Information Frictions and Heterogeneity in Valuations of Social Media Data

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Abstract

We investigate how consumer valuations of personal data are affected by real world information interventions. Proposals to compensate users for the information they disclose to online services have been advanced in both research and policy circles. These proposals may be hampered by information frictions that limit consumers' ability to assess the value of their own data. We use an incentive-compatible mechanism to capture consumers' willingness to share their social media data for monetary compensation and estimate distributions of valuations before and after an information treatment. We find evidence of significant dispersion and heterogeneity in valuations before the information intervention, with women, Black, and low income individuals reporting systematically lower valuations than other groups. In both samples, the provision of information leads to a reduction in dispersion in data valuations. The reduction takes the form of increasing valuations by low-valuation individuals. We interpret these results through a theoretical framework that combines beliefs, instrumental, and intrinsic motivations for valuing data. The findings suggest that strategies aimed at increasing information availability in markets for personal data may affect consumer welfare gains from data markets.

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1 Introduction

Personal data generates significant value for digital platforms as a source of revenue or as an input facilitating algorithmic targeting (Elsaify and Hasan, 2020). To address concerns over the potentially unequal allocation of value between data holders (the platforms) and data subjects (the users/ consumers), proposals to share data-based revenues with consumers have emerged in both policy and academic circles. Gavin Newsom, the Governor of California, has proposed data "dividends" to compensate consumers who create online footprints (Ulloa, 2019; Au-Yeung, 2019). Academics have argued that users' online data should be viewed as "labor" and compensated accordingly (Arrieta-Ibarra et al., 2018). A growing number of startups are setting up mechanisms to pay users for their online data (e.g. Permission.io, YouGov), and some scholars and policymakers have proposed setting up personal data markets with data intermediaries that have fiduciary duties (Seim et al., 2022).

Starting with Kenneth Laudon, who suggested in 1996 the establishment of "national information markets" through which consumers could trade rights over the usage of their data (Laudon, 1996), personal data markets have been proposed as mechanisms to ensure fair allocation of the value of data between platforms and users. In data markets, consumers provide companies access to their data through various selling mechanisms, including negotiated prices (Spiekermann et al., 2015; Yang, 2022; Seim et al., 2022). The design of frameworks for data markets or data dividends, however, faces challenges arising from information frictions. Whereas platforms can typically quantify the value they can accrue from user data, users face a more significant hurdle in pinpointing the value of data to *themselves*. Empirical research on consumer valuation of data and data privacy across disciplines has highlighted that individuals' valuations of personal information are highly uncertain and marred by endemic problems of asymmetric information (Acquisti et al., 2016; Tomaino et al., 2023). Not only do consumers rarely know how their data is used, but they often lack information on the value that other entities extract from it (Shiller, 2021), or the costs they may ultimately incur when their data is misused. Thus, when interacting with platforms, consumers may be uninformed and may fail to extract optimal levels of surplus from those markets. Unlike established markets for traditional goods (such as cars or shares of a company), where consumers have access to a plethora of information, markets for personal data are nascent, with limited market information. In such markets, consumers incur costs to learn about their own preferences (Cao and Zhang, 2021).

Whether those information frictions can be offset with information treatments (such as making consumers better aware of the value that others extract from their data, or the costs that may accrue when their data are compromised) is an open question. We use a data market setting and an incentive compatible mechanism in a mixed between- and within-subjects experiment to estimate participants' willingness to share personal data for monetary compensation (their Willingness to Accept, or WTA) before and after an information treatment. We focus on social media data, and capture the distribution of compensation participants require to share their Facebook profile data. Facebook data serves as a useful setting for us because these data are used by the platform to target ads. Moreover, there have been concerns over the past decade about the use of sensitive non-public Facebook data including photos as part of ads on the platform. [1] Social media data is also becoming increasingly important in the age of LLMs for training models. Meta uses Facebook data for training its AI agents including the most widely used open-source LLM Llama.

We randomly assign participants to one of two information treatments, each providing participants with information from real-world transactions involving users' social media data. We focus on scenarios that have become central to the debate over data payments and data privacy (Seim et al., 2022): the value companies extract from utilizing user data and the compensation users may receive from data holders when their data is abused. In each case, we theorize that exposure to market information may reduce value uncertainty regarding personal data, and thus affect participants' own valuations of their data. We are interested in whether, and how, valuations of personal data are affected by interventions that reduce consumers' information asymmetry by presenting them with data points based on real-world transactions involving personal information. We gather our theoretical insights into a simple model which provides a lens through which we view our empirical results.

For our primary empirical study, we recruit experimental participants from a representative sample of U.S. internet users recruited in collaboration with YouGov (YouGov sample). We augment our analysis with an additional experiment conducted on members of the Data Dividend Project (DDP), a data advocacy group started by former Democratic presidential candidate Andrew Yang (DDP sample). Members of the DDP are interested in ensuring that technology companies share a part of their revenue when they monetize data and are more likely to believe in digital privacy as a fundamental right (Yang, 2020). They are expected to be, on average, more data- and privacy-conscious

[1] See https://mashable.com/archive/facebook-ads-photo and https://www.theverge.com/2018/11/15/18096724/facebook-photo-family-demographics-data-mining-patent-application as examples.

than the representative sample. The two samples allow us to compare whether and how information treatments differentially affect individuals who are likely heterogeneous in their fundamental views on personal data.

Our analysis focuses on capturing changes in the *distribution* of data valuations before vs. after information treatments and differences in those distributions across demographic groups. We do not focus on pinpointing individual ground-truth valuations of data, since prior work has firmly established that personal data valuations are context dependent (Xu and Zhang, 2022; Acquisti et al., 2016). Before the information treatment, we find evidence of significant dispersion and heterogeneity in valuations in both samples, with White users valuing their data more than Black users, male users valuing their data more than female users and higher income users valuing their data more than lower-income users.[2]

After eliciting baseline valuations, we implement information treatments by randomly providing each individual with details either about Facebook revenue or the amount of payout following a recent legal settlement involving data misuse by Facebook. Following the information treatments, nearly one-third of participants in both samples revise their data valuations. In both treatments, we use the same $400 valuation so that we can isolate the impact of the scenarios and not the particular dollar value mentioned. The probability of revision is highly asymmetric, with individuals with a WTA<$400 (below the dollar amount mentioned in the treatment) driving the effect with a 53% probability of revision. Furthermore, 98.2% of individuals who update their valuations do so by revising up to a higher valuation.

Our analysis of the mechanism for these results suggests that, in both samples, the provision of information reduces dispersion by reducing uncertainty around valuations. The reduction takes the form of increasing valuations by low-valuation individuals—in which women, low income, and Black participants are over-represented.[3] This implies that, by revealed preference, certain groups of online users may be more likely than others to benefit from informational interventions. Additionally, text analysis of open-ended responses and a follow up experiment demonstrates that individuals' uncertainty around valuations reduced as a result of the information interventions. Taken together, both the ex-ante distributions of valuations and the ex-post variations suggest that information

[2] These differences persist after controlling for education, income, privacy beliefs, and Facebook usage itself, suggesting that certain demographic groups appear to value their data less relative to others.

[3] In our experiment, participants with low valuations and high probability of revisions belong to groups that are traditionally associated with lower levels of digital literacy (Martin and Robinson, 2007).

frictions related to privacy could partially explain low personal data valuations in the literature (Athey et al., 2017).

This study contributes to a few strands of the academic literature. First, in the field of information systems, there have been recent studies analyzing the value of data and privacy. From a firm's perspective, Sun et al. (2024) directly quantifies the value of data by running a large-scale experiment that experimentally switches personal data on or off in the recommendation system of a large e-commerce platform. Sun et al. (2024) finds that switching off personal data leads to a significant decline in customer engagement and platform transactions, with the effect more pronounced for niche merchants and customers. Leveraging the same experiment, Yuan et al. (2025) documents the substitutability between recommendation systems and search channels on e-commerce platforms. Huang et al. (2021) explores the value of additional data that online shopping platforms have on users if they already register for an account before engaging in shopping behavior. Huang et al. (2021) finds that ex-ante registrations lead to more purchases by consumers and increased revenue for the platforms. Burtch et al. (2015) documents the cost of increased privacy on crowdfunding platforms when funders can conceal their identity and contribution amounts. Burtch et al. (2015) finds that this leads to a decrease in the average contribution amount. While these papers show that data is valuable from the firms' perspective, what is missing from this literature is the value of data from the users' perspective. From the users' perspective, Goh et al. (2015) documents externalities in privacy in the context of Do Not Call registries. Goh et al. (2015) finds evidence of positive externalities in this context, where early adopters cause later adopters to sign up. However, what is missing from this literature is the value users' assign to their data and how these valuations are influenced by information frictions, which is the focus of our current study.

In our study, we contribute to the literature on economic valuations of personal data and online privacy from the users' perspective. Over the years, several studies have investigated both individuals' willingness to pay to protect personal information (WTP; for instance, Beresford et al. (2012)), and individuals' willingness to accept payments to share it (WTA; for instance, Danezis et al. (2005) and Hui et al. (2007)). Recent work has started disentangling the extent to which preferences for privacy are influenced by "intrinsic" (subjective) versus "instrumental" (more quantifiable and objective) factors (Lin, 2022). Our paper differentiates from these studies by focusing on information frictions as a key factor impacting data valuations, and by analyzing whether information provision can reduce the dispersion in data valuations. Moreover, we focus on and provide clear regularities in systematically lower valuations by certain demographic groups.

Our results are also related to the literature that attempts to provide information treatments to increase awareness and make individuals take more informed decisions in a variety of contexts including political information (Henry et al., 2022), financial information (Beshears et al., 2009) and privacy related information and it's impact on consumer behavior (Beke et al., 2018; Adjerid et al., 2013; Tsai et al., 2011). This literature, together with our results, suggests that there could be a large payoff to information campaigns by policymakers and data advocates.

2 Conceptual Framework

Here we introduce an analytical model of users' valuations for their data. Consumers, indexed by i, form valuations for their personal data v_i as follows

$$v_{it} = \alpha_i + \beta_i \tilde{m}_{it} + \varepsilon_{it} \tag{1}$$

where α_i is consumer i's baseline value of their data irrespective of monetary concerns, $\tilde{m}_{it}$ is consumer i's subjective belief about the monetary value of their data at time $t \in \{0, 1\}$, β_i captures the sensitivity of consumer i's valuation to their perceived monetary value of their data, and ε_{it} is a mean-zero preference shock (or reporting noise). This model of data valuations can be interpreted as a combination of intrinsic preferences for data (α_i) and instrumental preferences for sharing data ($\beta_i \tilde{m}_{it}$).

We will interpret our study through the lens of this simple model. The information treatments we provide may influence participant beliefs about the monetary value of their data causing participants to update valuations in response to the information.

Proposition 1. *Individuals systematically revise their valuations in response to the information treatments if and only if they revise their beliefs about the monetary value of their data and have some instrumental preference for sharing data. Formally,* $E[v_{i1}] \neq E[v_{i0}]$ *if and only if* $\beta_i \neq 0$ *and* $E[\tilde{m}_{i1}] \neq E[\tilde{m}_{i0}]$.

Proof. This proposition follows immediately from the assumption that $E[\varepsilon_{it}] = 0$ which implies that

$E\left[v_{i1} - v_{i0}\right] = \beta_i \left(E\left[\tilde{m}_{i1}\right] - E\left[\tilde{m}_{i0}\right]\right).$ □

Remark 1. In this model, for a participant to systematically revise their valuation in response to the information treatment (i.e. not due to changes in ε_{it}) then they must (1) update their beliefs about the monetary value of their data and (2) have some instrumental preferences over sharing data (i.e. $\beta_i \neq 0$). This provides a straightforward interpretation of individuals who systematically revise their valuations in response to the information treatments. For these individuals, instrumental preferences over sharing data represent an important component of data valuations.

Remark 2. Interpreting individuals who do not systematically revise their valuations in response to the information treatments is more nuanced. These individuals could either not revise their valuation because their intrinsic preference over data sharing dominate their instrumental preference or because they do not update their beliefs about the monetary value of their data in response to the information treatment. Directly eliciting $\tilde{m}_{it}$ allows us to disentangle these two potential channels.

3 Experimental Design

We conduct a pre-registered incentive-compatible online experiment in which we solicit consumers' willingness to accept (WTA) monetary compensation to share their Facebook data.[4] For our main experiment, we partner with YouGov and recruit from its probability sample of adult respondents based in the USA (YouGov sample). Unlike other commonly used online panels, which are opt-in (e.g., Amazon MTurk), YouGov adopts a probability sampling approach where they randomly reach out to a representative sample of the US population and invite them to participate in their panel in exchange for monetary compensation. YouGov selects respondents for our study so that they are representative of the US Internet population in terms of age, gender, region, race, and education based on the US Census Current Population Survey (2018).[5] This is one of the highest quality samples that can be obtained to collect data on a truly representative sample of the US population (Mercer et al., 2017). Verified demographic data of participants are collected directly from YouGov and shared with us. Participants were required to have a Facebook account to participate in the

[4] Preregistration in the American Economic Association Registry for randomized control trials (RCT ID: [Blinded for peer review])

[5] While our sample is representative on observables, as is common in studies involving human participants, we cannot rule out selection on unobservables. That said, selection on unobservables does not influence the internal validity of our results.

study. Facebook membership and usage are verified and were provided directly by YouGov to us.

Participants are provided a link to access an online survey. Respondents' WTA valuations are captured using a Becker–DeGroot–Marschak (BDM) mechanism (Becker et al., 1964). BDM mechanisms are common in recent literature estimating the value of online services (Allcott et al., 2020; Brynjolfsson et al., 2019; Mamadehussene and Sguera, 2023). Respondents are asked for the minimum amount of money they would require to share the entirety of their Facebook data with the researchers. Our approach to measuring WTA in dollars is consistent with a recent study by Tomaino et al. (2023) that shows that individuals understand data values better in dollars than in return for a product like in a barter system. The data include posts, photos, private messages, likes, and comments (See Figure A.7 in the Appendix). Facebook offers a simple way to download a copy of a user's data, and the process is explained to the participants (Facebook, 2021b). To make responses incentive-compatible, we explain the BDM mechanism to participants and test their comprehension of the mechanism to ensure that everyone understands it before proceeding to the rest of the study. Participants are informed that a random payment will be generated at the end of the study, and if the random generated payment is greater than the minimum WTA entered by the respondent, the participant will be asked to upload their data in exchange for the payment. Participants who incorrectly answer comprehension questions that test their understanding of the BDM mechanism are screened out. To avoid deception, we inform participants that the data will be used for research purposes.

After baseline valuations are elicited, participants are randomly assigned to one of two information treatments: the revenue treatment or settlement treatment (Figures A.8 and A.9). Across treatments, the monetary amount associated with the value of a Facebook's user data is held constant. In the revenue treatment, participants are informed that Facebook is expected to earn around $400 per North American user in the next three years. This information is based on Facebook's 10-K filings in January 2021 (Facebook, 2021a). This treatment is motivated by provisions in the draft regulations of the new California Consumer Privacy Act which stipulate that businesses should provide consumers with good-faith estimates of the value of consumer's data. New companies in the data market space (eg. mePrism) use similar metrics to encourage individuals to get paid for their personal data, as seen in Figure A.1 in the Online Appendix. In the settlement treatment, participants are informed that each affected Facebook user in a 2020 Facebook data settlement was paid $400. This information is based on a lawsuit that was settled by Facebook in Illinois (Sun-Times Staff, 2020). This treatment is based on growing number of privacy class action cases that attempt to indemnify users for misuses of their data. For both treatments, we provide a link to the source of the information in case an individual wants to access more details. We focus on a revenue frame, and a data misuse frame as those two dimensions have become salient in public and academic discourses around data and privacy (Elsaify and Hasan, 2020; Feygin et al., 2021). Both policy makers and managers emphasize these two dimensions in different contexts. Moreover, similar to the methodology and approach in Hjort et al. (2021), we use these treatments as one way to assess whether real-world information impacts user valuations. Although our information treatments are accurate summaries of true information, we are careful to not tell users that this is what their data are exactly worth to Facebook or precisely reflective of the costs if their data are used improperly.

Following the information treatment, we allow participants to revise their valuations. These revised valuations are considered for the BDM lottery, and hence are incentive compatible. We also ask participants to explain why they revised their valuations or why they did not revise their valuations, in a mandatory open-ended text box. Then, we ask endline questions related to how intensively individuals use Facebook on a daily basis, and participants' views about data privacy. Finally, participants are entered in the BDM lottery. If the random payment is greater than the minimum WTA entered by the participant, the participant is asked to upload their data in exchange for the random payment. Participants receive their payment if and only if they upload their Facebook data. We verify that uploaded files are authentic by checking their metadata (directory names, sizes, and formats). If the random payment is less than the minimum WTA, the selected respondents do not receive any payment and do not upload their data. Participants are unaware of the payment distribution, in line with best practices for BDM research (Allcott et al., 2020). Prior research shows that explicitly stating the distribution of payments can bias valuations in a BDM study (Bohm et al., 1997; Mazar et al., 2014). Details of our BDM elicitation mechanism are described in the Appendix (see Appendix C.1). We further ensure that this dimension of experimental design does not drive our results by carrying out several additional studies that test the robustness of our results to various alternate dimensions of experimental design (see Section 4.1).

4 Baseline Results

The study was completed by 4,149 participants from the YouGov sample in June-July 2021 (these respondents passed the comprehension tests and provided both baseline and revised valuations).[6] We show covariates for the YouGov sample (as well as the DDP sample) in Table A.1. Roughly half of respondents use Facebook less than 30 minutes per day; the average account was created in 2009.

We plot the distribution of baseline valuations in Figure 1. Valuations are highly dispersed. In fact, with these dispersed valuations, there is bunching of WTA at low dollar values (less than $250) and at very high values (at least $10,000). For ease of representation, we truncate valuations at $10,000 in the histogram (at the 75th percentile). We plot the CDF of valuations in the bottom panel of Figure 1 (median WTA is $750). The spikes in the distribution take place around whole numbers (e.g., $1,000, $5,000 etc), suggesting that users utilize heuristics while attempting to determine an otherwise highly uncertain value. The figure demonstrates how focusing on a single summary statistic, as much of the prior work has done, hides substantial heterogeneity in valuations. We interpret extremely high valuations as an expression of the respondents' unwillingness to part with their data. Moreover, all respondents in the sample passed the BDM comprehension questions; hence, they knew that an extremely large WTA makes it unlikely that they would have to upload their data.[7]

Valuations are also highly heterogeneous across race, gender, and income. Figure 2 shows the CDF of valuations for White and Black (and also Hispanic) individuals indicating a stark racial divide (see Figure A.4 for additional race and ethnicities).[8] Black Facebook users value their data significantly less than White users, as the distribution of valuations for White respondents first-order stochastically dominates that of Black respondents (median WTA for a White user is $1,000, whereas it is $500 for a Black user). Women value their data less than men (Figure 2), as the WTA of male respondents first order stochastically dominates the distribution of WTA of female respondents (median valuation for female respondents of $558 relative to $1,000 for men). The differences in valuations across genders are still muted relative to differences based on race. While descriptive

[6] We discuss results from the DDP sample and how they compare to the YouGov sample in Section 6.

[7] That 14 of the 18 participants (approximately 80%) selected to upload their Facebook data based on the BDM lottery uploaded their data and subsequently received payments (totaling over $2,000) reinforces this point. In this sample of uploads, we observe individuals making their private messages and pictures available. Given the small size of this sample, we do not carry out further heterogeneity analysis based on the size of the files across different data dimensions.

