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Nothing to hide? Gender and age differences in willingness to share data

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Nothing to hide?
Gender and age differences in willingness to share data[*]

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Abstract

Many digital applications in finance and elsewhere rely on the willingness of users to voluntarily share personal data. Yet some users may be less comfortable sharing data than others, potentially limiting the representativeness of resulting datasets. To document differences in the willingness to share data, we draw on questions to a representative sample of U.S. households added to the New York Fed's Survey of Consumer Expectations. We find that women are less willing than men, and older individuals less willing than the young, to share their financial transaction data in exchange for better offers on financial services. These differences can only partly be explained by variation in related attitudes and concerns. Through a randomized priming experiment using information about the California Consumer Privacy Act, we demonstrate that privacy regulation can increase individuals' willingness to share data, though this effect does not vary significantly by gender or age.

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1 Introduction

The digital economy is made possible by the ubiquity of data, particularly personal data. The use of such data can reduce search costs, verification costs, and other frictions (Goldfarb and Tucker, 2019) and thus allow for better and more personalized services. For example, smartphones transmit geolocation data, supporting everything from ride-hailing apps like Uber to various health apps that record footsteps or sleep patterns. Social media applications collect valuable data on individuals' contacts and social connections (Graham, 2015). In financial services, the ability to "port" data through screen scraping apps and open banking has allowed for greater competition and better offers on services such as credit (Berg et al., 2022; Nam, 2022; He et al., 2023; Babina et al., 2025).

Yet as the volume of personal data has grown, so too have concerns about how these data are used. A growing literature shows how the protection of privacy interacts, in sometimes subtle ways, with consumer welfare (Acquisti et al., 2016; Jones and Tonetti, 2020; Cong et al., 2021). And individuals have a range of specific concerns. They worry about data being harvested for unwanted advertising or for price discrimination (Bar-Gill, 2021; Croxson et al., 2022). Alternatively, they may worry about a data breach, when their personal information is leaked or becomes publicly available online.[1] In some cases, leaking of personal information could have a harmful impact on personal reputation, and individuals may worry about the impact of the sharing of certain data on their personal safety (Armantier et al., 2021).[2] Finally, even where some individuals think they have

[1] An example is the 2017 Equifax breach, in which names, birth dates, addresses, social security numbers, and other information of over 160 million U.S., British, and Canadian consumers were accessed in a cyber-attack.

[2] For instance, individuals may worry about violence and harassment by former partners, estranged family members, or strangers; about theft and kidnapping by criminals; and about threats from political

"nothing to hide," their own actions may impinge on the privacy of others, for instance when their data helps to derive information about their contacts or those similar to them (Acemoglu et al., 2022; Bergemann et al., 2022; Liu et al., 2023).

The balance between the efficient use of personal data and appropriate protection of user privacy is thus an important issue for consumer welfare and public policy (Acquisti et al., 2016). Yet one aspect has received comparatively little attention: to what extent does the willingness to share data differ across demographic groups? In particular, because women face unique online privacy risks, such as stalking, non-consensual image sharing, or cyberbullying, they may be more concerned about sharing personal data online. Similarly, more vulnerable or disadvantaged agents, such as older or lower-income people, may be reluctant to share data because they attach less value to the potential benefits this may provide.

The question of demographic differences in data sharing has important implications. Sharing data can in principle lead to better products and services. For example, it can improve loan market outcomes through better screening. These benefits could be particularly large for individuals from traditionally under-served groups, including minority and low-income applicants, as current credit scores do not paint an accurate picture of their future creditworthiness (Blattner and Nelson, 2021; Di Maggio et al., 2022). If, however, one group is structurally more willing to share personal data than another, the datasets being used to develop products, personalize services, and price credit may be biased due to an over-representation of this group relative to the group that is less willing to share data. This could, in turn, mean that data-dependent products—be they fintech apps or generative artificial intelligence (AI) tools—may provide inferior services to indi-

authorities.

viduals belonging to groups that are more concerned about data sharing. Hence, because of disparities in willingness to share data, some demographic groups may be prevented from enjoying fully the benefits of the digital economy, thereby creating or exacerbating existing inequalities.

