppose for simplicity the transaction occurs at date 0 or date 1, costs are constant starting the date of the transaction (i.e. $C^0 = (c, c, \dots)$ and $C^1 = (0, c, c, \dots)$), and consumers were offered a one time payment for their data as in our experiment. Then, if the transaction were to occur at date 0, the break even WTA would be given by

$$m^0 = c + \beta \frac{\delta c}{1 - \delta}$$

while if the transaction were to occur at date 1, the break even WTA would be given by

$$m^1 = \frac{c}{1 - \delta}$$

Comparing the two, we find

$$m^0 - m^1 = \frac{(1 - \delta)c + \beta \delta c - c}{1 - \delta} = \frac{\delta(\beta - 1)c}{1 - \delta} \leq 0$$

Given our experimental results where $m^0 > m^1$, it seems to reject the above model. The immediate transaction seems to make privacy more salient, increasing valuations and dominating any potential present bias effects. This is predicated on $\beta \leq 1$. If $\beta > 1$, the model would be consistent with our experimental results, but this would contradict a long line of behavioral economics literature finding present biased consumers. We find it more plausible that the salience of an immediate transaction alters the perceived costs of selling one's data.

(a) Median WTA by Transaction Time

(b) Median WTA by Transaction Time

Figure 9: Heterogeneity by Usage

4 Conclusion

We provide evidence that consumers' valuations for the entirety of their social media data are quite substantial, with the median valuation for a single platform at \$300. Despite these large baseline valuations, we find evidence that consumers do respond to interventions giving consumers a signal about the value of their data from previous settlements. Specifically, we find that consumers revise their valuations upwards towards the settlement amount, with large settlements reducing much of the observed heterogeneity in baseline valuations. Finally, we investigate how time preferences may impact privacy valuations. Our data reject a simple model of present bias, as selling one's data immediately may alter perceived costs due to the salience of privacy.

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