[8] At any dollar value on the horizontal axis, the distribution plots the share of people with valuations less than that dollar value. This implies that a CDF shifted towards the right will have higher valuations associated with it.

in nature, this is among the first results about user data values in the literature across race and gender. To test whether race and gender differences are driven by income, education, or patterns in Facebook usage, we analyze the logarithm of the valuations within a regression framework in Table 1. In these regressions, we consider both Black and Hispanic participants when analyzing how valuations vary by race. As can be seen, the descriptive results hold in univariate regressions for gender (column (1)), race (column (2) and (3)), gender and race together in column (4). We find that racial and gender differences persist after adjusting for income, education, age, as well as Facebook usage and privacy beliefs, in column (5). While a variety of factors could influence *individual* valuations, these results suggest that systematic regularities persist across demographic groups even after controlling relevant observables, including intensity of daily Facebook usage. In addition, column (4) highlights that valuations are negatively correlated with Facebook usage. This is consistent with privacy conscious individuals spending less time online. Appendix H considers additional interactions between Facebook usage and demographic variables.

We also look at differences in valuations by income (Figure 3). The differences are stark: individuals in higher income groups value their data significantly more. Interestingly, individuals who decide not to disclose their income are the ones who value their data the most across all income groups, consistent with the interpretation that these individuals are very high income individuals and/or value their income data and do not want to disclose it. The lower data values for under-represented groups suggest that such individual level data dividends could further exacerbate existing inequalities.

While we do not focus on point-wise estimates in our analysis, we examine the plausibility of our baseline valuations in the context of the literature. We focus on the median valuation ($750) to account for outliers. This valuation corresponds to the entire "stock" of an individual's Facebook data.[9] The median respondent in our sample has been using Facebook for 12 years, since 2009. This leads to a median value of $73 per year and a monthly valuation of $6.1 per month for their data. Our estimates exceed those in existing studies (Prince and Wallsten, 2022; Benndorf and Normann, 2018; Lin, 2022). Relative to Lin (2022) and Benndorf and Normann (2018), the data we asked for is larger in quantity as well as sensitivity (because it consists of participants' entire Facebook data, including personal messages, since they first created the account). Prince and Wallsten (2022) find, within a

[9] In a pilot study, we analyzed the WTA for the entire stock of Facebook, Instagram, and Twitter data. The median valuations for Facebook and Instagram were higher than Twitter, potentially due to more personal information being available on Facebook and Instagram.

hypothetical setting, that the average US respondent has a WTA of $5 per month to let Facebook share information from texts sent using Facebook Messenger. In contrast, our incentive compatible setting presents participants with an actual possibility of having to share all their Facebook data, likely leading to sightly higher (and potentially more realistic) valuations. This exercise provides us with more confidence in the external validity of our estimates and approach. Our median baseline valuations seem to fall within a reasonable range relative to the existing literature.

4.1 Robustness of baseline valuations: Alternative Experimental Designs

Here, we summarize several follow-up experiments where we test the robustness of our experimental design. These experiments were conducted on a sample of Facebook users recruited from CloudResearch's MTurk Toolkit.[10] This panel consists of a selected sample of respondents from Amazon Mechanical Turk respondents who are known for providing high-quality responses.

We first show that the baseline results are robust to varying the distribution of payment in BDM and varying whether we disclose the distribution to participants (Table A.3). Second, we demonstrate that the valuation we elicit are very similar if we use a simpler, but less powered, take-it-or-leave-it mechanism (Figure A.11). Our results are not sensitive to the elicitation mechanism. Third, we demonstrate that our results are not sensitive the stated use of the data consistent with Buckman et al. (2019) (Table A.4). Finally, we demonstrate that individuals place a non-trivial probability of receiving an offer (Appendix C.3). This is true across the valuation distribution (Figure A.12), which implies truthful reporting is a dominant strategy.

5 Information Treatments and Updating Behavior

5.1 Treatment Effects

In this section, we present aggregate results across the two information treatments in the YouGov sample. A randomization check (Table A.5) and balance tests (Table A.6) provide evidence that the randomization worked as expected.

Figure 4 shows that individuals revise their valuations in response to the information interventions—but do so asymmetrically.[11] As a reminder, the dollar amount mentioned in both the settlement and

[10] https://www.cloudresearch.com/products/turkprime-mturk-toolkit/

[11] Figure A.3 plots the joint distribution between baseline and revised valuations.

the revenue treatment is \$400.[12] Most participants who revise have baseline WTAs lower than \$400. At higher baseline valuations, there is no difference between the baseline WTA and revised WTA. This holds even when extending the distribution to \$10,000 (see Figure A.2). Focusing on the individuals who revise and have baseline WTA less than \$400, we note that 98.2% revise their valuations upwards. This makes the overall distribution of the revised valuations less dispersed than the distribution of the initial baseline valuations. In particular, after the treatments, the proportion of individuals with a WTA of \$400 or more increases from 60.9% to 70.1%. The share of participants whose valuations were exactly \$400 increases from about 1% to 7.3% post-treatment.

We find that women are more likely to update their valuations in response to the information treatment than men (column (3), Table 2). Similarly, Black respondents are more likely to update their valuations than White. To get a sense of the magnitudes, we also use a Logistic regression in column (4). These estimates imply that women revise 28% more than men (exp(0.249)) and Black participants revise 26% more (exp (0.238)).[13] The effect is similar for low vs. high income, measured at the \$50K annual income threshold, with low income individuals more likely to revise. Additional heterogeneity is explored in Appendix H. These results suggest that information treatments can lead individuals to reassess their valuations, and that providing actual market information can reduce dispersion and heterogeneity in valuations. Given that disadvantaged groups respond significantly more to these interventions, we conclude that information frictions play a role in individuals from these groups' ability to value their own data.[14]

Although the information treatments increase the valuations of marginalized groups, dispersion and heterogeneity in valuations persist ex post. Objective information alone does not eliminate differences in valuations. This suggests that data valuations might comprise both objective factors (including, for instance, market information about transactions involving personal data) and subjective factors (e.g., views on privacy). To examine this further, we analyze how an individual's baseline valuation and propensity to revise varies with their self-reported beliefs about privacy being a fundamental human right and the ability of the free market to value data correctly.[15] We code each

[12] In a pilot study, we found that different dollar values associated with the information treatments lead to qualitatively similar results. The results are available from the authors upon request.

[13] Interestingly, we do not see Hispanic participants revising their valuations in response to the information interventions.

[14] This phenomenon could also be broadly related to the limited digital literacy for individuals in these demographics (Martin and Robinson, 2007).

[15] The statements used in the endline survey are: (1) Privacy is a fundamental human right and (2) I trust that the free market leads to appropriate privacy protection.

variable as one if the individual either agrees or strongly agrees with a certain statement. In column (1) of Table 2, we find that individuals who think that privacy is a fundamental human right value their data significantly more. Similarly, those who think that the free market provides an appropriate degree of privacy protection value their data less. Consistent with the intuition of valuations being driven by a composite of objective and subjective factors, individuals who think that privacy is a fundamental human right are less likely to revise their beliefs, whereas market-oriented individuals are more likely to revise (column (3)).

5.2 Mechanism: Why do Individuals Update Valuations?

In this section, we interpret the asymmetric updating behavior that we observe through the lens of the conceptual model presented in Section 2. In addition, we unpack the heterogeneous motivations for revising valuations across the two information treatments.

Individuals systematically revise their valuations if two conditions hold, according to the model in Section 2. First, individuals have an instrumental value for their data (i.e. $\beta_i \neq 0$). Second, individuals' beliefs about the monetary value of their data must respond to the information treatments.

This framework can help us understand why we observe asymmetric updating. Our theory predicts that individuals with low baseline valuations who overwhelmingly update their valuations must both place a value on the instrumental value of their data and update their beliefs about the monetary value of their data. Our theory can also help us understand why individuals with high baseline valuations are less likely to revise. Either the intrinsic component dominates their preferences or their beliefs do not respond to our information treatments (i.e. they are already informed about the monetary value of their data).

We therefore conduct another experiment (N=250, recruited from MTurk using CloudResearch's toolkit) that measures individuals' beliefs about the settlement treatment before and after the informational intervention.[16] We ask participants before and after the information treatment what value they believe a court would set damages for Facebook violating privacy laws, with possible responses ranging from \$100 to more than \$1000 and we included a potential response of "I don't know".

Figure A.18 plots the probability of participant's revising their beliefs about the value of their data pre- and post-treatment separately for users with baseline valuations above and below \$400. In

[16] We focus on the settlement treatment to reduce the complexity and increase power for this experiment. We do not incentivize beliefs, as we want to avoid participants searching for the answer using external sources.

addition, Figure A.18 plots the probability a respondent reports "I don't know" and a valuation of less than \$400 at baseline. We notice a stark difference in beliefs following the informational intervention, offering one explanation for the asymmetric updating behavior we observe. Participants with higher baseline valuations are less likely to update their beliefs in response to the information treatments and more likely to have baseline beliefs about the monetary value of their data of at least \$400. This is consistent with individuals with high baseline valuations having more precise beliefs about the monetary value of their data, and therefore responding less to the information treatments. That said, a non-trivial share of individuals with high baseline valuations do revise their beliefs about the monetary value of their data. This suggests that, for these individuals, the intrinsic component plays a large role. Therefore, our results suggest that two mechanisms may explain the asymmetric updating finding. First, individuals with high baseline valuations are less likely to update their beliefs about the monetary value of their data, suggesting there is asymmetric information in the market for personal data. Second, the intrinsic component plays a relatively larger role for individuals with high baseline valuations, leading them not to revise their valuations even if they update their beliefs.

5.2.1 Differences in Information Treatments

For individuals with a valuation below \$400, both treatments induce a large share of respondents to update their valuations: the settlement treatment led 55% of individuals to update, while the revenue treatment induced 49% of individuals to update their baseline valuations. Since both treatments refer to the same monetary value (\$400), the mechanism behind the updating of valuations may emanate from how individuals view the information they received.

After subjects were presented with the informational intervention and given the opportunity to revise their valuations, we asked all participants in the main study why they did or did not change their answer and about their general attitudes towards privacy and how their data is used. To better understand what was inducing subjects to revise their valuations, we conducted a post-hoc text analysis. While all participants were required to enter some text, some entered a small number of characters in this field. Therefore, we restricted this analysis to participants who entered at least 20 words in their response resulting in 2025 respondents for this analysis.

For our text analysis, we used the top2vec algorithm proposed in Angelov (2020) that automatically handles stop-word removal, lemmatization, and selection of the number of clusters. Moreover, this algorithm, relative to bag-of-words approaches such as Latent Dirichlet Allocation, takes advantages of advances in word embeddings that account for the context of a word in a document. We find four relatively coherent topics emerge from the data.

We labeled these four clusters through manual inspection of the top 10 most closely aligned responses within each cluster. As shown in Table A.7 in the Appendix, we see that this cluster contains many statements concerning the amount of money Facebook earns off of their data. As such, we refer to this cluster as the Revenue cluster. Turning to Table A.8 in the Appendix, we see that this cluster contains statements concerning the use of an individual's data. The algorithm failed to separate individuals who are both concerned and those who are not concerned about how their data is used, and this cluster contains both types. Therefore, we refer to this as the Data Use cluster. The third cluster, shown in Table A.9 in the Appendix, contains individuals who are privacy conscious and, for that reason, do not share much information on Facebook. We refer to this as the Careful Sharing cluster. Finally, Table A.10 in the Appendix contains many responses that indicate an individual is extremely privacy conscious and is unwilling to share their data for anything but a very high price. We label this the Extreme Privacy cluster.

The results in Figure A.19 show that the distribution of responses across clusters are different between the two information treatments. First, we find that those in the revenue treatment are substantially more likely to be in the revenue cluster ($p < 0.01$). This suggests that the revenue treatment induces individuals to revise by encouraging users to think about the value of their data to the firm, which also impacts their own user valuations. The settlement treatment, however, induces more individuals to be members of the extreme privacy clusters ($p < 0.01$). This suggests that the settlement treatment induces respondents to revise their valuations by evoking concerns about the potential harms of sharing their data and envoking prevention-based information processing. While it is difficult to pin down whether these treatments work by updating users beliefs about the potential value, or potential harm of their data, or by evoking existing beliefs about these concepts, it is clear that the treatments encourage users to think about different aspects of the value of their data. This analysis also shows that individuals do not go into the details of the data settlement lawsuit or the specifics of Facebook's revenue streams. The responses of users are generic and centered around the broad themes found in the text analysis.

The baseline updating results also show that the settlement treatment led to a slightly higher increase in updating relative to the revenue treatment, even though the absolute increase across the two treatments was high (55% vs. 49% with $p<0.01$). To understand the quantitative difference in revision across the two treatments, we conducted a post-hoc survey on Amazon Mechanical Turk using CloudResearch's toolkit (N=250). We test whether this difference might arise due to the fact that individuals are more uncertain about settlement amounts relative to how much revenue Facebook earns. We asked subjects to predict the monetary values associated with Facebook revenues as well as the data settlement lawsuit. We found that there was significantly more uncertainty about the settlement treatment, consistent with the hypothesis that the settlement treatment induced larger updates in individuals' beliefs about the value of their data. In particular, subjects were 10 percentage points more likely ($p<0.01$) to respond saying "I don't know" when trying to predict the settlement amount (N=79) relative to the revenue amount (n=53).[17] That said, there was still substantial uncertainty and underestimation about the amount of money Facebook would earn per user, consistent with the relatively smaller, but still substantial, share of revisions we observed in the revenue treatment. This survey suggests that individuals are especially uncertain about settlement values, leading to a higher effect of the settlement treatment relative to the revenue treatment.

Finally, the text analysis can also shed light on baseline valuations. Figure A.20 plots the distribution of text responses across the different clusters conditional on baseline valuations. The most stark difference is that individuals with low baseline valuations (< 400) are more likely to be in the revenue cluster while individuals with high baseline valuations (≥ 400) are more likely to be in the data use cluster. That low value users are more likely to be in the revenue cluster is consistent with the analysis in Section 5.2, where we argue that our results are consistent with low-value participants having a larger instrumental component of valuations relative to high-value participants.

5.3 Robustness of Updating Behavior

Here we summarize the additional analyses that is presented in Appendix E to demonstrate the robustness of the treatment effects we estimate and explore the boundary conditions of the treatment effects. First, we rule out experimenter demand effects by conducting additional robustness experiments with placebo information treatments (Appendix E.1). Next, we conduct a study in which we vary the dollar amounts used in the treatment (Appendix E.2). This allows us to demonstrate

[17] These elicitations were not incentivized, so as to avoid subjects searching for the exact answer.

that the asymmetric updating result is not an artifact of the specific dollar amounts used in the primary study and is a more general feature of valuations for personal data. Next, we conduct another robustness study to explore whether the sensitivity of the data solicited in the valuation exercise previously drives the results by varying the type of data (all of Facebook data vs. only public profile data) and find that our results are consistent irrespective of whether we solicit more or less sensitive data (Appendix E.3). Finally, in Appendix E.4, we demonstrate that the key result of asymmetric updating is not universal. In particular, we find that for a standard good such as a mug, the asymmetric updating result disappears. Therefore, we conclude that the asymmetric updating result is not universal and does not hold for a standard product.

6 Replicating results on a privacy focused sample

A potential drawback of using the YouGov sample is that these individuals are part of an online panel and self-select into doing an online survey. While they might be similar on observables, their unobservable preferences for data and privacy might be different. To ensure further robustness of our study, we replicate our experiment on a privacy-focused sample. We partner with the Data Dividend Project (DDP), a data advocacy group started by former Democratic presidential candidate Andrew Yang, to replicate our study.[18] Members of the DDP are interested in ensuring that technology companies share a part of their revenue when they monetize data and are more likely to believe in digital privacy as a fundamental right (Yang, 2020). Replicating our study on a privacy-focused sample allows us to compare whether and how information treatments differentially affect individuals who are likely heterogeneous in their fundamental views on personal data. We recruit subjects for this study through email solicitations sent directly by the DDP to its entire member base, inviting them to participate in our study (DDP sample). In general, it is challenging to conduct studies about data valuation and privacy on private individuals since they are probably not signing up to take part in research studies. Access to the DDP sample gives us a rare insight into information frictions associated with personal data valuations for individuals whom we expect to be more conscious and better informed about data and privacy. Six hundred and fifty-two respondents completed the experiment.

In this section we report the results of the experiment with the DDP sample. Table A.2 shows

[18] https://web.archive.org/web/20201101005326/https://www.datadividendproject.com/

this DDP sample to be more concerned about privacy than the YouGov sample, as DDP members provide significantly different responses to nearly all of the endline privacy attitude questions. For example, DDP members are more likely to believe that privacy is a fundamental right and that tech companies earn too much, and less likely to believe that the free market will lead to the appropriate amount of privacy. In terms of demographics, DDP members are more likely to be Asian and less likely to be Black, Table A.1. In addition, men are over represented in the DDP sample.

Figure 5 presents the distribution of valuations across the DDP and the YouGov sample. The WTA distribution in the DDP first order stochastically dominates that of the representative sample. Figure 5 shows an additional nuance: individuals in the DDP sample are more likely to have very high WTA and less likely to have very low valuations relative to the YouGov sample (in fact, the median baseline valuation for the DDP sample is \$1000, which is 33% higher than the median valuation of \$750 in the YouGov sample). These results confirm that this sample is more concerned with privacy and provide confidence in the experimental approach. Analyzing the WTA heterogeneity by race, we find that the median Black respondent (N=29) has a WTA of \$500, whereas that of a White respondent is \$1000.[19] In line with the YouGov sample, WTA increases with income, with a median WTA of \$600 for the lowest income bracket (less than \$30K) and a WTA of \$1000 for those with income greater than \$100K. Also in line with the YouGov sample, those individuals who prefer not to report their income (N=65) have the highest median valuations: \$10,000. Finally, the median valuations by gender are the same at \$1000, though female WTA is lower after the 75th percentile.

We find remarkably similar responses to the information treatments across the two sample of respondents. The probability of revision in the DDP sample is 29.4% (28.6% in the YouGov sample). As in the YouGov sample, the probability of revision in the DDP sample is asymmetric, with 58.7% of individuals whose WTA is less than \$400 revising their valuations (Figure 5). All participants who revise their WTA revise it higher. Additionally, in line with the YouGov sample, we see that individuals are 12% more likely to respond to the settlement treatment relative to the revenue treatment. This effect is noisy (and not statistically significant), due to the smaller sample size and should be interpreted as suggestive. These results are notable as they demonstrate that even individuals who care about the core issue of data dividends and privacy have a hard time valuing personal data for which there is no active market. This highlights the widespread prevalence of

[19] This analysis is based on a smaller sample than the YouGov analysis. Therefore, some of its results should be taken as suggestive.

information frictions in data valuations.

7 Conclusion

As policymakers explore introducing data dividends and companies experiment with new business models around data markets, it is essential to understand the economic valuations of consumers' personal data. In this paper, we provide evidence documenting substantial dispersion and heterogeneity by gender, race, and income in users' data valuations for their social media data through incentive compatible studies on a representative sample of US internet population as well as a privacy conscious sample. Marginalized individuals have significantly lower data valuations in both samples even after controlling for income, education, and Facebook usage. Through a randomized intervention, we find evidence that participants respond to information giving them a signal about the value of their data from legal settlements and revenue projections. Specifically, we find that low WTA users in both samples revise their valuations upwards towards the settlement amount while high WTA users do not revise downwards. These revisions significantly reduce the observed heterogeneity in baseline valuations for marginalized individuals. Dispersion and heterogeneity in valuations, however, persist following the information treatments, consistent with theories of data and privacy valuations that construed them as amalgams of objective and subjective factors. Ours results are remarkably similar for the privacy conscious Data Dividend Project sample and are further validated through several additional robustness studies. Taken together, these studies provide robust evidence documenting heterogeneity in valuations for personal data across different demographic groups and updating of valuations in the presence of information treatments.