This paper assesses demographic differences in preferences toward sharing personal data online based on a survey of U.S. consumers. It draws on special questions that were added to the Federal Reserve Bank of New York (FRBNY) Survey of Consumer Expectations. The SCE is a rotating panel of roughly 1,300 nationally representative U.S. household heads. Beyond questions on privacy preferences, the survey includes detailed demographic information, including the respondent's gender, race, age, income, education, financial literacy, and willingness to take risks (Armantier et al., 2017).

We document a significant gender gap in the willingness of individuals to share data. When asked about sharing with a hypothetical credit card company, women consistently express less willingness to share such data than men, and report that they would demand a higher dollar figure for doing so. These differences are robust to various individual controls including race/ethnicity, income, and education.

We then study whether gender differences in preferences or attitudes can explain the overall gender gap. This is a priori plausible because we do find significant gender differences across several tailored questions eliciting these preferences or attitudes. In particular, women are much less willing to take financial risks (in line with, e.g., Borghans et al., 2009 and Croson and Gneezy, 2009). They are more likely to worry about negative consequences if their personal data are to become public, including higher costs and risks to personal safety. Female respondents in our sample also display lower financial literacy, as proxied by a survey question on financial decision making in the household, and numeracy, as assessed by five questions. We then show that these differences indeed explain part of the overall gender gap in the willingness to share data, but only about 40% of its total magnitude.

In addition to gender, we identify strong heterogeneity in willingness to share data by age. Older respondents are also significantly less willing to take risk, and they worry significantly more about negative consequences or that their data become publicly available. They are also significantly less willing to pay a fee to continue using online banking or social media. However, controlling for these various factors does not materially reduce the gap in the willingness to share data between older and younger respondents.

We then analyze whether preferences toward data sharing as well as trust in different types of financial intermediaries are influenced by privacy regulation. To test this, we "prime" a randomly-selected subset of participants by asking questions about the California Consumer Privacy Act (CCPA), which introduces consumer rights around data and monetary compensation for consumers who suffer a data breach. Among respondents randomly treated with information about the CCPA, there is substantial disagreement about whether such a framework would give them more confidence to use online services that require sharing data. In particular, female respondents are relatively more likely to agree that the CCPA would make them more comfortable, while older respondents are not.

Respondents that are positive toward the CCPA subsequently indicate a lower required compensation for sharing data when we ask them to assume that the CCPA framework would be in place in their state. However, the CCPA does not significantly change the relative willingness of men versus women or older versus younger respondents to share data.

Finally, we study how much individuals would trust different types of financial intermediaries with their personal data. Our survey respondents indicate more trust in banks than in fintechs or big techs. Importantly, the relative distrust of fintechs is significantly stronger for females and older respondents, which may inhibit the adoption of new financial products by these groups. However, this distrust is somewhat attenuated for those respondents that were shown the CCPA prompt.

Our findings underscore the importance of gender and age in data privacy concerns. They also suggest that privacy legislation can be helpful in reducing consumer perception of potential harm, and fostering trust in non-traditional intermediaries. Nevertheless, privacy laws appear insufficient to close the gap between demographic groups. While our findings suggest a number of factors related to preferences and attitudes can explain demographic differences in willingness to share data, further research will be needed to better understand the residual drivers of the gender and age gap, and whether policy interventions could (or should) be used to influence it.

Related literature. Our findings have a bearing on current debates around data privacy legislation and regulation of personal data in financial services. They also contribute to three strands of research.

First, they contribute to a growing body of studies looking at people's willingness to share data. Earlier work found a "privacy paradox" (Athey et al., 2017)—a gap between people's self-reported value of their privacy and their actual behaviors in protecting it. Yet more recent evidence suggests that while the paradox can arise in some circumstances, people's attitudes and behaviors are in other cases more aligned (Acquisti et al., 2020; Solove, 2021) or that privacy concerns may positively correlate with the valuation of digital services (Chen et al., 2025). Meanwhile, a series of recent studies finds that consumers value their privacy and hence demand a price for sharing their data (Wathieu and Friedman, 2007; Tang, 2020; Fernandez Vidal and Medine, 2020; Bijlsma et al., 2022; Bian et al., 2023). The price demanded by users in our study is higher than in other studies, potentially because we were asking about sharing a full year of geolocation, social media, or financial transaction data, which is much more extensive than the simple details (name, address, etc.) used in other studies. Our finding that women and older respondents demand a higher price to share data is in line with Cvrcek et al. (2006). While Cvrcek et al. (2006) focus exclusively on location data, our study examines broader categories of personal and financial data. We find that gender differences in willingness to share are more pronounced for financial data compared to other personal data types, and these observed differences cannot be fully accounted for by attitudes, preferences, or other socioeconomic factors.

Second, our study contributes to literature on financial technology (fintech) and financial inclusion. Several studies emphasize the potential of fintech to include underserved groups, including women (Philippon, 2019; Demirgüç-Kunt et al., 2022). Yet, with a survey of 27,000 individuals in 28 countries, Chen et al. (2023) find a statistically significant fintech gender gap in use of fintech products and services. Doerr et al. (2022) show that around the world, older generations are less likely to use digital payments and fintech than younger generations. Similar findings are obtained by Aldasoro et al. (2024a,b) as well as Otis et al. (2024) for the use of generative artificial intelligence tools. Our results complement these findings and show that differences in willingness to share data may be one part of the explanation for the gender gap. Our results thereby also inform the debate on central bank digital currencies (CBDCs) and the extent to which they need to ensure privacy (Garratt and Van Oordt, 2021; Auer et al., 2022; Agur et al., 2025; Ahnert et al., 2025). Our findings suggest that without adequate privacy protection, women and older citizens may be less likely to adopt CBDCs.[3]

Third, our study informs the debate on policy approaches to data protection. For instance, Godinho de Matos and Adjerid (2022) study the impact of the European Union General Data Protection Regulation (GDPR) on consumer and firm behavior. Canayaz et al. (2022) study the impact of the CCPA on the market for personal data, while Doerr et al. (2023) analyze the effect of the CCPA on users' willingness to share data with banks and fintechs. These studies help to inform the optimal design of data protection laws. Cong et al. (2021) show theoretically that the overuse of data by firms can also be mitigated through subsidizing innovators, rather than data regulation. Yet, if there are strong differences in preferences toward data sharing within society, this may form a challenge to the definition of common rules and policies.[4]

Relative to the existing literature, we focus specifically on the willingness to share data online and on possible demographic differences. Further, our analysis relies on a representative survey of consumers in the United States, and assesses how the impact of privacy legislation may affect attitudes. Our study therefore complements existing literature by formally identifying a gender and an age gap in data sharing preference that further research can build on.

[3] Similarly, based on a randomized online survey experiment of 3,500 individuals in South Korea, Choi et al. (2023) show that greater privacy protections entice users to use CBDC more for online transactions, and that this effect is more important for female users.

[4] See Collis et al. (2021), Lin (2022), and Prince and Wallsten (2022) for further evidence on heterogeneity in the valuation of personal data.

2 The Survey of Consumer Expectations

We investigate the attitudes towards data privacy of Americans in the Survey of Consumer Expectations (SCE). The SCE is a high-quality monthly, internet-based survey designed and conducted by the Federal Reserve Bank of New York (FRBNY) and fielded by the private firm NielsenIQ. Launched in 2013, the SCE has been used extensively to help researchers and policymakers understand how expectations are formed and how they affect consumer behaviour.