Our findings have policy and managerial implications. Although some scholars and policymakers have viewed data markets as a means to compensate consumers fairly for their data (Seim et al., 2022), our results suggest that information frictions may impair the ability of those consumers to engage with those markets in a meaningful manner. However, strategies aimed at reducing information asymmetries may be helpful to consumers, especially those from lower-income and other historically marginalized groups. Such information provision would aid the functioning of personal data markets and may allow consumers to extract more surplus in these markets. Various recent regulatory efforts in the privacy field have, in fact, aimed at addressing and reducing informational asymmetries (Shiller, 2020). Provisions in the draft regulations of the CCPA stipulate conditions under which businesses should share with consumers information on their data valuation methods; similarly, the EU General Data Protection Regulation (GDPR) requires firms to disclose how collected consumer data is used. Our findings also have managerial implications for strategy around pricing and marketing. A number of companies are aiming to establish data markets and becoming data brokers (e.g., YouGov.com, Permission.io, Brave.com, etc.) using a variety of pricing mechanisms (Yang, 2022). On the other end of the spectrum, some firms are pledging not to collect or sell data generated by users' online activity (Holtrop et al., 2017). Our results help firms understand how to price their product, in line with the recent literature (e.g., Huang et al. (2022); Cao and Zhang (2021)), taking this heterogeneity and frictions into account, as well as use strategies to inform individuals about the value of their data to increase customer acquisition (e.g., mePrism.com - see Figure A.1). Finally, the focus of our study is social media data. With growing interest in LLMs, this data is becoming increasingly important for training models. Having access to first-party data is a competitive advantage that companies such as Meta have over others, such as OpenAI and Anthropic. Meta uses Facebook data for training its LLMs. Other social media platforms, such as Reddit, have started to license their data to OpenAI. Our study provides a framework for platforms and regulators to quantify the value users place on their social media data, which can be useful for pricing data and designing regulations.

Our research is not without limitations. We only focus on the user side of data markets. Furthermore, we focus only on social media data from one platform, Facebook. Although studying Facebook data is important because it is the largest social media platform in the world, it would be informative to replicate these results for other types of data that might range in their degree of sensitivity. Future research could also study how firms value user data, how these valuations vary based on user characteristics, and how markets for personal data evolve towards equilibrium. We hope that our current paper spurs future research in this nascent field of personal data markets.

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Tables and Figures

Table 1: Race and Gender Regression results

	(1) Log(WTA)	(2) Log(WTA)	(3) Log(WTA)	(4) Log(WTA)	(5) Log(WTA)
Female	-0.378**			-0.384**	-0.405**
	(0.157)			(0.157)	(0.161)
Black		-0.557**		-0.618***	-0.495**
		(0.217)		(0.220)	(0.219)
Hispanic			-0.568***	-0.656***	-0.536**
			(0.214)	(0.216)	(0.215)
FB Usage - 31-60 minutes					-0.182
					(0.203)
FB Usage - <10 minutes					0.354
					(0.226)
FB Usage - >60 minutes					-0.101
					(0.177)
Privacy is a Right					0.942***
					(0.153)
Market is Correct					-0.753***
					(0.188)
Age					0.009**
					(0.004)
High Income					0.612***
					(0.144)
Prefer Not to Report Income					2.139***
					(0.367)
Intercept	7.751***	7.607***	7.597***	7.879***	6.217***
	(0.130)	(0.082)	(0.082)	(0.141)	(0.277)
Obs	4141	4141	4141	4141	4140
Adj. R^2	0.001	0.001	0.001	0.003	0.032

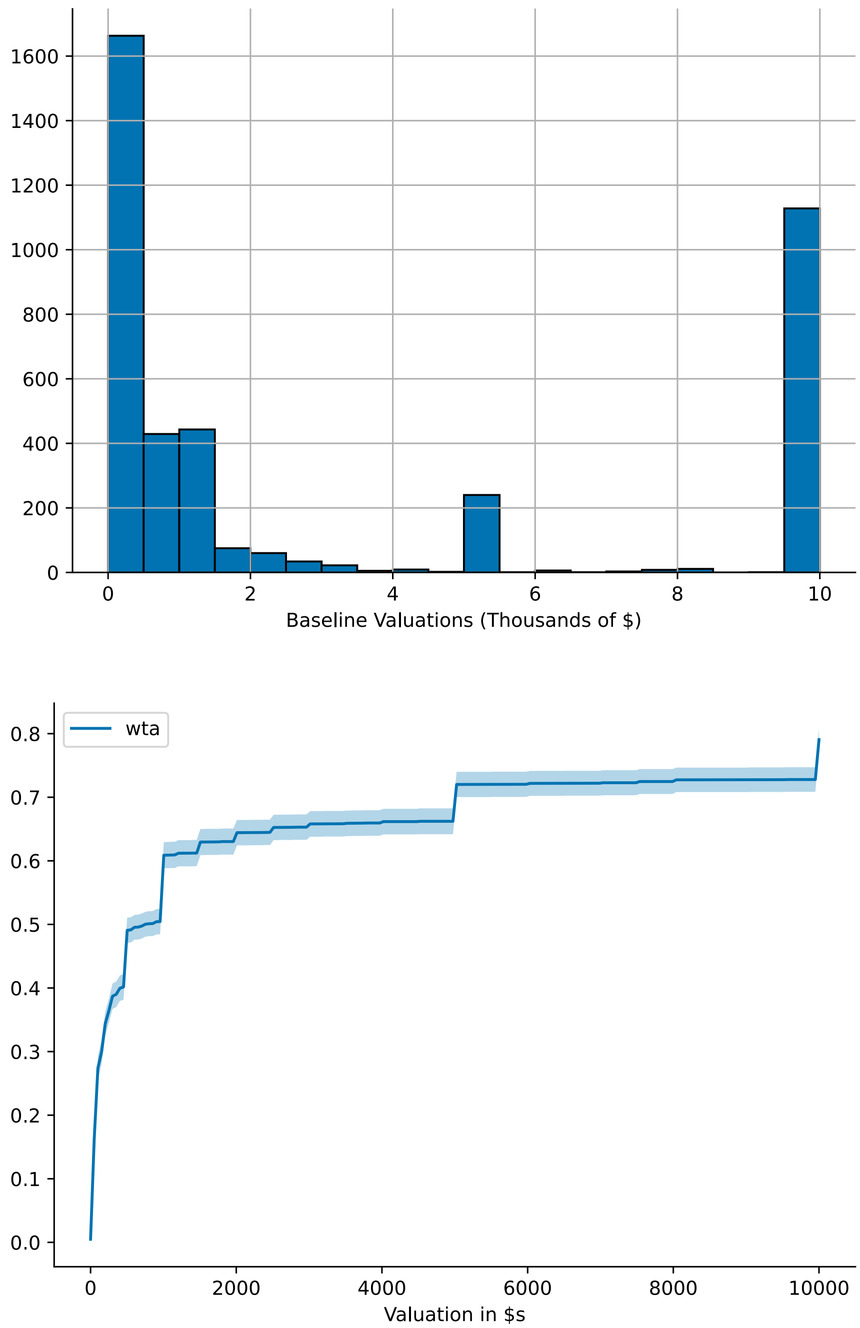
The unit of observation is the individual respondent. Regression of log of baseline valuation on demographic and survey variables. Female, Black, and Hispanic are indicators equal to one if the participant is Female, Black, or Hispanic, respectively. FB Usage captures the self-reported amount of time users spend on Facebook per day on average (10-30 minutes is the excluded category). Privacy is a Right and Market is Correct are dummy variables based on the endline questions about beliefs about privacy and whether the market correctly values personal data. These variables are equal to 1 if the participant reports at least some-what agreeing with the claim. High income is an indicator equal to one if the participant's income is at least $50k and Prefer Not to Report Income is an indicator equal to one if the participant did not report income. Robust standard errors in parentheses. The estimates are based on an OLS regression. * $p < 0.1$, ** $p < 0.05$ *** $p < 0.01$.

Table 2: Mechanism Regression results

	(1) Log(WTA)	(2) Log(revised WTA)	(3) OLS Prob(Revise)	(4) Logit Prob(Revise)
Female	-0.405**	-0.333**	0.048***	0.240***
	(0.161)	(0.158)	(0.014)	(0.071)
Black	-0.495**	-0.416*	0.051**	0.242**
	(0.219)	(0.213)	(0.024)	(0.110)
Hispanic	-0.536**	-0.482**	0.014	0.069
	(0.215)	(0.210)	(0.025)	(0.122)
Privacy is a Right	0.942***	0.923***	-0.001	-0.005
	(0.153)	(0.150)	(0.017)	(0.084)
Market is Correct	-0.753***	-0.810***	0.094***	0.438***
	(0.188)	(0.181)	(0.022)	(0.098)
Age	0.009**	0.012***	-0.001	-0.003
	(0.004)	(0.004)	(0.000)	(0.002)
High Income	0.612***	0.514***	-0.059***	-0.287***
	(0.144)	(0.140)	(0.015)	(0.075)
Prefer Not to Report Income	2.139***	2.119***	-0.061***	-0.298**
	(0.367)	(0.364)	(0.023)	(0.117)
FB Usage - 31-60 minutes	-0.182	-0.274	0.009	0.043
	(0.203)	(0.199)	(0.021)	(0.099)
FB Usage - <10 minutes	0.354	0.294	-0.044**	-0.227**
	(0.226)	(0.223)	(0.019)	(0.098)
FB Usage - >60 minutes	-0.101	-0.189	-0.013	-0.062
	(0.177)	(0.172)	(0.019)	(0.093)
Obs	4140	4140	4140	4140
Adj. R^2	0.032	0.033	0.015	

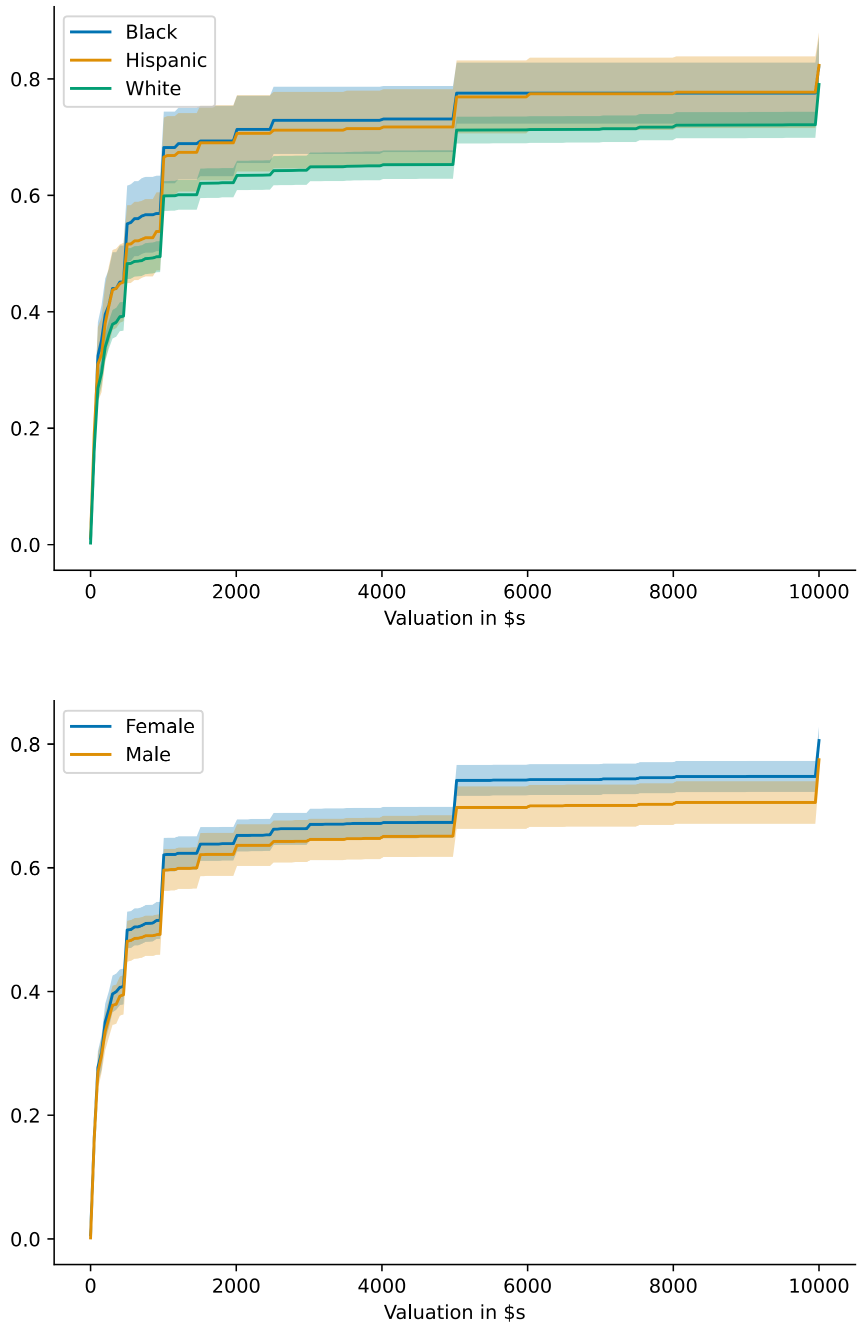
The unit of observation is the individual respondent. Robust standard errors in parentheses. Columns (1)-(3) are based on an OLS regression while Column (4) is a logistic regression. Regression of log valuation (Column (1) is baseline valuation, Column (2) is revised) or an indicator if the participant revised their valuation (Columns (3)-(4)) on demographic and survey variables. Female, Black, and Hispanic are indicators equal to one if the participant is Female, Black, or Hispanic, respectively. FB Usage captures the self-reported amount of time users spend on Facebook per day on average (10-30 minutes is the excluded category). Privacy is a Right and Market is Correct are dummy variables based on the endline questions about beliefs about privacy and whether the market correctly values personal data. These variables are equal to 1 if the participant reports at least some-what agreeing with the claim. High income is an indicator equal to one if the participant's income is at least $50k and Prefer Not to Report Income is an indicator equal to one if the participant did not report income. * $p < 0.1$, ** $p < 0.05$ *** $p < 0.01$.

Figure 1: Distribution of Baseline Valuations: Full Sample



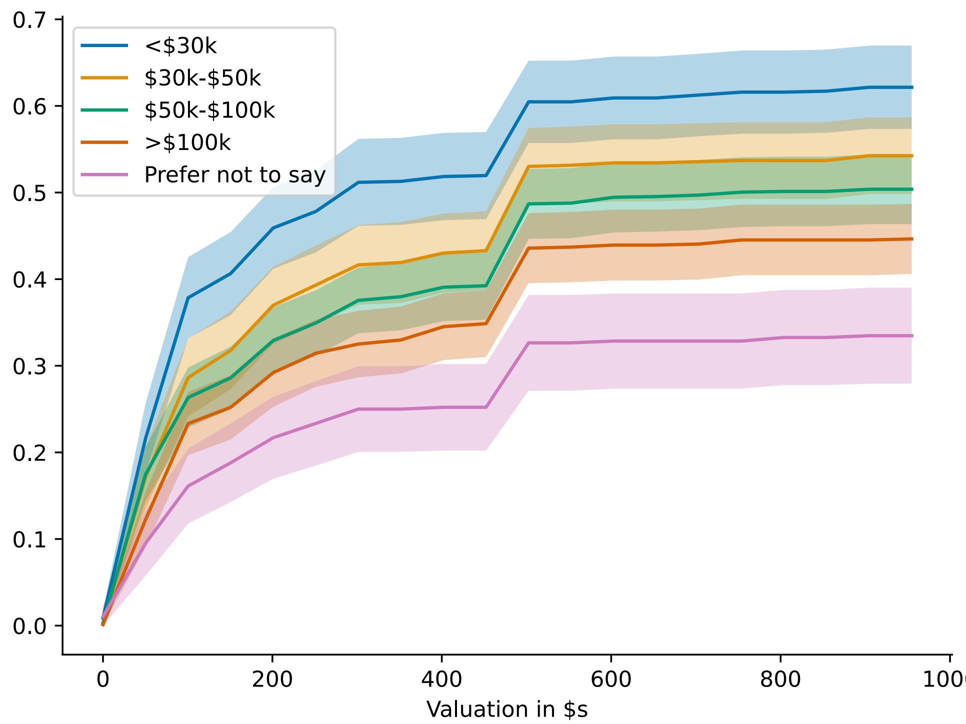
The top panel shows a histogram of the distribution of baseline valuations for the YouGov sample at $250 intervals. In this figure, all values above $10,000 are displayed in the bar at $10,000. The bottom panel shows the cumulative distribution function (CDF) of baseline valuations for the YouGov sample. Each point in this curve captures the share of respondents with a valuation less than the amount on the x-axis. The shaded area represents the 95% uniform confidence interval for the distribution.

Figure 2: Distribution of Baseline Valuations: Race and Gender Heterogeneity



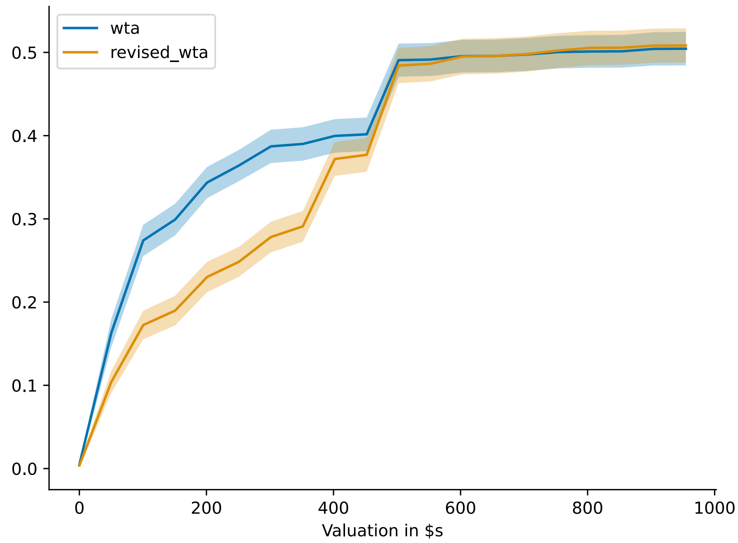
The figure in the top panel shows CDF of the baseline WTA split up by race. The Online Appendix contains distributions of valuations for additional race and ethnicities. The bottom panel shows the CDF of WTA by gender. Each point in these curves captures the share of respondents in each group with a valuation less than the amount on the x-axis. The shaded area represents the 95% uniform confidence interval for the distribution.