The SCE uses a 12-month rotating panel of roughly 1,300 nationally representative U.S. household heads. New respondents are drawn each month to match demographic targets from the American Community Survey (ACS), and they stay on the panel for up to 12 months before rotating out. The survey's main objective is to collect expectations for a wide range of economic outcomes (e.g. inflation, income, spending, household finance, employment, and housing). The survey includes detailed demographic information, including the respondent's gender, race, age, income, education, financial literacy, and willingness to take risks (Armantier et al., 2017). The SCE aims to be representative of a U.S. household head with respect to education, income, age, and region, in line with ACS target values.

To understand how consumers value their data privacy and what determines their willingness to share data, the January 2022 survey contained an additional module.[5] The module asked detailed questions on respondents' attitudes towards data privacy, for ex-

[5] An earlier, similar module was fielded in September 2020 and analyzed in Armantier et al. (2021), with a focus on which types of firms consumers trust with their data, and how willingness to share data was affected by the Covid-19 pandemic period. While that earlier module featured similar questions, the wording and order of the questions differed, so that results are difficult to directly compare.

ample how much they trust different counterparties to safeguard their data, or whether users think that sharing data could have negative consequences for them. We report the relevant module questions in the appendix.

To elicit consumers' willingness to share data, we ask them the following question: "Imagine you were to sign up for a new credit card. The credit card company has approved your application and is now offering you a sign-up bonus (in the form of money credited to your card account) if you provide the company with access to your full bank transaction history from the past year. Please select for each of the following amounts whether you'd be willing to share this data." Respondents are then shown the following amounts: \$20, \$50, \$100, \$250, \$500, \$1000, \$2500, and \$5000 with the options "No, do not share data" and "Yes, share the data" for each amount. The survey also asks the same question about respondents' "geolocation and social media data" instead of their "full bank transaction history." The survey interface was designed such that respondents were alerted in case their selections violated monotonicity—e.g. somebody who is willing to share their data for \$500 should also be willing to do so at any higher amount. Therefore, we observe for every respondent a single "switching point" (except if they say no to all provided amounts).

To understand what determines users' willingness to share data, the survey then asks them whether they have concerns about sharing their personal data. To this end, respondents were asked: "Are you concerned that sharing your personal data could have negative consequences for you?"; "Are you concerned about companies using this information to charge you more money for other goods or services?"; and "Are you concerned that your personal data might become publicly available?". To answer each question, the respondent had to use a Likert scale from 1 (not at all concerned) to 7 (extremely concerned).

We further ask, “What are you specifically concerned about if your personal data were to become publicly available?” with the answer options: “My personal safety,” “Negative effects on my reputation,” “Identity theft,” and “Abuse of my data for unintended purposes (in the news or media, for political agenda, targeted ads, . . .).” In addition, we ask to what extent consumers agree with the following statement: “Even if I have no immediate concerns about my reputation or safety, I do not want to share my data because ‘my data are nobody’s business’.”

A randomly selected half of respondents was shown information and asked questions about the California Consumer Privacy Act (CCPA) before proceeding with the questions on data sharing. We defer a detailed discussion of this “CCPA treatment” to Section 3.3.

Finally, we ask respondents how they value products that use digital financial technology in the areas of online banking, digital payments or social media. Specifically, we ask: “Imagine you now had to pay an annual fee in order to keep using [*online banking*] / [*digital payment technologies*] / [*social media*]. How much would you be willing to pay for the coming year?” Users are then shown the following amounts: \$10, \$20, \$50, \$100, \$250, \$500, \$1000, and \$2500 with the options “No, would not pay” and “Yes, would pay” for each amount. We use the highest amount with an affirmative response as the person’s valuation.

Summary statistics Our final sample has information on questions related to data sharing and privacy for 1,106 respondents. Table 1 shows summary statistics for the main variables from the survey. The average age of respondents is 50. About 85% of respondents are White, 9.6% are Black, and 4% are Asian. 7% are Hispanic of any race. Regarding other characteristics, 57% of respondents have a bachelor’s degree or higher, 35%

have an income above \$100,000, and 58% are working full-time, with a further 11% working part-time. 71% own their primary residence. The analyses below will use weights to make the sample representative of U.S. household heads in terms of education, income, age and region.[6]

The bottom half of the table summarizes attitudes and proxies for preferences such as risk aversion or general trust that we will use as additional controls in what follows. While these variables will be discussed in more detail later, for now we note that there is substantial variation in almost all of them.

3 Empirical strategy and results

To investigate how attitudes towards sharing data differ by gender and with age, we estimate the following regression at the respondent (i) level:

$$y_i = \beta \; Female_i + \gamma \; Age_i + \rho \; controls_i + \varepsilon_i. \tag{1}$$

As the dependent variable y_i we will use different measures of consumers' willingness to share data or concerns about data sharing. Depending on the outcome variable, we will estimate either ordered logit or binary logit models.[7] All regressions are weighted by the provided sample weights to ensure that our sample is representative. Standard errors are robust. Our main coefficients of interest indicate to what extent male and female respondents (β) as well as older and young respondents (γ) differ in their attitudes.

[6] Table 10 in the online appendix provides a weighted version of the summary statistics.

[7] We have verified that our main results are also robust to the use of interval or OLS regressions.

We include a rich set of individual level controls, which we will refer to as 'demographic' and 'socioeconomic' controls. 'Demographic controls' include dummies for whether the respondent owns their primary residence, whether they are married, whether they belong to a racial or ethnic minority, whether they are working (with separate dummies for full-time and part-time work), and whether they are living alone. Under the label 'socioeconomic controls,' we further control for the respondent's educational attainment (9 categories), a quadratic function of the household's income category, and whether they have been subject to a data breach in the past. Controlling for socio-economic status is important as it affects, among other outcomes, individuals' optimism about future economic developments and learning from financial information (Kuhnen and Miu, 2017; Das et al., 2020). Finally, all regressions control for whether the respondent was randomly subject to the CCPA treatment (analyzed in Section 3.3).

3.1 Gender, age, and the willingness to share data

A plot of the share of respondents and the dollar amounts they request to share data (Figure 1) suggests that women have a lower willingness to share data than men. Panel (a) looks at bank transaction histories, panel (b) at geolocation and social media data. The y-axis reports the cumulative fraction of women and men that indicate they are willing to share their data with the credit card company when offered the amount of money on the x-axis. Almost nobody is willing to share their data for $20 or $50, while at higher amounts, more respondents become willing to do so. Importantly, for any given amount, fewer women indicate they are willing to share their data. For instance, for both types of data, less than half the women indicate that they would be willing to share the data when offered the highest amount, $5,000. Among men, this share is about 10 percentage points higher.

We note that in general, these amounts demanded for sharing data appear very high. Existing research has argued for a "digital privacy paradox," i.e. that people's stated aversion to sharing personal data does not match their behavior (Athey et al., 2017; Acquisti et al., 2020). In our case, this is not an issue to the extent that we are not interested per se in the level of compensation required (dollar amounts), but how they compare across respondents with different characteristics. The maintained assumption in what follows is that the extent to which aversion to sharing data is overstated in surveys vs. real-world decisions does not systematically vary by gender or with age.

Table 2 investigates the relationship between the requested amount to share data and personal characteristics in the regression setup of Equation (1). We first discuss the gender dimension, and then differences with respect to age. Estimating an ordered logit specification where the dependent variable y is a categorical variable indicating the lowest amount at which a person indicates they are willing to share their data, column (1) shows that women require a significantly higher amount than men to share their data.