Figure 3: Distribution of Baseline Valuations: Income Heterogeneity



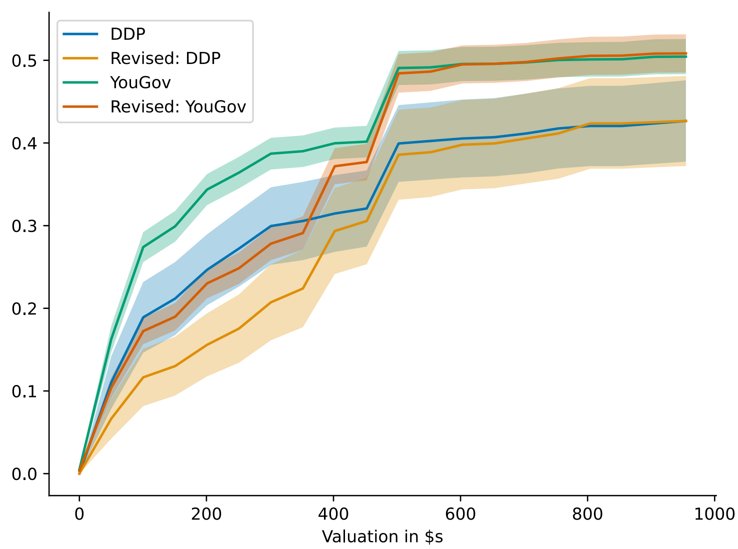
The figure shows the CDF of the baseline WTA by Income. Each point in this curves captures the share of respondents within the group with a valuation less than the amount on the x-axis. The shaded area represents the 95% uniform confidence interval for the distribution

Figure 4: Revision of Baseline Valuations



The figure shows the CDF of baseline and revised WTA, where the revised WTA is the valuation measured after the information interventions. Each point in these curves captures the share of respondents with a valuation less than the amount on the x-axis. The shaded area represents the 95% uniform confidence interval for the distribution

Figure 5: CDF of Valuations with Revisions: DDP vs. YouGov

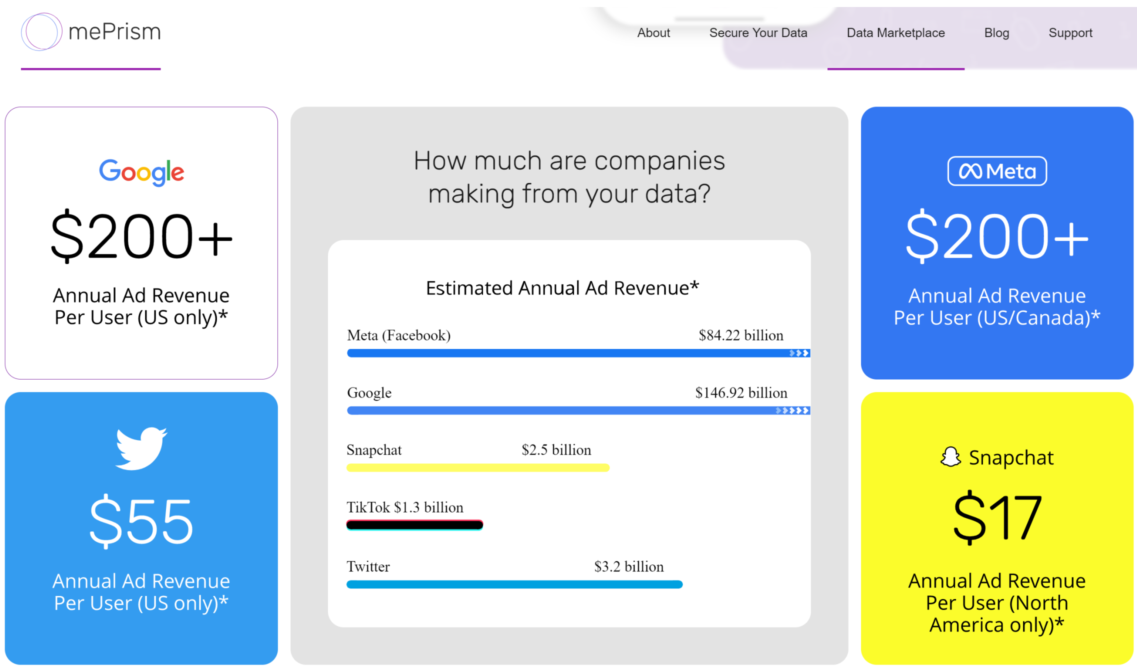


The figure shows the CDF of baseline and revised WTA for the YouGov and DDP samples, where the revised WTA is the valuation measured after the information interventions. Each point in these curves captures the share of respondents with a valuation less than the amount on the x-axis. The shaded area represents the 95% uniform confidence interval for the distribution

Online Appendix

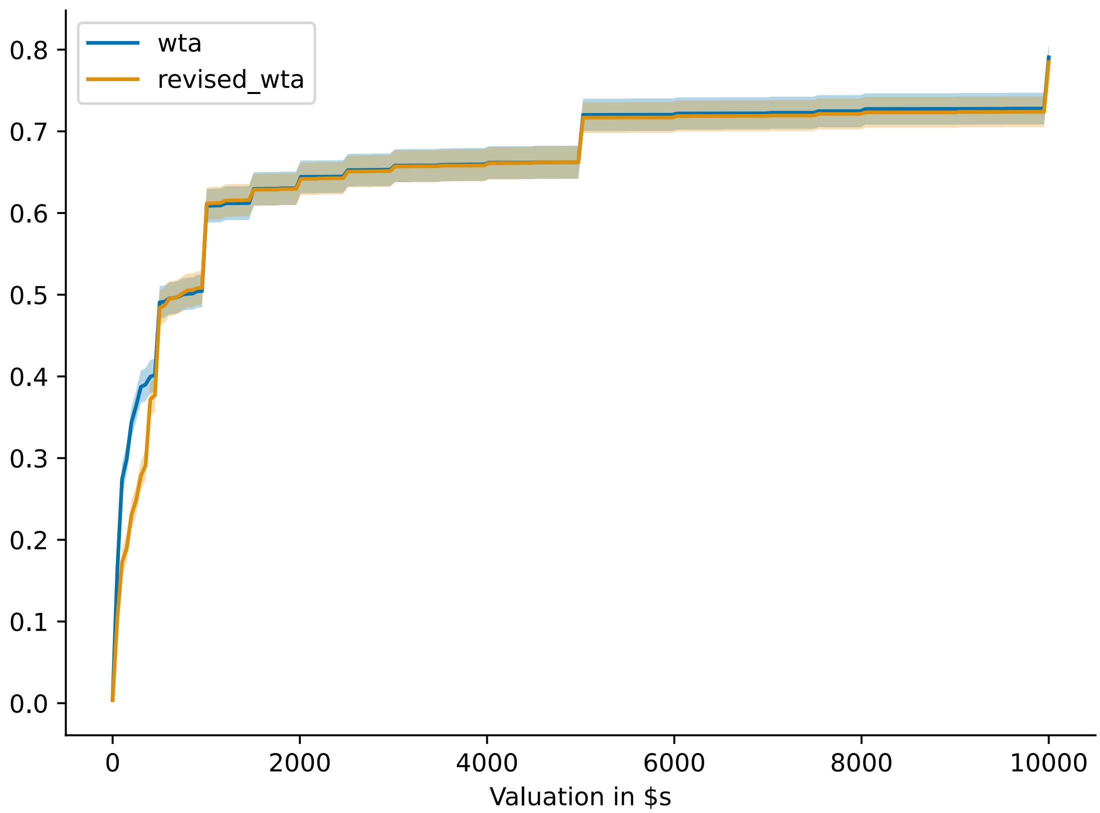
The first figure is an image of metrics used by a platform called mePrism to encourage users to part with their data in exchange for monetary compensation. Next, we plot the distribution of baseline and revised valuations in more detail. Figure A.2 plots the distribution of baseline and revise valuations for the YouGov sample extended out to $10,000. Figure A.4 plots the distribution of baseline valuations by race / ethnicity for all groups in the survey.

Figure A.1: mePrism Information Strategy



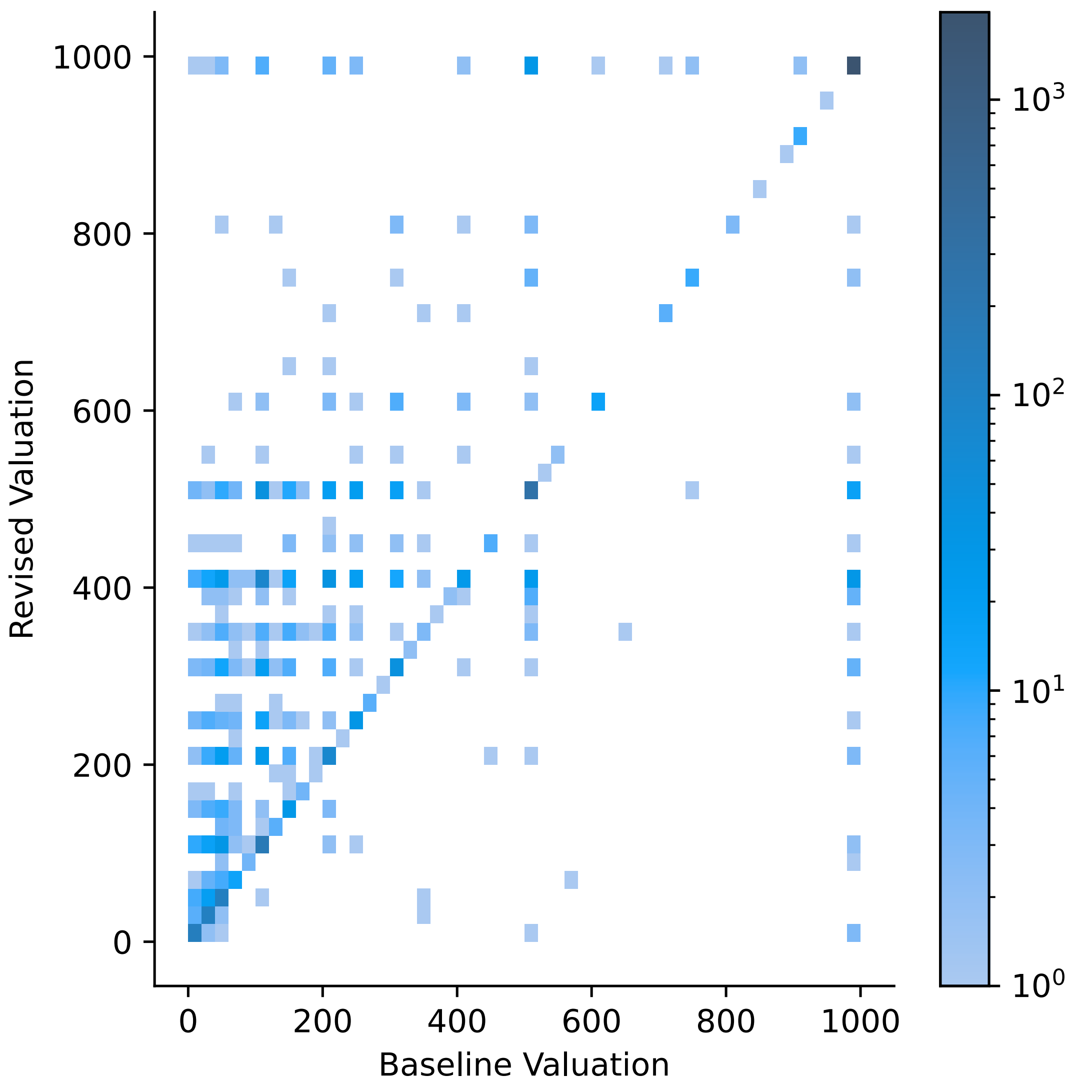
A snapshot of the metrics used by mePrism, a company setting up a data market, for providing information to potential users.

Figure A.2: Revision of Baseline Valuations



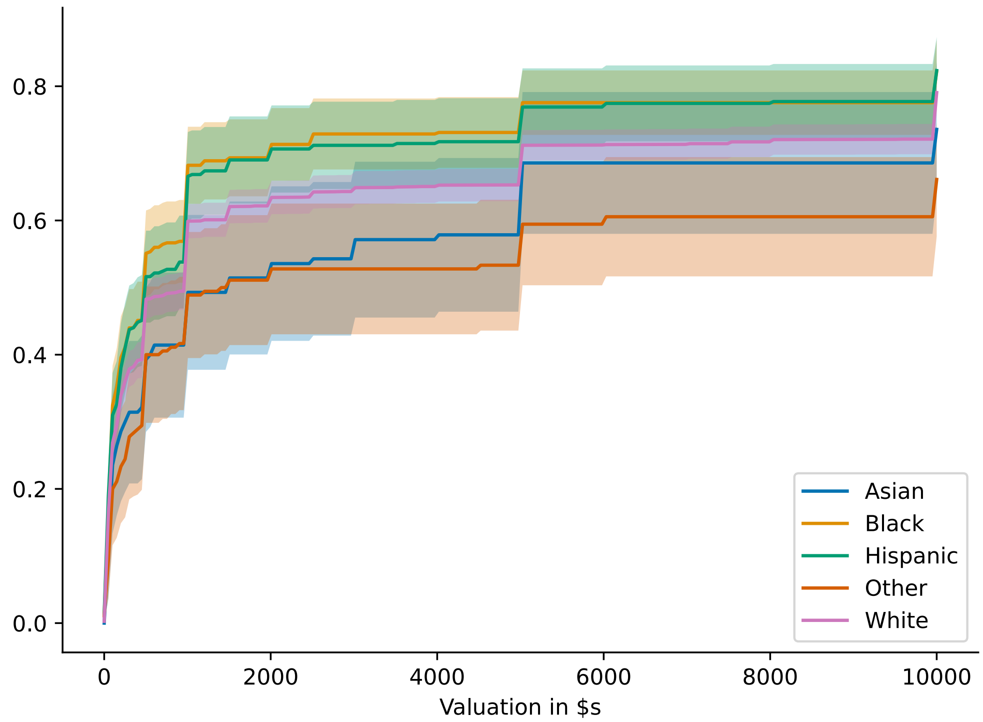
The figure shows the CDF of baseline and revised WTA for the YouGov sample, where the revised WTA is the valuation measured after the information interventions. The shaded area represents the 95% uniform confidence interval for the distribution

Figure A.3: Joint Distribution of Baseline and Revised Valuations



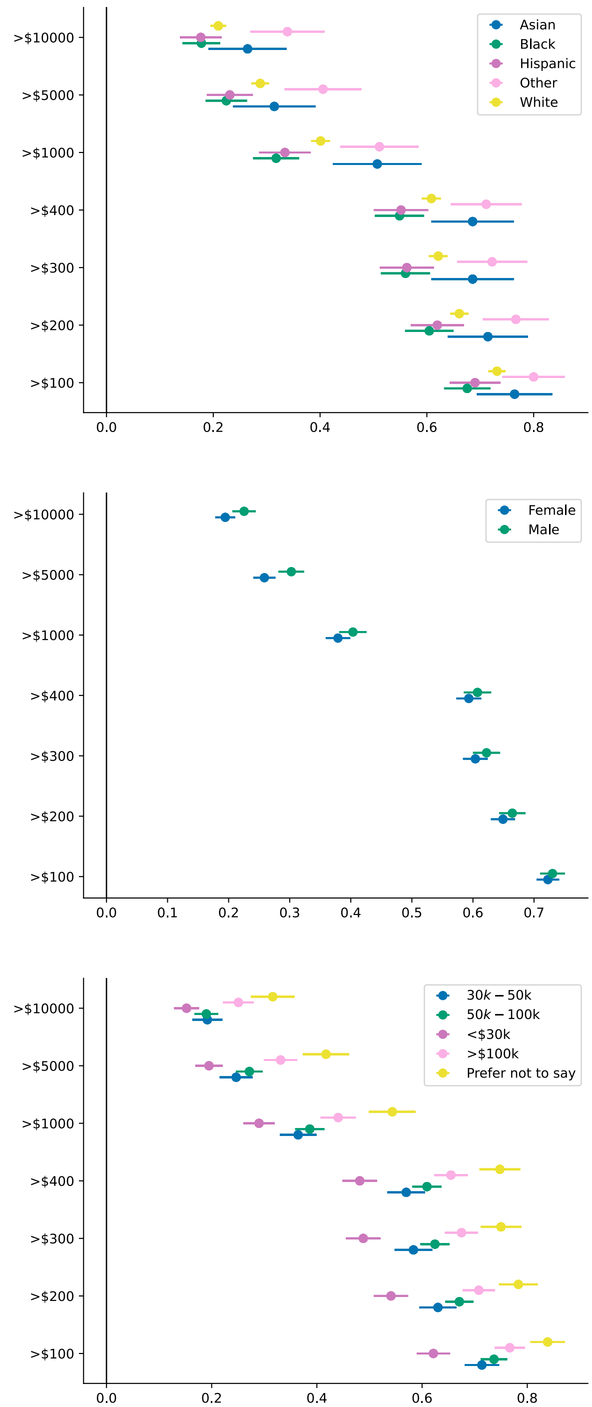
The figure shows the joint distribution of baseline and revised valuations, with all valuations over $1000 top-coded to $1000.

Figure A.4: Distribution of Baseline Valuations: Full Sample and Heterogeneity by Race



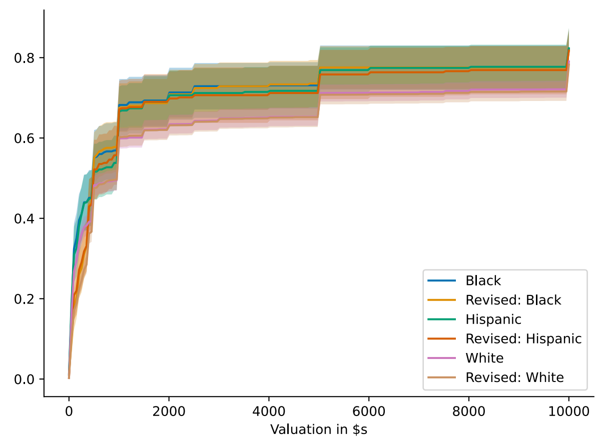
The figure in the top panel shows CDF of the baseline WTA for the whole sample while in the bottom panel it is the CDF split up by race. The shaded area represents the 95% uniform confidence interval for the distribution

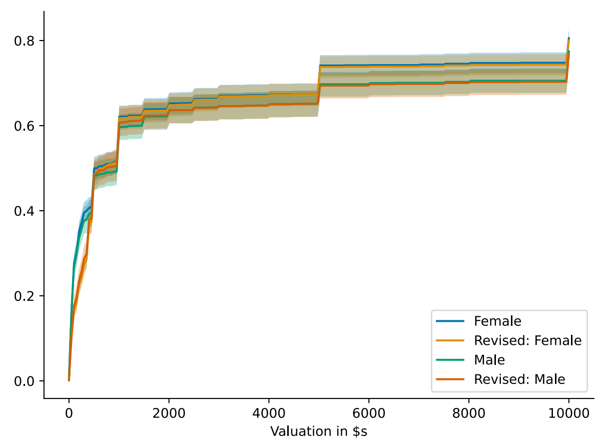
Figure A.5: Valuation Distribution Regressions



Distribution regressions of an indicator if an individual's valuation is greater than a threshold (y-axis) on demographic variables. The bars represent 95% confidence intervals.