When we add the rich set of demographic controls in column (2), the estimated coefficient remains highly significant and increases in magnitude. Further adding socioeconomic controls in column (3) leads to no material change in the magnitude of the estimated coefficient, which remains strongly statistically significant.[8] These patters suggest that the relationship between the willingness to share data and gender is not explained by a rich set of (observable) respondent characteristics. Column (4) uses a dummy as the dependent variable that takes on a value of one if the amount of money required to

[8] Based on computed average marginal effects, women are significantly less likely to indicate that they are willing to share data for any amount up to $5,000, and are about 14 percentage points more likely to select no sharing at $5,000.

share data is at least \$2,500. Estimating a logistic regression with demographic and socioeconomic controls yields a positive coefficient of 0.72, significant at the 1% level. Based on implied average marginal effects, women are about 14.7 percentage points (pp) more likely to demand at least \$2,500 than men.[9]

Columns (5) and (6) repeat the estimation exercises from columns (3) and (4), but focus on respondents' willingness to share social media/geolocation data (rather than their bank history). Also for social media/geolocation data, our empirical results show that women are significantly less willing to share their data, i.e. they demand higher amounts for doing so. The differences are slightly smaller: in column (6), the calculated average marginal effect implies an 8.2 pp higher likelihood for women to demand at least \$2,500 to share their data.

Beyond gender, the coefficient on respondents' age is positive and strongly statistically significant in each regression. These results suggest that older respondents are generally less willing to share their bank history or social media/geolocation data than younger respondents. Computed average marginal effects imply that an additional year of age increases the likelihood that a respondent demands at least \$2,500 to share their data by 0.7 pp for bank history data and by 0.6 pp for social media/geolocation data.

3.2 Examining explanations for the gaps

What could account for the observed gender gap in the willingness to share data? Based on previous work, a number of explanations seem plausible. First, women are on average more risk-averse than men (Borghans et al., 2009; Croson and Gneezy, 2009), so

[9] Overall, 57.6% of respondents (or 60.8% weighted) answered that they require \$2,500 or more.

differences in general or financial risk aversion between genders could help explain the gap. For example, women could put a greater weight on the potential financial costs or downside risks of sharing data. Second, research has found that women are less trusting in general (Alesina and La Ferrara, 2002), which might extend to financial services companies storing personal data. Third are potential differences in financial literacy and numeracy (see Lusardi and Mitchell (2011) for a survey). If there are significant differences in these variables across genders, this may influence perceived costs and benefits of data sharing. Fourth are potential differences in specific concerns around sharing data (e.g. reputational costs, risks that data become public or personal safety). And finally, men and women might value the benefits of using financial technology differently (Chen et al., 2025), which could in part reflect biased information provision about the benefits of technology (Lambrecht and Tucker, 2019), with implications for their willingness to share data and associated benefits. We investigate these explanations in what follows.

To start, Table 3 uses different respondent characteristics as outcome variables to assess whether they vary by gender. All regressions include demographic and socioeconomic controls. Column (1) shows that women's stated willingness to take financial risks is significantly lower, and column (2) shows similar results for the willingness to take risk in general. Column (3) indicates directionally lower trust by women, though this effect is not significant. In contrast, column (4) indicates that women in our sample have significantly lower numeracy, measured in the SCE based on a standard test with five questions.[10]

Columns (5)–(7) turn to the concerns about sharing data. The dependent variables are

[10] See the last page of https://www.newyorkfed.org/medialibrary/Interactives/sce/sce/downloads/glossary/FRBNY-SCE-ChartGlossary.pdf for the wording of the five questions.

on a scale from 1 to 7, where 7 means strongly concerned. Women appear to be significantly more concerned that sharing their personal data could have negative consequences for them, as well as about companies using this information to charge them more money for other goods or services (columns (5) and (6)). When asked "Are you concerned that your personal data might become publicly available?," column (7) shows that women are also significantly more concerned along this dimension.