Figure A.6: Baseline and Revised Valuations by Demographic



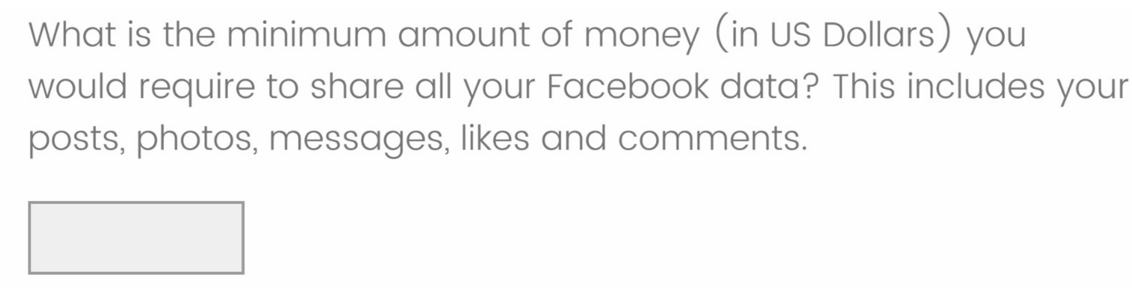


The figure shows the CDF of baseline and revised WTA for the YouGov sample by Race (top figure) and Gender (bottom figure), where the revised WTA is the valuation measured after the information interventions. The shaded area represents the 95% uniform confidence interval for the distribution

A Survey Materials

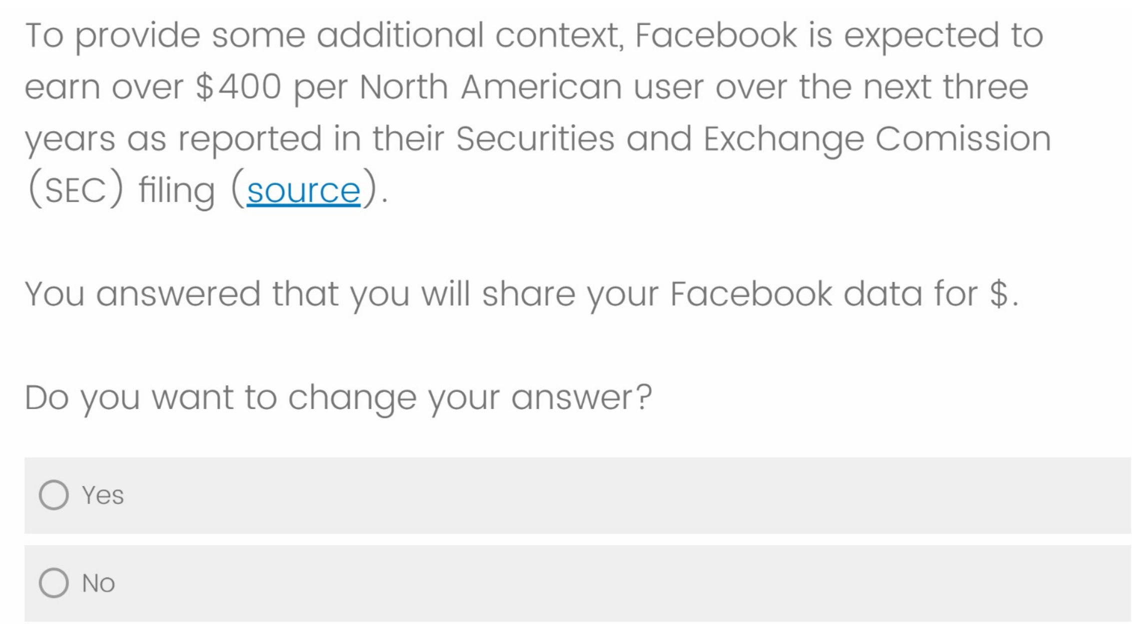
Here we share screenshots of key parts of the survey instrument. Figure A.7 shows the text of the question where subjects entered their valuations, Figure A.8 shows the Revenue treatment and the opportunity for subjects to revise their valuations, and Figure A.9 shows the Settlement treatment and the opportunity for subjects to revise their valuations.

Figure A.7: Baseline Question Screenshot


What is the minimum amount of money (in US Dollars) you would require to share all your Facebook data? This includes your posts, photos, messages, likes and comments.

The screenshot shows the question asked to the respondents to elicit their baseline valuations.

Figure A.8: Revenue Information Treatment Screenshot


To provide some additional context, Facebook is expected to earn over $400 per North American user over the next three years as reported in their Securities and Exchange Comission (SEC) filing (source).

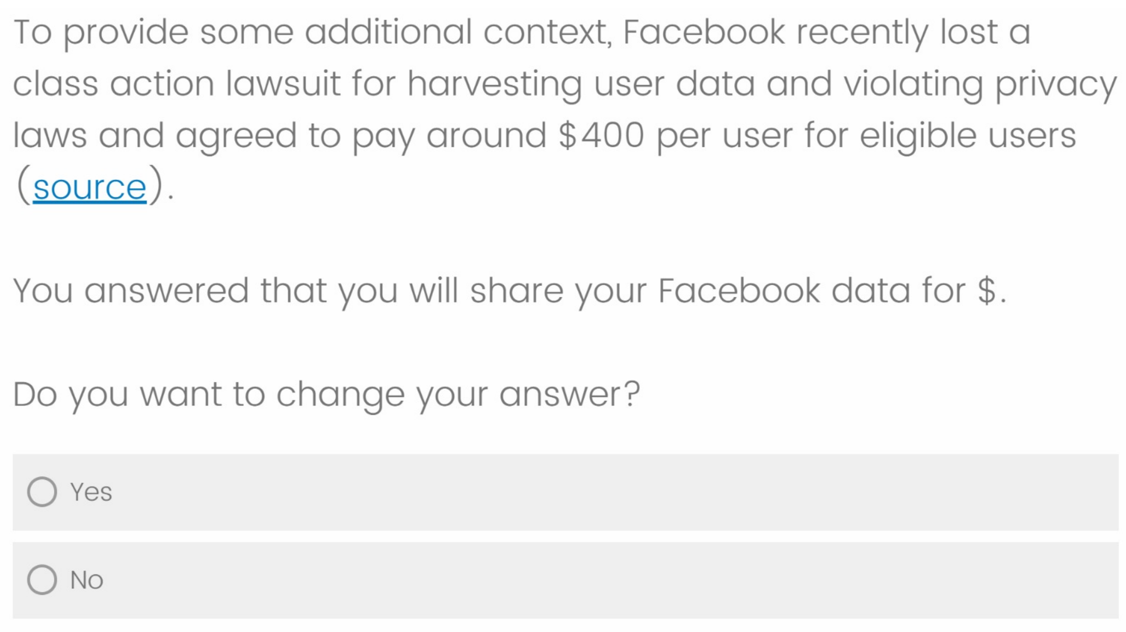
You answered that you will share your Facebook data for $.

Do you want to change your answer?

- Yes
- No

The screenshot shows the revenue information treatment after eliciting baseline valuations.

Figure A.9: Settlement Information Treatment Screenshot



To provide some additional context, Facebook recently lost a class action lawsuit for harvesting user data and violating privacy laws and agreed to pay around $400 per user for eligible users (source).

You answered that you will share your Facebook data for $.

Do you want to change your answer?

- Yes
- No

The screenshot shows the settlement information treatment after eliciting baseline valuations.

B Sample Characteristics

In Table A.1, we plot the distribution of demographic characteristics by sample. Table A.2 shows the difference in privacy attitudes between the two main samples, YouGov and DDP.

Table A.1: Demographics Across Samples

	YouGov	DDP	Data Use	Beliefs	No Dollar Amt	Data Sensitivity
N	4141	820	517	250	305	442
White	0.71	0.66	0.79	0.72	0.70	0.70
Female	0.54	0.33	0.59	0.46	0.50	0.49
Age - Under 40	0.38	0.73	0.59	0.64	0.62	0.41
FB >60 Min / Day	0.27	0.19	0.32	0.16	0.15	0.21
Income - <$30k	0.22	0.14	0.19	0.12	0.14	0.15
Income - $30k-$50k	0.18	0.12	0.21	0.19	0.15	0.18
Income - $50k-$100k	0.29	0.28	0.38	0.36	0.43	0.36
Income - >$100k	0.21	0.37	0.21	0.31	0.26	0.30
Income - Prefer not to say	0.12	0.09	0.01	0.02	0.02	0.01

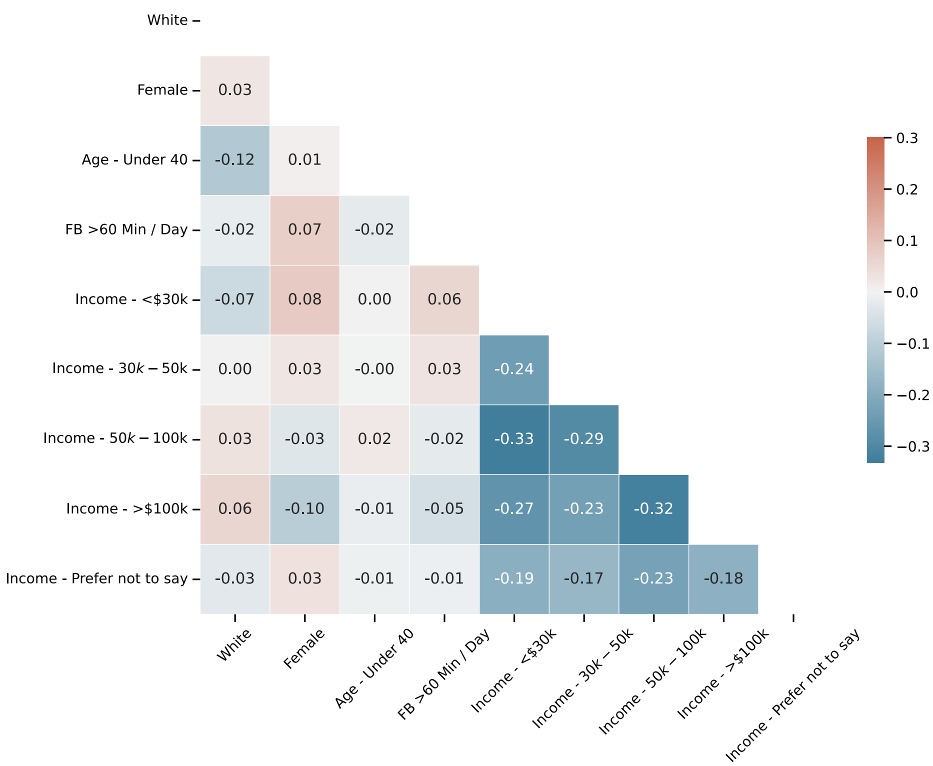
Pre-treatment covariate means for all respondents who completed the survey for the main samples (YouGov and DDP) and the various robustness checks.

Table A.2: Endline Privacy Attitudes Across Samples

	DDP		YouGov		P-Val
Endline Fundamental Human Right	5.295	(1.110)	5.065	(1.307)	0.000
Endline Careful	4.637	(1.240)	4.705	(1.290)	0.192
Endline Free Market	1.360	(1.594)	2.253	(1.809)	0.000
Endline Misuse	5.077	(1.176)	4.514	(1.403)	0.000
Endline Earn Too Much	5.135	(1.371)	4.683	(1.417)	0.000

Means and standard deviations for all respondents who completed the survey for both samples. The p-values come from a test of equality of means across the two treatments.

Figure A.10: Correlation Between User Features



C Robustness of Valuations

Here, we provide evidence that the elicitation method is robust. First, we explain in additional detail the elicitation method used in our study and then provide evidence that our valuations are robust to alternative methods of eliciting valuations.

C.1 Details of Elicitation Mechanism

We rely on the method to elicit valuations described in Becker et al. (1964) (henceforth BDM) to elicit participants' willingness-to-accept, or valuations, for their personal data. In this exercise, users are explained how the lottery will work and asked to enter their valuations. Every user then receives an offer to upload their personal data in exchange for a payment. The offer is randomly sampled from a mixture distribution that is generated from a Bernoulli draw ($x1 \sim Bern(1/150)$) and an independent Normal draw with mean 0 and standard deviation 100 ($x \sim 2N(0, 100)$) to get $x = x1|x2|$. Importantly, this distribution has positive support on the positive reals. If a subject's offer exceeded their valuation, they were made this offer in the survey and paid if they shared their data. If the offer was less than their valuation, they were not asked to share their data and did not receive the payment. To ensure we do not have access to personally identifiable information and comply with our IRB approval, we do not actually save the uploaded data but instead use a script that verifies in real time that the uploaded files are authentic by checking their metadata (directory names, sizes, and formats). Importantly, subjects are not aware that their uploaded data is not actually saved on our end, hence preserving incentive compatibility.

C.2 Alternative Elicitation Mechanisms

In the main experiment, we used best practices following the literature and did not inform individuals about the underlying payment distribution. To ensure that this dimension of the design is not driving the results, we carry out a follow-up experiment. We recruited 256 participants from CloudResearch's MTurk Toolkit. The follow-up experiment tests that the valuations we elicit are not sensitive to the distribution used in the BDM exercise or to whether participants are explicitly informed about the distribution. This follow-up experiment follows the same design as our main experiment, but randomly assigns participants to (1) receiving the same instructions as in the main study, (2) being additionally told about the shape of the offer distribution, and (3) being given offers drawn from a simpler uniform distribution (U[0,600]). We found that there were no significant differences in valuations, time spent on the instructions, or the endline question eliciting the probability of receiving an offer among these groups. The results are available in Table A.3.

A concern with the BDM method implemented to elicit valuations is that it may be hard to understand for the layperson. Our main experiment includes comprehension checks, and participants who did not pass those were not allowed to proceed with the survey. Despite this, we wanted to rule out the possibility that the results are driven by the exact elicitation method. In an additional follow-up experiment (N=691, recruited using CloudResearch's MTurk Toolkit), we implement a simple Take It Or Leave It (TIOLI) method to elicit baseline valuations. In particular, participants in one experimental condition were offered six different dollar values from \$100 to \$600, with each participant having a 1 in 100 chance of being randomly selected for actual payments. Participants in the control condition, instead, were presented with the same BDM method to elicit valuations as in the main experiment. As seen in Figure A.11, We fail to reject the null hypothesis that the share of respondents with valuations less than the price point are equal across the two elicitation mechanisms at the 5% level (p=0.50). This demonstrates the results found in our study are robust to a different elicitation mechanism and gives us confidence that the valuations we elicit are incentive-compatible.

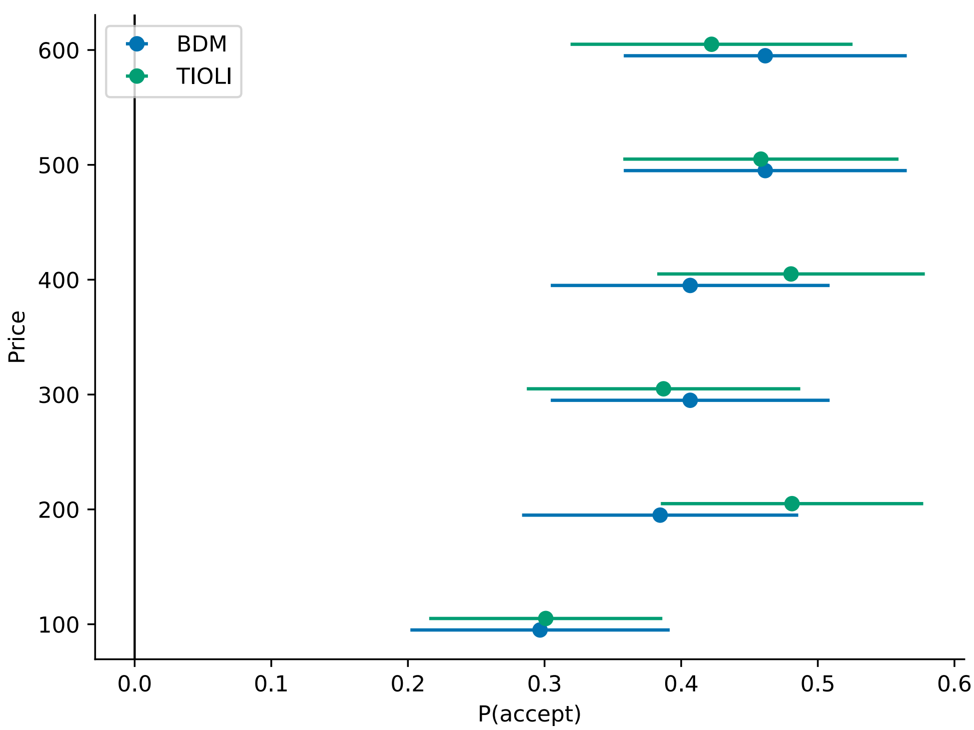
Table A.3: Robustness of Elicitation Method

	Endline Belief	Time Instructions	Log WTA
Explained distribution	-1.38	3.70	-0.26
	(3.47)	(10.14)	(0.59)
Uniform	-2.77	-12.93	1.52
	(3.31)	(8.48)	(1.18)
Intercept	17.71***	69.61***	7.18***
	(2.54)	(6.60)	(0.37)
Number of Observations	256	256	256
R-Squared	0.00	0.01	0.01

*$p < 0.1$; **$p < 0.05$, ***$p < 0.01$

This table presents treatment effect estimates of being given a full description of the Becker et al. (1964) distribution and using a uniform distribution between \$0 and \$600 relative to the protocol used in the main study on beliefs about receiving an offer, the time spent on the instructions, and log-valuations.

Figure A.11: Comparison of BDM to TIOLI

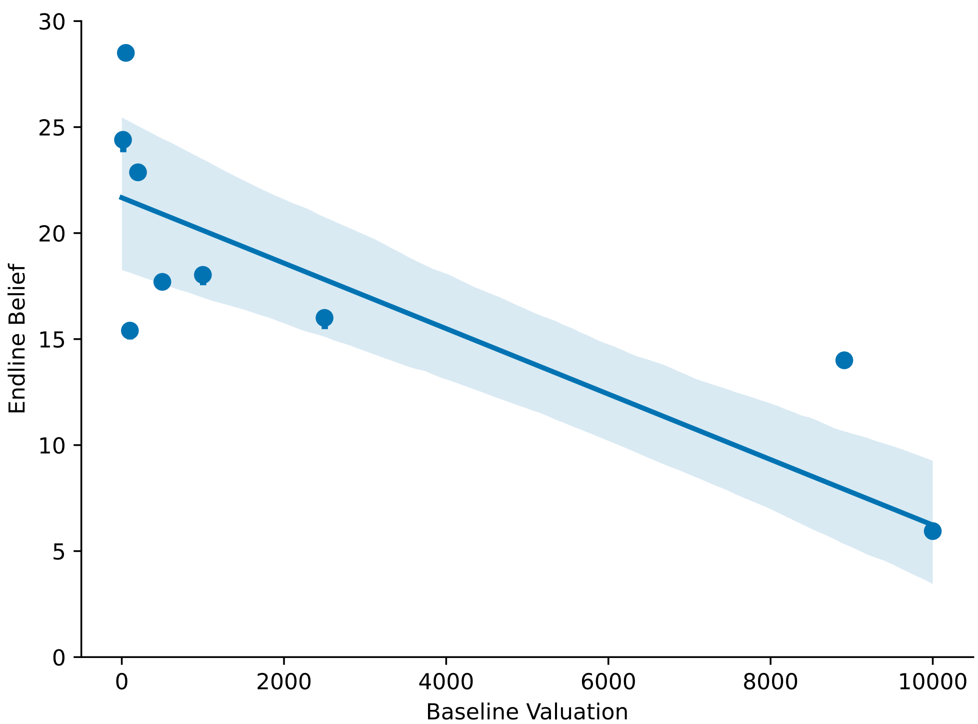


This figure plots the share of users accepting a TIOLI offer for each price point in addition to the share of users whose valuations were elicited via BDM who would accept an offer at the same price. Error bars represent 95% confidence intervals.

C.3 Perceived Likelihood of Receiving an Offer

In a follow-up experiment, we ask subjects explicitly to report the probability they would receive an offer and get paid for their data. We find that for valuations up to around \$1,000, subjects believe they have a 20% chance of receiving an offer. Even for higher amounts (including participants who reported valuations of at least \$10,000), we find that individuals have assigned a probability of at least 5% on average of receiving such an offer. Valuations will be incentive-compatible as long as the respondents believe that there is a non-trivial chance of actually getting the cash. Subjects know that getting cash is not certain (i.e. 100%), but even a 5% belief of getting \$10,000 cash amount is significant enough to achieve incentive compatibility (Becker et al., 1964; Brynjolfsson et al., 2019). Hence, it is in their best interest to reveal their true valuation. The results are in Figure A.12.

Figure A.12: Relationship Between Belief on Receiving an Offer and Baseline Valuations



This figure plots a binned scatter plot of baseline valuation and users' endline beliefs of receiving an offer and being paid for their data.

C.4 Varying Perceived Use of Data

In the main experiment, we inform respondents that their data will only be used for research purposes. We carry out an additional experiment as a robustness exercise, to ensure that our results are not sensitive to this stated data use. Buckman et al. (2019) finds a null result comparing differences in valuations for personal data when the data is shared with third parties or not. To confirm this finding in our setting, we recruit N=517 participants using CloudResearch's MTurk Toolkit, and manipulate information presented to respondents on whether we will use their Facebook data for research purposes or commercial purposes. Respondents are randomized into one of these two conditions, each with about 250 participants. Half the participants are told that their "data would be used for research purposes," as in the main experiment. The other half were told that their "data may be used for commercial purposes." We do not find any significant differences in initial valuations for Facebook data across these two groups (p=0.67). The estimates are provided in Table A.4.

Table A.4: Varying Perceived Use of Data

	Log(WTA)	Revise	Researcher Trust
Commercial Treatment	-0.17	0.04	0.07
	(0.40)	(0.04)	(0.14)
Intercept	7.47***	0.26***	3.65***
	(0.30)	(0.03)	(0.10)
Number of Observations	517	517	517
R-Squared	0.00	0.00	0.00

*$p < 0.1$; **$p < 0.05$, ***$p < 0.01$

This table shows treatment effect estimates from a follow-up study (N=517) where we manipulate whether we randomize whether we use data for research or commercial purposes. In the research group, we tell participants their "data would be used for research purposes" and in the commercial treatment we tell them their "data may be used for commercial purposes". We report treatment effect estimates of the commercial treatment relative to the research control on log valuations (Column 1), an indicator if they revise (Column 2) and and endline question on how much they trust the researcher (Column 3)

D Randomization Checks

Table A.5: Randomization Check

	Revenue		Settlement		P-Val
Treatment	0.490	(2031)	0.510	(2110)	0.225

Here we plot the share of respondents who received the Revenue and Settlement information treatments and the results from a test of the null that these shares are equal.

Table A.6: Balance Tests

	Revenue		Settlement		P-Val
Race / Ethnicity: Asian	0.029	(0.167)	0.039	(0.193)	0.066
Race / Ethnicity: Black	0.115	(0.319)	0.103	(0.304)	0.220
Race / Ethnicity: Hispanic	0.083	(0.276)	0.095	(0.293)	0.172
Race / Ethnicity: Middle Eastern	0.000	(0.022)	0.004	(0.061)	0.021
Race / Ethnicity: Native American	0.012	(0.108)	0.012	(0.108)	0.993
Race / Ethnicity: Other	0.047	(0.212)	0.040	(0.196)	0.240
Race / Ethnicity: White	0.714	(0.452)	0.708	(0.455)	0.651
Gender: Female	0.538	(0.499)	0.540	(0.498)	0.866
Gender: Male	0.440	(0.497)	0.441	(0.497)	0.970
Gender: Non-Binary / Third Gender	0.022	(0.147)	0.019	(0.136)	0.469
Age: 10000 - 10019	0.000	(0.022)	0.000	(0.000)	0.317
Age: 18 - 39	0.372	(0.483)	0.386	(0.487)	0.336
Age: 40 - 59	0.327	(0.469)	0.321	(0.467)	0.652
Age: 60 - 79	0.290	(0.454)	0.284	(0.451)	0.689
Age: 80 - 99	0.011	(0.104)	0.009	(0.094)	0.553
Income: $30K-$50K	0.168	(0.374)	0.184	(0.387)	0.191
Income: $50K-$100K	0.284	(0.451)	0.289	(0.453)	0.721
Income: <$30K	0.223	(0.416)	0.209	(0.406)	0.257
Income: >$100K	0.211	(0.408)	0.199	(0.399)	0.332
Income: Prefer Not To Say	0.114	(0.318)	0.120	(0.325)	0.537
Fb Usage: 10-30	0.301	(0.459)	0.267	(0.442)	0.015
Fb Usage: 31-60	0.197	(0.398)	0.208	(0.406)	0.417
Fb Usage: Less Than 10	0.236	(0.425)	0.258	(0.438)	0.109
Fb Usage: More Than 60	0.265	(0.442)	0.268	(0.443)	0.862
Fb Age	2009.757	(3.925)	2009.740	(3.828)	0.891
Political Views: Conservative	0.150	(0.357)	0.140	(0.347)	0.344
Political Views: Extremely Conservative	0.067	(0.251)	0.068	(0.251)	0.968
Political Views: Extremely Liberal	0.135	(0.342)	0.141	(0.348)	0.585
Political Views: Liberal	0.210	(0.408)	0.225	(0.418)	0.246
Political Views: Moderate	0.232	(0.422)	0.232	(0.422)	0.991
Political Views: Other	0.050	(0.218)	0.055	(0.227)	0.536
Political Views: Slightly Conservative	0.069	(0.253)	0.060	(0.237)	0.227
Political Views: Slightly Liberal	0.086	(0.281)	0.081	(0.272)	0.515

Pre-treatment covariate means and standard deviations for all respondents who completed the survey for both information treatments. The p-values come from a test of equality of means across the two treatments.

E Robustness of Updating Behavior

E.1 Experimenter Demand and Placebo Information

Experimenter demand effects could be a concern, since participants could infer that the researchers may want a particular outcome and act accordingly. The literature suggests that such effects are minimal in anonymous online settings like ours (De Quidt et al., 2018). To ensure that the updating behavior is not a simple artifact of experimenter demand (in that individuals may update simply because we asked them if they would like to revise their valuations, following the information treatment), we carry out two robustness checks. First, we run an additional online study (N=251, recruited from MTurk using CloudResearch's toolkit) in which we do not provide participants with any information about valuations, but simply ask them whether they would like to revise their valuations without any information treatment. In this placebo check, we find that only 2.3% of the individuals (6 participants) revise their valuations. The revision probability in our main analysis is about 12 times higher and our placebo estimates are significantly lower than estimates of similar checks in the literature (Allcott and Taubinsky, 2015), providing confidence that our estimates are not driven by experimenter demand. Second, to further test the robustness of this placebo check, we run another study (N=221, recruited from CloudResearch) where we provide a placebo information treatment unrelated to data valuations which stated: "To provide some additional context, recent traffic analyses show that most web pages are first accessed in the late afternoon local time, with browsing activity distributed fairly evenly across the rest of the day". In this study, we find that only 4.6% of individuals revised their valuations as opposed to the 28.6% who revise in our main experiment. Moreover, we find no evidence of asymmetric updating, which further validates our main experimental findings. Overall, the clear regularities in response to our information treatments and the placebo estimates show that we are estimating meaningful effects that are not driven by experimenter demand.

E.2 Sensitivity of Findings to Treatment Dollar Amount

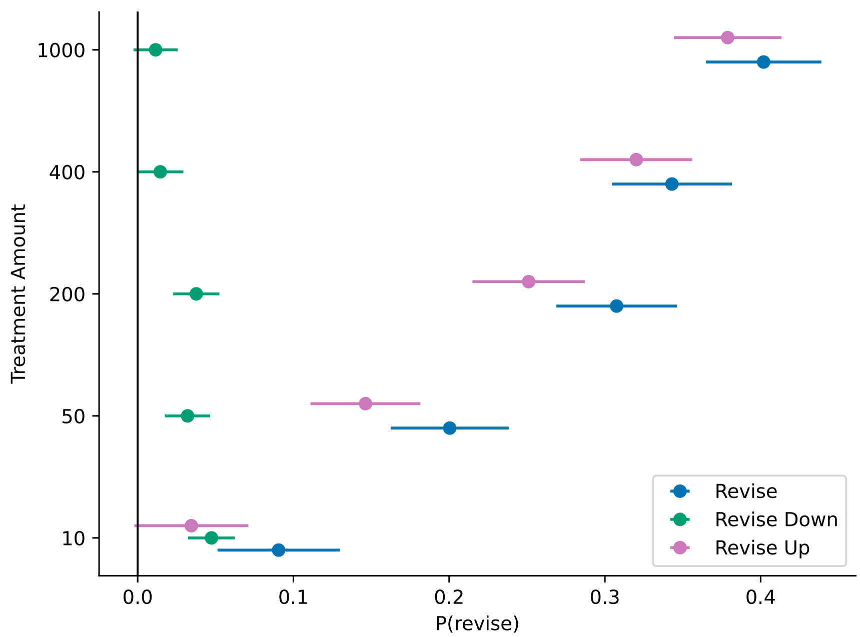
The dollar amounts used in the informational interventions in the primary study were practically and policy-motivated: they were based on actual information in the marketplace. We are interested in determining whether the patterns of updating we observed in that study are sensitive to the dollar amounts used in the treatment. While the dollar amount referenced in the treatment should be reasonably expected to affect the degree to which consumers update their valuations, we wondered whether the key finding of asymmetric updating (consumers with valuations lower than the treatment being more likely to update their valuations upwards, while consumers with valuations lower than the treatment largely keeping their valuations unchanged) would be robustness to different treatment amounts.

Here we show results from a study (N=2,442) in which the dollar amount mentioned in the treatment was randomly sampled from five possible options: \$10, \$50, \$200, \$400, and \$1000. Figure A.13 plots the probability that a participant revises their valuation, the probability they revise their valuation higher, and the probability they revise their valuation by an amount lower then the dollar value they were assigned.

A first takeaway from the analysis is that the dollar amount in the treatment does impact the overall likelihood of participants revising their valuations. The probability of revising is monotonically increasing with the dollar amount mentioned in the treatment. This is entirely driven users being more likely to revise their valuations higher when higher treatment amounts are mentioned.

More importantly, however, Figure A.14 plots the probability of revision based on both the dollar amount the participant saw and their baseline valuation. In particular, we group participants based on whether or not their baseline valuation was below the dollar amount mentioned in the treatment. It is apparent that the key result of asymmetric updating is not sensitive to the dollar amount referenced, as the probability of revision is substantially higher for participants who have a baseline valuation below the referenced dollar amount for all dollar amounts except \$10.[20] In fact, the asymmetric updating finding explains the heterogeneous response to various dollar amounts. As the referenced dollar amount increases, by definition more participants have a baseline valuation below the reference amount. Considering that participants below the reference amount are more likely to revise their valuations, we would expect to see the probability of revision across all participants monotonically increasing with the dollar amount as seen in Figure A.13.

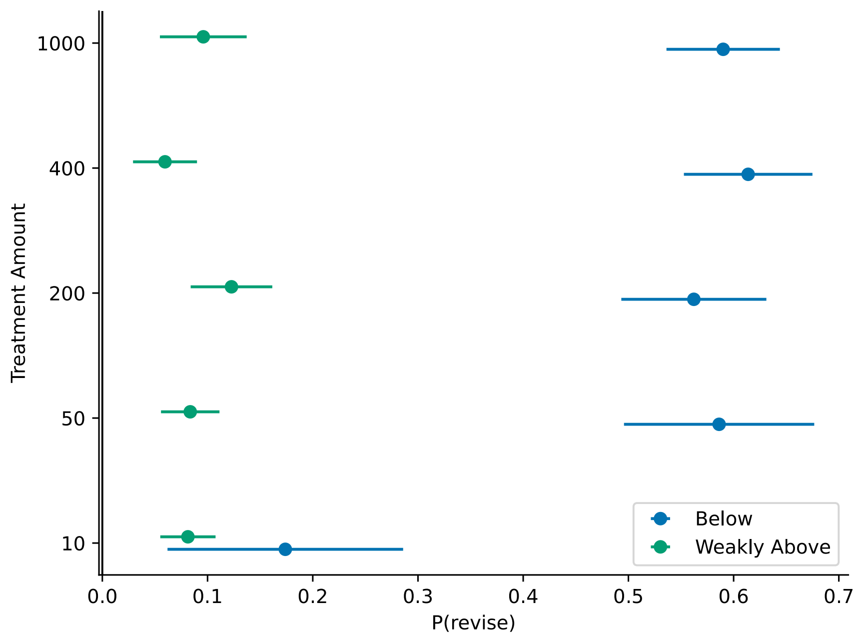
Figure A.13: Probability of Revising by Treatment Dollar Amount



This figure plots the probability of revising valuations by the dollar amount included in the treatment. In addition, we plot the probability of revising by direction (revising higher or lower). Error bars represent 95% confidence intervals.

[20]For the \$10 treatment, the point estimates suggest asymmetric updating, but these estimates may be imprecise given the small number of consumers with baseline valuations below \$10

Figure A.14: Probability of Revising by Treatment Dollar Amount and Baseline Valuation

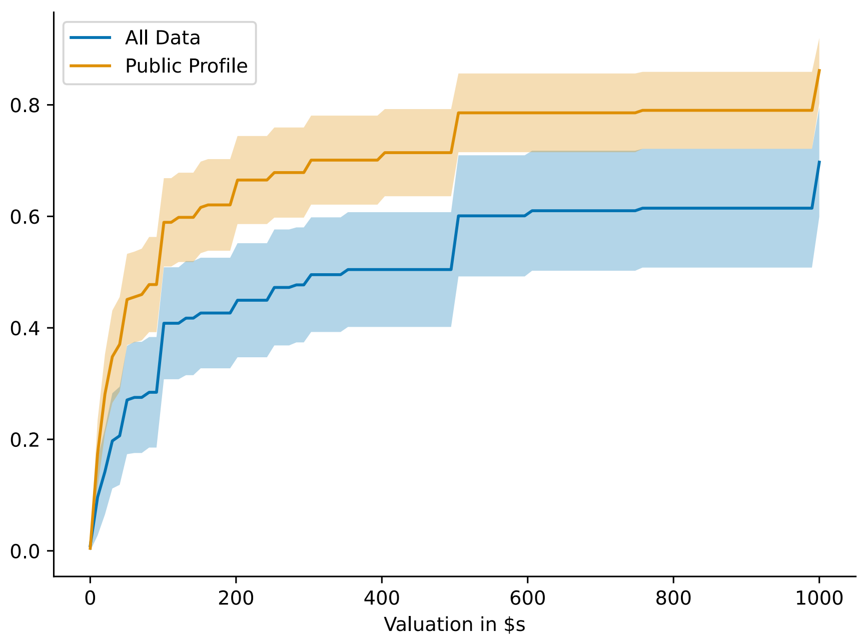


This figure plots the probability of revising valuations by the dollar amount included in the treatment and baseline valuation. The 'Below' points show the probability of revising valuations among individuals with a baseline valuation below the dollar amount included in the treatment and the points labeled 'Weakly Above' plot the probability of revising valuations among individuals with a baseline valuation equal or above the dollar amount. Error bars represent 95% confidence intervals.

E.3 Varying Sensitivity of Data

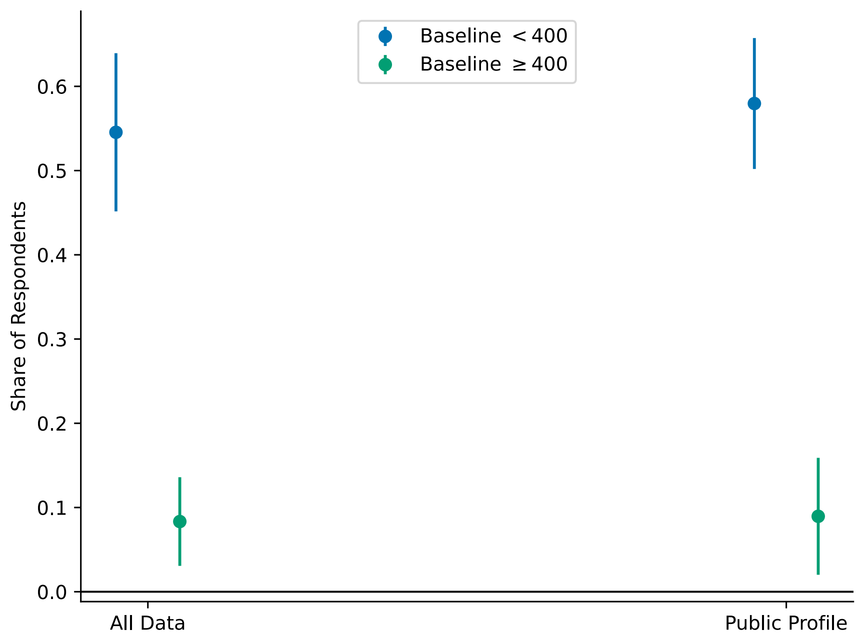
A feature of the Facebook data that we solicit in our main experiment is that this bundle of data includes sensitive data such as private messages. To test the generalizability of our results to other types of more commonly tradable data which is less sensitive, we ran another experiment (N=439, recruited from CloudResearch) where we randomly assign participants to one of two treatment arms. The first arm asked them for their valuation and provided the same information intervention (settlement information treatment) for their entire stock of Facebook data, while the second arm did the same but for only their public profile data on Facebook, which is less sensitive. The results from this experiment highlight two key things: (1) Individuals value the entire data bundle more than their public profile only as seen in Figure A.15, and (2) the probability of revision is not statistically different across the two data bundles both for valuations above and below $400 as seen in Figure A.16. These results suggest that asking for extremely sensitive private Facebook information is not driving our result on asymmetric updating.

Figure A.15: Baseline Valuations by Data Sensitivity



Distribution regressions of an indicator if an individual's valuation is greater than a threshold (y-axis) for the study where the sensitivity of data requested is randomized. We estimate the distribution separately for those where all data is requested and those where only public profile data is requested. The bars represent 95% confidence intervals.

Figure A.16: Revision Rates by Data Sensitivity



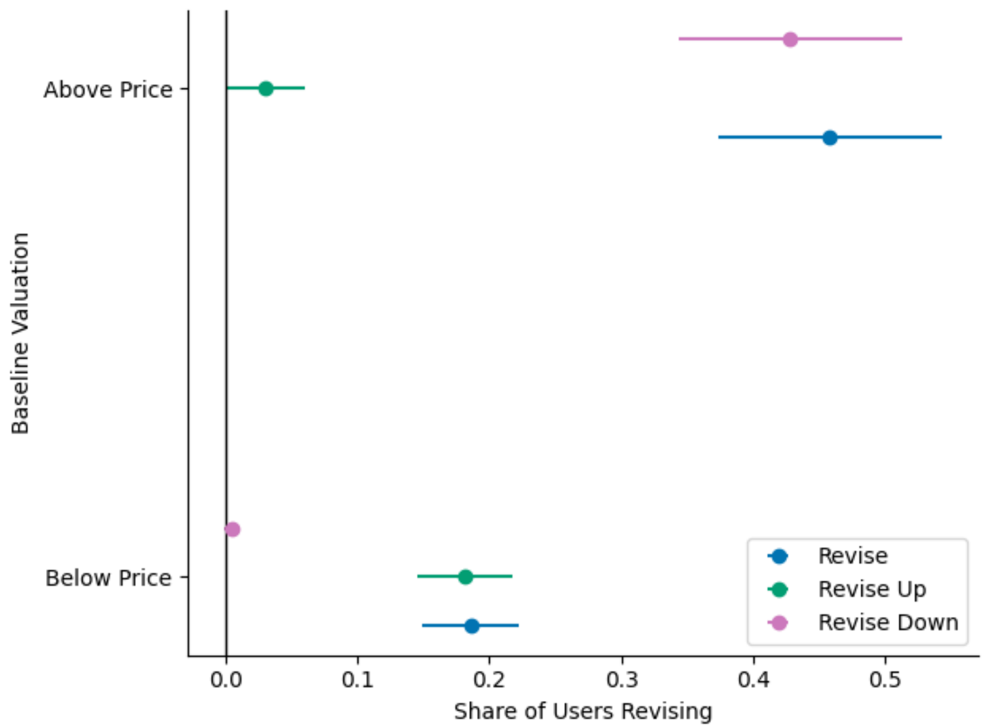
Probability of revising valuations by baseline valuation and sensitivity of data requested for the study where the sensitivity of data requested is randomized. The vertical bars represent 95% confidence intervals.

E.4 Data Valuations vs. 'Standard' Product

A possible concern arising from the above results could be that they can be explained as a standard anchoring effect. This is unlikely to be the case. A standard reference point or anchoring effect, within a Bayesian setting, would imply that individuals both above and below would move towards the dollar amount mentioned. In other words, a reference point effect would imply a symmetric revision of valuations. In the above results, there is a stark asymmetric updating of valuations by individuals. A significantly larger proportion of individuals revised their valuations upward after the information intervention relative to individuals with baseline valuations greater than $400. In other words, informational interventions may not impact users in the Bayesian way in our context since data, due to privacy concerns, is not a standard product. In fact, we would expect symmetric updating of valuations for a standard product, with a clear market price, in the face of informational interventions—as opposed to asymmetric updating for data, where it is *not just* anchoring. Indeed, these results suggest that an individual's data valuations are driven in part by objective information and in part by subjective beliefs about data and data privacy (Lin, 2022). It is important to note that the dollar number mentioned matters, as we see with the individuals moving their (incentive-compatible) valuations towards the $400 amount. This suggests that platforms and policymakers could use information interventions about data valuations to educate consumers. Such strategies are being used by platforms in the data markets space (e.g., MePrism).

To test our intuition that such asymmetric updating would be absent for a standard product for which there is a clear market price, we conduct another experiment. We focus on a standard good for which a market price is readily available: a Tumbler. The experimental design remains the same as in the primary experiment, except that we solicit valuations for the Tumbler instead of Facebook data. We inform participants (N=569, recruited from MTurk using CloudResearch's toolkit) that they have the chance of getting a Tumbler at the end of the experiment and elicit their valuations for giving up the Tumbler. This design allows us to solicit willingness to accept (WTA) for giving up the tumbler once they have it, making it comparable to our primary experiment. We then provide them with real information (taken from Amazon) about the true market price of the Tumbler. We then elicit their valuations again to see whether the revision of valuations is asymmetric (as in our data context) or, in fact, symmetric. The result of revisions of valuations is provided in Figure A.17. As can be seen, the revision in response to price information is symmetric. That is, among the participants who revise their valuations, participants with valuations below the actual price revise their valuations upwards. This is exactly in line with our data experiment. Differently from our data context, however, participants with initial valuations above the price revised their valuations downwards. In line with our intuition, when the baseline valuation is above the actual price, all the variation of people revising comes from a downward revision. Hence, we see that in the case of a standard good, there is symmetric updating in response to information interventions that contain details about product valuations. This experiment provides evidence in line with our hypothesis.

Figure A.17: Symmetric Revision with a Standard Good



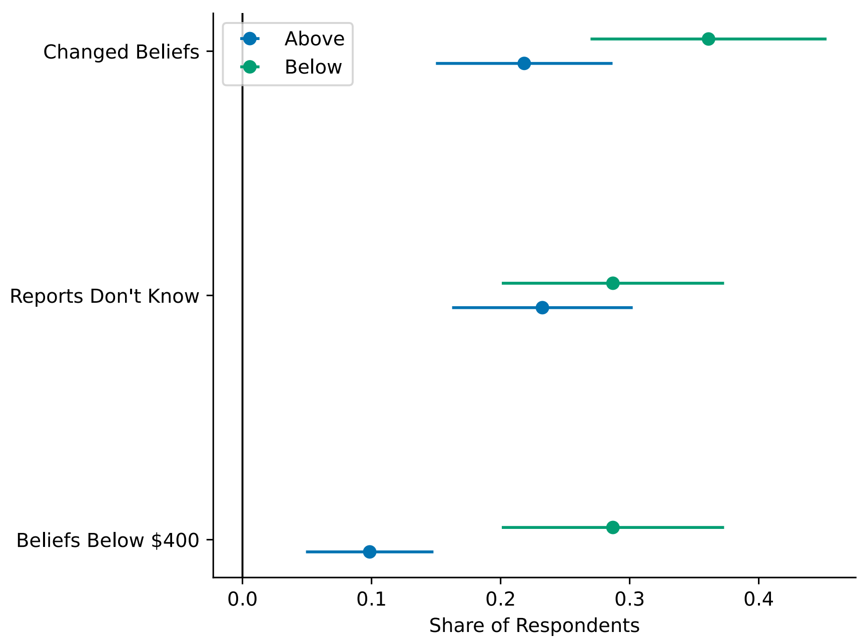
This figure plots the probability a user revises their valuation in the tumbler experiment depending on whether or not their baseline valuation for the tumbler is above or below the price shown.

F Mechanism

F.1 Effect of Treatment on Beliefs

Here, we analyze an additional study that elicited beliefs about the settlement treatment both before and after the informational intervention. The study involved 250 participants. Figure A.18 plots the share of respondents, conditional on their baseline valuation, who updated their beliefs in response to the treatment and the share who reported a belief about the settlement of 'I do not know' and a value less than $400.

Figure A.18: Effect of Settlement Treatment on Beliefs



This figure plots the results from a study (N=250) that elicited beliefs about the settlement treatment both before and after the treatment. Each row represents an outcome variable, 'Changed Beliefs' is an indicator if the respondent updated their beliefs before and after the treatment, 'Reports Don't Know' is an indicator if the respondent reported 'I do not know' before seeing the treatment, and 'Beliefs Below $400' is an indicator if the respondent reported a belief below $400 in the baseline elicitation. The points labeled 'Above' represent participants whose baseline valuation is at least $400 and the points labeled 'Below' represent participants whose baseline valuation is less than $400. Error bars represent 95% confidence intervals.

G Analysis of Text Responses

Table A.7: Sample of responses from revenue cluster

Sample	Text Response
1	if i cared about my privacy, i would not be using facebook. but my data is worth a lot to facebook, so i should be paid just an insane amount of mo...
2	i changed my facebook data valuation because i figured if facebook is willing to pay that amount for certain users then that must mean my data alon...
3	yes, it made me think my data is worth more. facebook must be using my data for a lot of purposes if it is worth so much to them, even up to $400. ...
4	because i realized how much revenue facebook is making from people sharing their data on facebook, so i decided my data is worth more than i previo...
5	in my opinion my data has a value which i feel is a fair amount related to what facebook does with my data and information. they are making a treme...
6	i believe people underestimate how much money facebook makes off our data. i would not want to share my data for a modest amount. less than the num...
7	it just seems like my data is more valuable than i previously thought. especially if facebook is paying out that much.
8	i care about privacy and if my data is misused but in this case i don't use facebook much and there isn't much data i care about. however i do nee...
9	if facebook is making that amount of money off of me, that means my data and information is worth at least that much.
10	i honestly have never thought about it before, but obviously the thought is frightening. i am worried about my data being misused, and i think seei...

Table A.8: Sample of responses from data use cluster

Sample	Text Response
1	i'm happy with the way my data is being used to the best of my knowledge. i'm not really worried that my data has been or will be misused. i do car...
2	i am not concerned about my data as there is not enough data that would affect me on facebook. i am not worry about my data being misused. i do car...
3	i changed my evaluation because you said facebook settled a lawsuit for around $400 per user. i am not terribly concerned about my privacy because ...
4	i changed my mind because the information i would be sharing contains some very personal data. i am ok with the way my data is being used. i am not...
5	i am not happy with the way my data is being used, nor how it is gathered. i definitely worry about my data being misused, and i care about my priv...
6	no, i am not happy with how my data is being used and i am always worried that my data will be misused. my privacy is very important to me and i do...
7	i'm not exactly sure how my data is being used, but it doesn't bother me that much. i'm not overly concerned with my data being misused. kinda care...
8	i wouldn't because i feel that my information is worth at least $500. i'm not happy with the way my data is being used because i feel like i'm bein...
9	i am not worried about my data being misused for purposes of this study. i do care about privacy, but nothing shared online is truly private. so if...
10	i am worried about my data being misused. i care about my privacy. i am not happy with my data being used the way it is. i am worth at least that a...

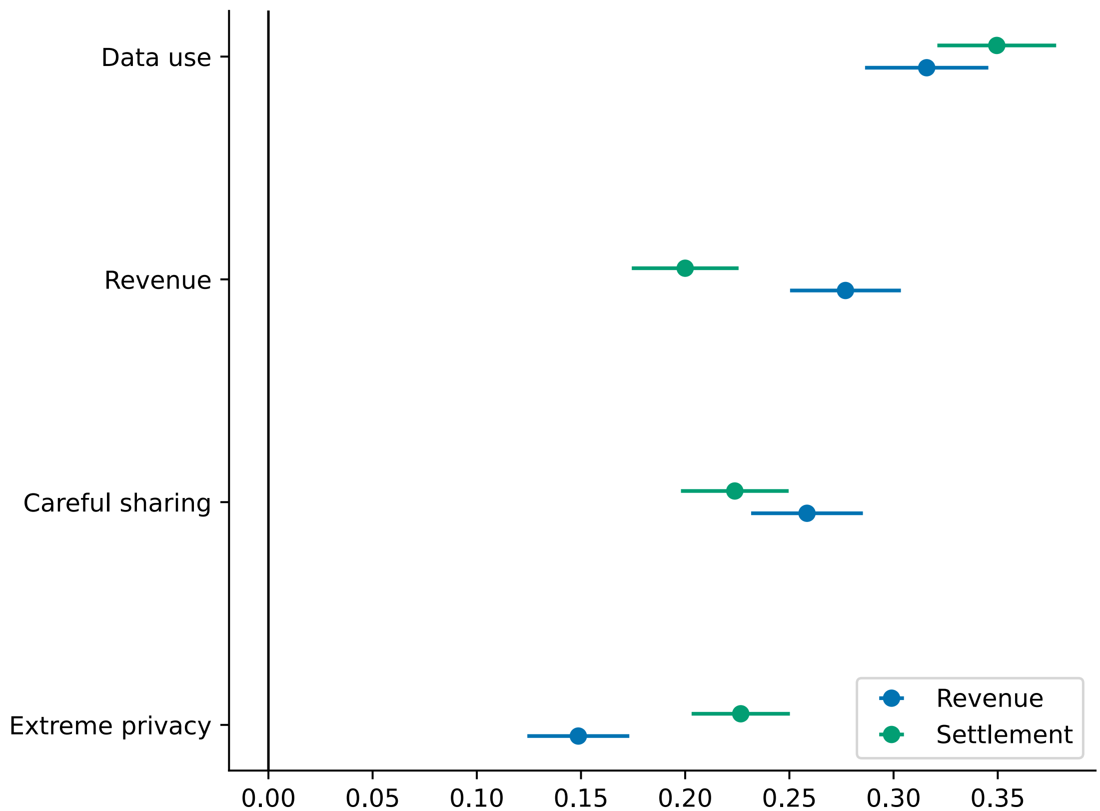
Table A.9: Sample of responses from careful sharing cluster

Sample	Text Response
1	i worry about data misuse and i value my privacy highly. for that reason, i do not share sensitive information on facebook and only very few pictu...
2	i think $10,000 is a fair amount to be sharing all my information. i think the $400 offered by fb is way too little. privacy is a big concern for m...
3	i changed the amount when i saw how much money facebook will make on each north american user over three years. i am not happy with the way facebo...
4	i worry about ever facebook does and do all i can to maintain my privacy and not allow facebook to use my information without my consent.
5	i don't really care about privacy on facebook because i am not ashamed of anything tied to my activity. but if facebook wants access to my data, i ...
6	i really care about privacy . i'm always very careful when sharing stuff on facebook especially my location . i don't fully trust facebook company ...
7	i really enjoy facebook but it would take alot of money for me to share my data it is personal i dont want anything i share misused and it does wor...
8	honestly i don't really know how facebook uses my data . i do care about privacy and i am curious as to what they use the data on. i would like it ...
9	if facebook is getting $400, i should get at least half of it. i care about my privacy. however there is nothing stopping anyone from getting my data.
10	i am not totally sure how facebook uses my data. i am not worried about my data on facebook since i try to not post things i am not comfortable wit...

Table A.10: Sample of responses from extreme privacy cluster

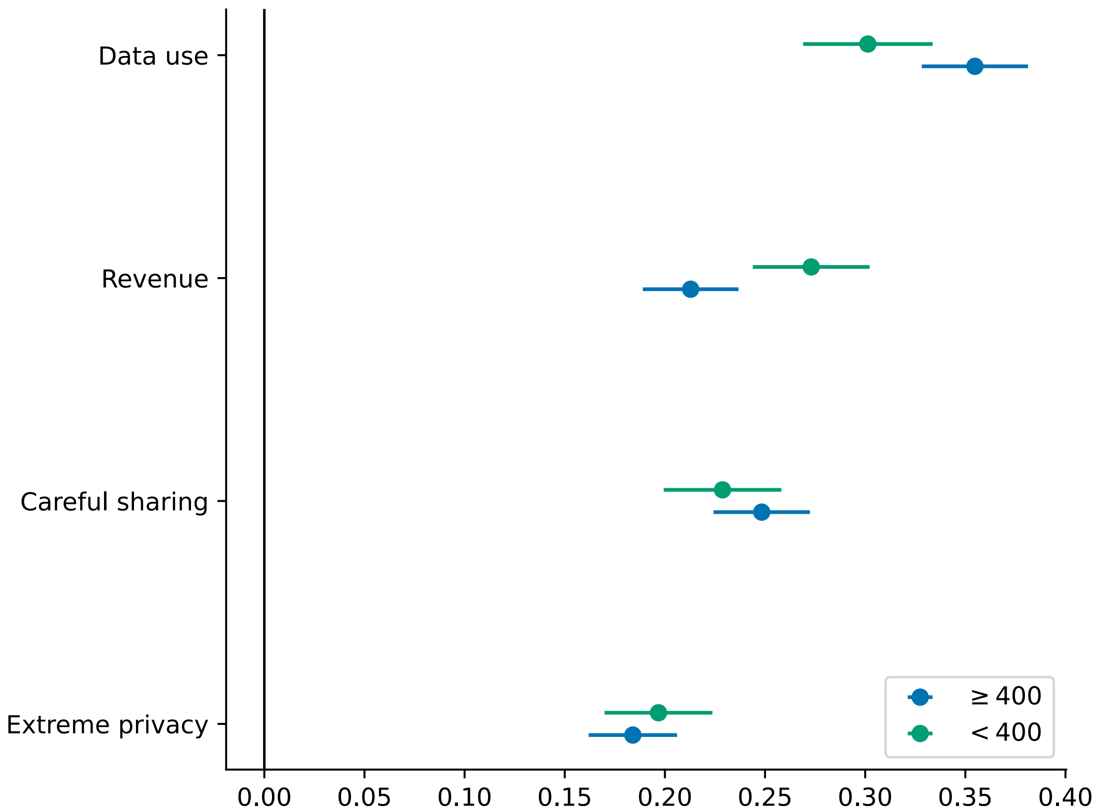
Sample	Text Response
1	i care deeply about my privacy which is why i put such a high number. at that payout price i could afford to handle any repercussions from my data ...
2	after seeing that each person was only getting $400 as compensation for data that was used illegally then it really can't be worth that much. i'd s...
3	if you want my data you will pay for it. my data is not worth that much but not sharing it for less.
4	i care about my privacy and don't want to share my data. i chose a fairly high dollar amount in order to price my data high enough that it would no...
5	i honestly put 0 before because i wasn't going to share my data, but if i'm getting paid for it i might as well share the data.
6	i just don't feel comfortable with sharing my data unless it's for a certain sum of money because it does have value
7	i believe sharing my data is worth more money. i am worried about my data being misused.
8	if i'm going to voluntarily give my data, i'd want to be well paid for it. $400 is not what that many years of data is worth.
9	most of the data is being used without my permission anyway. the amount i chose seems reasonable for the one-year profit from my information.
10	i don't want to share my data for any monetary amount, so that's why i picked such a high borderline insane number like $1,000,000. you did not giv...

Figure A.19: Text Explanation Clustering by Revision Group



Here we plot coefficients from regressions of an indicator for cluster membership on treatment. The horizontal bars represent 95% confidence intervals.

Figure A.20: Text Explanation Clustering by Baseline Valuation



Here we plot coefficients from regressions of an indicator for cluster membership on indicators for whether or not a participant's baseline valuation is above or below $400. The horizontal bars represent 95% confidence intervals.

H Heterogeneity Analysis

Table A.11: Interaction Between Facebook Usage and Demographics

VARIABLES	(1) Log(WTA)	(2) Log(WTA)	(3) Log(WTA)	(4) Log(WTA)	(5) Prob(revise)	(6) Prob(revise)	(7) Prob(revise)	(8) Prob(revise)
Female	-0.377	-0.404**	-0.407**	-0.362	0.0321*	0.0484***	0.0486***	0.0315*
	(0.230)	(0.161)	(0.161)	(0.234)	(0.0190)	(0.0141)	(0.0141)	(0.0190)
High FB Usage	-0.268	-0.372**	-0.159	-0.186	-0.00249	0.0219	0.0132	-0.00275
	(0.251)	(0.161)	(0.224)	(0.346)	(0.0203)	(0.0149)	(0.0203)	(0.0266)
Female x High FB Usage	-0.0621			-0.0936	0.0357			0.0369
	(0.305)			(0.313)	(0.0281)			(0.0283)
Black	-0.441**	-0.735**	-0.438**	-0.714**	0.0498**	0.0704**	0.0496**	0.0700**
	(0.217)	(0.302)	(0.217)	(0.305)	(0.0238)	(0.0322)	(0.0238)	(0.0323)
Black x High FB Usage		0.639		0.599		-0.0451		-0.0441
		(0.428)		(0.431)		(0.0474)		(0.0477)
High Income	0.624***	0.621***	0.764***	0.748***	-0.0588***	-0.0588***	-0.0627***	-0.0630***
	(0.144)	(0.145)	(0.216)	(0.220)	(0.0154)	(0.0154)	(0.0202)	(0.0203)
High Income x High FB Usage			-0.293	-0.268			0.00775	0.00909
			(0.302)	(0.311)			(0.0282)	(0.0285)
Privacy is a right	0.945***	0.943***	0.942***	0.941***	-0.00180	-0.00145	-0.00151	-0.00159
	(0.153)	(0.153)	(0.153)	(0.153)	(0.0167)	(0.0167)	(0.0167)	(0.0167)
Market is correct	-0.794***	-0.789***	-0.788***	-0.786***	0.0975***	0.0966***	0.0968***	0.0971***
	(0.189)	(0.188)	(0.188)	(0.189)	(0.0221)	(0.0220)	(0.0221)	(0.0221)
Age	0.00998**	0.00997**	0.00977**	0.00982**	-0.000549	-0.000540	-0.000534	-0.000544
	(0.00423)	(0.00423)	(0.00427)	(0.00427)	(0.000425)	(0.000425)	(0.000426)	(0.000426)
Prefer not to report income	2.152***	2.147***	2.162***	2.157***	-0.0625***	-0.0620***	-0.0626***	-0.0625***
	(0.369)	(0.368)	(0.368)	(0.366)	(0.0230)	(0.0230)	(0.0230)	(0.0230)
Constant	6.287***	6.337***	6.239***	6.255***	0.306***	0.295***	0.299***	0.306***
	(0.280)	(0.268)	(0.273)	(0.298)	(0.0293)	(0.0287)	(0.0290)	(0.0301)
Observations	4,140	4,140	4,140	4,140	4,140	4,140	4,140	4,140
R-squared	0.033	0.033	0.033	0.033	0.016	0.016	0.016	0.017

Notes. Robust standard errors in parentheses. Significance at the 10% level is represented by *, at the 5% by **, and at the 1% by ***. The unit of observation is the individual respondent. The estimates are based on an OLS regression.

Table A.12: Interaction Between Treatment and Demographics

VARIABLES	(1) Prob(revise)	(2) Prob(revise)	(3) Prob(revise)
Female	0.0566***	0.0485***	0.0485***
	(0.0200)	(0.0141)	(0.0141)
Black	0.0498**	0.0434	0.0498**
	(0.0238)	(0.0330)	(0.0238)
Treat(settle)	0.0130	0.00303	0.00398
	(0.0199)	(0.0147)	(0.0202)
Black x Treat(settle)		0.0132	
		(0.0473)	
High income	-0.0591***	-0.0590***	-0.0595***
	(0.0154)	(0.0154)	(0.0209)
Privacy is a right	-0.00154	-0.00167	-0.00163
	(0.0167)	(0.0167)	(0.0167)
Market is correct	0.0969***	0.0968***	0.0969***
	(0.0221)	(0.0221)	(0.0221)
Age	-0.000539	-0.000537	-0.000536
	(0.000425)	(0.000425)	(0.000425)
Prefer not to report income	-0.0626***	-0.0624***	-0.0624***
	(0.0230)	(0.0230)	(0.0230)
High FB Usage	0.0168	0.0169	0.0169
	(0.0142)	(0.0142)	(0.0142)
Female x Treat(settle)	-0.0158		
	(0.0279)		
High income x Treat(settle)			0.000971
			(0.0279)
Constant	0.291***	0.296***	0.295***
	(0.0304)	(0.0295)	(0.0301)
Observations	4,140	4,140	4,140
R-squared	0.016	0.016	0.016

Notes. Robust standard errors in parentheses. Significance at the 10% level is represented by *, at the 5% by **, and at the 1% by ***. The unit of observation is the individual respondent. The estimates are based on an OLS regression.

Table A.13: Interaction Between Facebook Usage, Treatment, and Demographics

VARIABLES	(1) Prob(revise)	(2) Prob(revise)	(3) Prob(revise)	(4) Prob(revise)
Black	0.0498**	0.0499**	0.0548	0.0497**
	(0.0238)	(0.0239)	(0.0443)	(0.0238)
High FB Usage	0.0108	-0.00460	0.0137	0.0126
	(0.0201)	(0.0287)	(0.0212)	(0.0291)
Treat(settle)	-0.00111	0.0120	-0.00447	0.00329
	(0.0189)	(0.0262)	(0.0199)	(0.0282)
High FB Usage x Treat(settle)	0.0119	0.00337	0.0158	0.00126
	(0.0281)	(0.0404)	(0.0295)	(0.0403)
Female	0.0486***	0.0450*	0.0485***	0.0487***
	(0.0141)	(0.0269)	(0.0141)	(0.0141)
High FB Usage x Female		0.0268		
		(0.0401)		
Treat(settle)x Female		-0.0258		
		(0.0378)		
High FB Usage x Female x Treat(settle)		0.0182		
		(0.0562)		
High Income	-0.0592***	-0.0590***	-0.0590***	-0.0584**
	(0.0154)	(0.0154)	(0.0154)	(0.0279)
Privacy is a right	-0.00152	-0.00168	-0.00131	-0.00134
	(0.0167)	(0.0167)	(0.0168)	(0.0167)
Market is correct	0.0970***	0.0978***	0.0963***	0.0970***
	(0.0221)	(0.0221)	(0.0221)	(0.0221)
Age	-0.000537	-0.000547	-0.000542	-0.000534
	(0.000425)	(0.000425)	(0.000425)	(0.000427)
Prefer not to report income	-0.0625***	-0.0629***	-0.0623***	-0.0627***
	(0.0230)	(0.0230)	(0.0230)	(0.0230)
High FB Usage x Black			-0.0248	
			(0.0661)	
treat(settle) x Black			0.0321	
			(0.0642)	
High FB Usage x Treat(settle) x Black			-0.0410	
			(0.0951)	
High FB Usage x High Income				-0.00376
				(0.0403)
Treat(settle) x High Income				-0.00870
				(0.0380)
High FB Usage x Treat(settle) x High Income				0.0220
				(0.0562)
Constant	0.298***	0.300***	0.297***	0.297***
	(0.0301)	(0.0321)	(0.0305)	(0.0321)
Observations	4,140	4,140	4,140	4,140
R-squared	0.016	0.016	0.016	0.016

Notes. Robust standard errors in parentheses. Significance at the 10% level is represented by *, at the 5% by **, and at the 1% by ***. The unit of observation is the individual respondent. The estimates are based on an OLS regression.

Table A.14: Interaction Between Facebook Sharing Type and Demographics

VARIABLES	(1) Log(WTA)	(2) Log(WTA)	(3) Log(WTA)	(4) Log(WTA)	(5) Prob(revise)	(6) Prob(revise)	(7) Prob(revise)	(8) Prob(revise)
Female	-0.542***	-0.570***	-0.571***	-0.545***	0.0738***	0.0553***	0.0553***	0.0747***
	(0.195)	(0.166)	(0.167)	(0.195)	(0.0246)	(0.0142)	(0.0142)	(0.0247)
Profile Share	1.087***	1.115***	1.047***	1.132***	-0.0268	-0.0452***	-0.0376*	-0.0262
	(0.231)	(0.153)	(0.205)	(0.312)	(0.0205)	(0.0161)	(0.0215)	(0.0273)
Female x Profile Share	-0.0447			-0.0388	-0.0287			-0.0301
	(0.298)			(0.304)	(0.0299)			(0.0302)
Black	-0.314	-0.0847	-0.315	-0.0859	0.0445*	0.0253	0.0448*	0.0257
	(0.216)	(0.266)	(0.216)	(0.268)	(0.0239)	(0.0356)	(0.0239)	(0.0359)
Black x Profile Share		-0.416		-0.414		0.0350		0.0346
		(0.419)		(0.421)		(0.0478)		(0.0482)
High Income	0.570***	0.573***	0.546***	0.570***	-0.0573***	-0.0576***	-0.0528**	-0.0522**
	(0.143)	(0.143)	(0.203)	(0.207)	(0.0154)	(0.0154)	(0.0247)	(0.0249)
High Income x Profile Share			0.0369	0.00363			-0.00710	-0.00828
			(0.279)	(0.287)			(0.0297)	(0.0301)
Privacy is a right	0.838***	0.840***	0.838***	0.840***	0.00227	0.00225	0.00234	0.00195
	(0.148)	(0.149)	(0.149)	(0.148)	(0.0168)	(0.0168)	(0.0168)	(0.0168)
Market is correct	-0.719***	-0.715***	-0.719***	-0.715***	0.0948***	0.0943***	0.0946***	0.0943***
	(0.185)	(0.185)	(0.185)	(0.185)	(0.0220)	(0.0220)	(0.0220)	(0.0221)
Age	0.0124***	0.0126***	0.0125***	0.0126***	-0.000630	-0.000636	-0.000626	-0.000642
	(0.00421)	(0.00422)	(0.00421)	(0.00421)	(0.000426)	(0.000427)	(0.000427)	(0.000427)
Prefer not to report income	2.067***	2.066***	2.069***	2.067***	-0.0592**	-0.0594***	-0.0598***	-0.0596***
	(0.366)	(0.366)	(0.363)	(0.363)	(0.0230)	(0.0230)	(0.0231)	(0.0231)
Constant	5.525***	5.494***	5.548***	5.485***	0.321***	0.332***	0.327***	0.322***
	(0.274)	(0.263)	(0.264)	(0.291)	(0.0308)	(0.0301)	(0.0311)	(0.0329)
Observations	4,140	4,140	4,140	4,140	4,140	4,140	4,140	4,140
R-squared	0.042	0.042	0.042	0.042	0.018	0.017	0.017	0.018

Notes. Robust standard errors in parentheses. Significance at the 10% level is represented by *, at the 5% by **, and at the 1% by ***. The unit of observation is the individual respondent. The estimates are based on an OLS regression.

Table A.15: Interaction Between Facebook Sharing Type and Treatments

VARIABLES	(1) Prob(revise)	(2) Prob(revise)	(3) Prob(revise)	(4) Prob(revise)
Black	0.0450*	0.0447*	0.00461	0.0451*
	(0.0239)	(0.0239)	(0.0483)	(0.0239)
Profile Share	-0.0292	-0.0362	-0.0377	-0.0291
	(0.0215)	(0.0291)	(0.0229)	(0.0303)
Treat(settle)	0.0189	0.00200	0.0120	0.0151
	(0.0242)	(0.0313)	(0.0260)	(0.0338)
Profile Share x Treat(settle)	-0.0229	0.0189	-0.0145	-0.0169
	(0.0296)	(0.0406)	(0.0315)	(0.0421)
Female	0.0553***	0.0540	0.0552***	0.0553***
	(0.0142)	(0.0351)	(0.0142)	(0.0142)
Profile Share x Female		0.0123		
		(0.0426)		
Treat(settle) x Female		0.0380		
		(0.0490)		
Profile Share x Treat(settle) x Female		-0.0802		
		(0.0598)		
High Income	-0.0576***	-0.0578***	-0.0578***	-0.0576
	(0.0154)	(0.0154)	(0.0154)	(0.0350)
Privacy is a right	0.00205	0.00211	0.00197	0.00191
	(0.0168)	(0.0168)	(0.0168)	(0.0168)
Market is correct	0.0946***	0.0949***	0.0939***	0.0945***
	(0.0220)	(0.0221)	(0.0220)	(0.0220)
Age	-0.000631	-0.000637	-0.000640	-0.000632
	(0.000427)	(0.000427)	(0.000427)	(0.000427)
Prefer not to report income	-0.0592**	-0.0597***	-0.0590**	-0.0596***
	(0.0230)	(0.0230)	(0.0230)	(0.0231)
Profile Share x Black			0.0639	
			(0.0663)	
Treat(settle) x Black			0.0449	
			(0.0711)	
Profile Share x Treat(settle) x Black			-0.0617	
			(0.0956)	
Profile Share x High Income				-0.000142
				(0.0424)
Treat(settle) x High Income				0.00787
				(0.0483)
Profile Share x Treat(settle) x High Income				-0.0124
				(0.0592)
Constant	0.320***	0.321***	0.327***	0.320***
	(0.0320)	(0.0347)	(0.0328)	(0.0350)
Observations	4,140	4,140	4,140	4,140
R-squared	0.018	0.018	0.018	0.018

Notes. Robust standard errors in parentheses. Significance at the 10% level is represented by *, at the 5% by **, and at the 1% by ***. The unit of observation is the individual respondent. The estimates are based on an OLS regression.

Table A.16: Interaction Between Facebook Usage Type (Active vs. Passive) and Demographics

VARIABLES	(1) Log(WTA)	(2) Log(WTA)	(3) Log(WTA)	(4) Log(WTA)	(5) Prob(revise)	(6) Prob(revise)	(7) Prob(revise)	(8) Prob(revise)
Female	-0.501***	-0.415**	-0.417**	-0.496***	0.0478***	0.0451***	0.0452***	0.0475***
	(0.182)	(0.161)	(0.162)	(0.182)	(0.0181)	(0.0141)	(0.0141)	(0.0181)
Passive	0.0359	0.174	0.232	0.140	-0.0519***	-0.0548***	-0.0604***	-0.0561**
	(0.266)	(0.176)	(0.259)	(0.399)	(0.0201)	(0.0153)	(0.0209)	(0.0267)
Female x Passive	0.229			0.213	-0.00729			-0.00623
	(0.338)			(0.353)	(0.0285)			(0.0287)
Black	-0.431**	-0.366	-0.430**	-0.358	0.0482**	0.0506*	0.0482**	0.0502*
	(0.216)	(0.248)	(0.216)	(0.248)	(0.0238)	(0.0297)	(0.0238)	(0.0298)
Passive x Black		-0.182		-0.211		-0.00708		-0.00549
		(0.471)		(0.477)		(0.0491)		(0.0494)
High Income	0.641***	0.638***	0.696***	0.691***	-0.0583***	-0.0583***	-0.0617***	-0.0614***
	(0.144)	(0.144)	(0.176)	(0.179)	(0.0153)	(0.0153)	(0.0189)	(0.0189)
Passive x High Income			-0.157	-0.146			0.00967	0.00858
			(0.331)	(0.351)			(0.0284)	(0.0288)
Privacy is a right	0.945***	0.944***	0.945***	0.945***	9.00e-06	3.63e-05	1.23e-05	-2.41e-05
	(0.152)	(0.152)	(0.153)	(0.153)	(0.0166)	(0.0166)	(0.0166)	(0.0166)
Market is correct	-0.815***	-0.816***	-0.818***	-0.816***	0.0954***	0.0955***	0.0956***	0.0955***
	(0.187)	(0.187)	(0.187)	(0.187)	(0.0220)	(0.0220)	(0.0220)	(0.0220)
Age	0.0102**	0.0102**	0.0101**	0.0103**	-0.000766*	-0.000760*	-0.000765*	-0.000764*
	(0.00426)	(0.00425)	(0.00427)	(0.00427)	(0.000431)	(0.000431)	(0.000431)	(0.000431)
Prefer not to report income	2.159***	2.155***	2.152***	2.148***	-0.0590**	-0.0591**	-0.0586**	-0.0587**
	(0.367)	(0.366)	(0.363)	(0.361)	(0.0230)	(0.0230)	(0.0230)	(0.0231)
Constant	6.140***	6.086***	6.069***	6.100***	0.335***	0.336***	0.338***	0.337***
	(0.277)	(0.270)	(0.280)	(0.299)	(0.0304)	(0.0299)	(0.0303)	(0.0311)
Observations	4,140	4,140	4,140	4,140	4,140	4,140	4,140	4,140
R-squared	0.032	0.032	0.032	0.032	0.019	0.019	0.019	0.019

Notes. Robust standard errors in parentheses. Significance at the 10% level is represented by *, at the 5% by **, and at the 1% by ***. The unit of observation is the individual respondent. The estimates are based on an OLS regression.

Table A.17: Interaction Between Facebook Usage Type (Active vs. Passive) and Treatments

	(1)	(2)	(3)	(4)
VARIABLES	Prob(revise)	Prob(revise)	Prob(revise)	Prob(revise)
Black	0.0485**	0.0487**	0.0142	0.0483**
	(0.0238)	(0.0238)	(0.0396)	(0.0238)
Passive	-0.0513**	-0.0231	-0.0604***	-0.0649**
	(0.0206)	(0.0286)	(0.0216)	(0.0298)
Treat(settle)	0.00867	0.0371	-0.000246	0.00117
	(0.0180)	(0.0267)	(0.0190)	(0.0257)
Passive x Treat(settle)	-0.00853	-0.0567	0.0107	0.00863
	(0.0285)	(0.0400)	(0.0299)	(0.0415)
Female	0.0451***	0.0729***	0.0450***	0.0453***
	(0.0141)	(0.0255)	(0.0141)	(0.0141)
Passive x Female		-0.0538		
		(0.0408)		
Treat(settle) x Female		-0.0498		
		(0.0360)		
Passive x Treat(settle) x Female		0.0907		
		(0.0570)		
High Income	-0.0582***	-0.0582***	-0.0588***	-0.0692***
	(0.0153)	(0.0153)	(0.0153)	(0.0260)
Privacy is a right	0.000141	0.000408	-0.000189	6.73e-05
	(0.0167)	(0.0166)	(0.0167)	(0.0167)
Market is correct	0.0954***	0.0950***	0.0951***	0.0955***
	(0.0220)	(0.0220)	(0.0220)	(0.0220)
Age	-0.000761*	-0.000774*	-0.000768*	-0.000759*
	(0.000430)	(0.000430)	(0.000431)	(0.000431)
Prefer not report income	-0.0594**	-0.0588**	-0.0598***	-0.0583**
	(0.0231)	(0.0231)	(0.0231)	(0.0231)
Passive x Black			0.0836	
			(0.0716)	
Treat(settle) x Black			0.0800	
			(0.0595)	
Passive x Treat(settle) x Black			-0.182*	
			(0.0984)	
Passive x High income				0.0272
				(0.0408)
Treat(settle) x High income				0.0154
				(0.0360)
Passive x Treat(settle) x High income				-0.0344
				(0.0570)
Constant	0.332***	0.317***	0.337***	0.337***
	(0.0310)	(0.0332)	(0.0314)	(0.0327)
Observations	4,140	4,140	4,140	4,140
R-squared	0.019	0.020	0.020	0.019

Notes. Robust standard errors in parentheses. Significance at the 10% level is represented by *, at the 5% by **, and at the 1% by ***. The unit of observation is the individual respondent. The estimates are based on an OLS regression.

Table A.18: Data Breach Event Robustness

VARIABLES	(1) Log(WTA)	(2) Log(WTA)	(3) Prob(revise)	(4) Prob(revise)
Female	-0.417***	-0.424***	0.0486***	0.0489***
	(0.154)	(0.155)	(0.0142)	(0.0142)
Black	-0.496**	-0.495**	0.0511**	0.0512**
	(0.220)	(0.220)	(0.0240)	(0.0240)
Hispanic	-0.530**	-0.527**	0.0140	0.0137
	(0.222)	(0.223)	(0.0251)	(0.0251)
Privacy is a right	0.948***	0.956***	-0.00166	-0.00204
	(0.152)	(0.154)	(0.0167)	(0.0167)
Market is Correct	-0.773***	-0.777***	0.0963***	0.0964***
	(0.187)	(0.187)	(0.0221)	(0.0221)
Age	0.00882*	0.00914**	-0.000523	-0.000532
	(0.00450)	(0.00457)	(0.000431)	(0.000432)
High Income	0.612***	0.601***	-0.0588***	-0.0584***
	(0.144)	(0.144)	(0.0154)	(0.0154)
Prefer not to report income	2.148***	2.139***	-0.0623***	-0.0620***
	(0.370)	(0.363)	(0.0230)	(0.0230)
Post Data Breach	-0.136	-1.069***	-0.00356	0.0337
	(0.719)	(0.282)	(0.0331)	(0.0443)
Treat(settle)		-0.0761		0.00829
		(0.142)		(0.0143)
Post x Treat(settle)		2.187		-0.0860
		(1.642)		(0.0652)
High FB Usage	-0.298**	-0.299**	0.0169	0.0168
	(0.151)	(0.152)	(0.0142)	(0.0142)
Constant	6.421***	6.450***	0.295***	0.291***
	(0.276)	(0.280)	(0.0294)	(0.0303)
Observations	4,140	4,140	4,140	4,140
R-squared	0.034	0.036	0.016	0.016

Notes. Robust standard errors in parentheses. Significance at the 10% level is represented by *, at the 5% by **, and at the 1% by ***. The unit of observation is the individual respondent. The estimates are based on an OLS regression.

Table A.19: Distance from Intervention Amount

VARIABLES	(1) Prob(revise)	(2) Log(revision size)	(3) Log(revision size)
Distance	-0.0379	-0.381**	-0.242
	(0.0294)	(0.163)	(0.221)
Treat(Settle)			2.228
			(1.787)
Distance x Treat(Settle)			-0.307
			(0.316)
Constant	0.745***	4.842***	3.807***
	(0.166)	(0.918)	(1.248)
Observations	1,820	1,805	1,805
R-squared	0.001	0.004	0.013

Notes. Robust standard errors in parentheses. Significance at the 10% level is represented by *, at the 5% by **, and at the 1% by ***. The unit of observation is the individual respondent. The estimates are based on an OLS regression.