Finally, columns (8) to (10) investigate the extent to which the benefits of using digital products differ across genders. In principle, women could derive a lower utility from using online banking or payment apps.[11] To this end, we ask users how much they would be willing to pay in an annual fee to keep using online banking, digital payment technologies, or social media, as described earlier. Results show no systematic gender differences across the willingness to pay for using digital financial technology, but women express a higher willingness to pay for social media. These findings are in line with Brynjolfsson et al. (2023), who find that women are willing to pay a higher amount to keep using Facebook compared to men.[12]

Given the at times large differences in attitudes in Table 3, Table 4 analyzes whether controlling for these factors can narrow or eliminate the gender gap in the willingness to share data. Column (1) focuses on the willingness to share bank history data and adds controls for respondents' risk aversion and trust. Relative to the baseline estimate (column (3) in Table 2), the estimated gap remains almost identical. In column (2), we add

[11] Chen et al. (2025) show for China that there is a positive correlation between the benefits of using new financial technology and concerns about data privacy. Thus, perhaps surprisingly, those users who value fintech the most may also be more worried about potential costs.

[12] Note that questions on the willingness to pay were only asked to respondents who answered that they use these services. For those that answered that they do not use these services, we set their willingness to pay to zero.

controls for numeracy and whether the respondent indicates that they make the financial decisions in their household – a proxy for financial literacy. Adding these controls narrows the gap somewhat.

Accounting for the gender differences in concerns about sharing data in column (3) further narrows the gender gap substantially; relative to the baseline, the implied marginal effect of being female on the likelihood of not being willing to share data for any of the offered amounts is reduced by almost 40%.[13] Yet it remains economically and statically significant. Finally, controlling for the (insignificant) differences in the willingness to pay for online banking or digital payment technologies does not materially affect the gap (column 4).

In columns (5) and (6), we repeat the same exercise for the willingness to share social media and geolocation data. Similar to bank transaction history, adding the additional controls reduces but does not eliminate the gender gap (although in the final column it is only mildly statistically significant).[14]

With respect to age, the patterns are qualitatively similar. Older respondents are significantly less willing to take risks and worry significantly more about negative consequences, or that their data become publicly available. However, they are also significantly less willing to pay a fee to continue using online banking or social media (see Table 3). However, controlling for the various factors does not materially reduce the magnitude of the age coefficient in columns (1) to (4) of Table 4 and reduces it only modestly in columns (5) and (6).

[13] The average marginal effect of being female in column (3) is 8.8 pp, vs. 14 pp in the baseline.

[14] For this outcome, we control for the stated willingness to pay for social media, rather than online banking and payment apps as before.

3.3 The role of privacy regulation—the CCPA

More and more jurisdictions are introducing privacy protection legislation. Could such legislation increase willingness to share data and help close the gender and age gaps in data sharing? To examine these aspects, the survey randomly primed half of respondents with information and questions about the California Consumer Privacy Act (CCPA).

The CCPA is a data privacy law covering the state of California that went into effect at the beginning of 2020. It endows Californians with several rights regarding the personal information that a firm may collect about them. In particular, Californians have the right to know what personal information is being collected, whether it is being sold and to whom, and the right to access their personal information, to delete it, and to opt out of the sale of such information (Camhi and Lyon, 2018).

The rights included in the CCPA directly address some of the concerns that individuals list when it comes to sharing their data, like identity theft or abuse of data. A consumer concerned with these issues can request under CCPA that her data not be sold or that her data be deleted after she finishes transacting with a firm. Therefore, the CCPA likely increased certainty around the use of personal data: by assuring consumers that they can safeguard their privacy if they choose to do so, it could increase consumers' willingness to share their data (Doerr et al., 2023).

To understand how the CCPA has affected individuals' willingness to share data, we provided a random half of the survey respondents with the following information:

> *The California Consumer Privacy Act (CCPA) ensures privacy rights for consumers in California. The law is widely considered to provide the strongest consumer data*

> *protection in the U.S. The law provides consumers with the right to know the personal information that a business collects about them, and the right to delete such personal information. The law also provides consumers with the right to opt out of the sale of personal information to third parties. In addition, if there is a data breach and personal information is stolen (e.g. a consumer's name or driver's license number), then the consumer can sue the business for damages up to $750.*

We then asked them: "*To what extent do you agree with the following statement? Please indicate your level of agreement on a scale from 1 (do not agree at all) to 7 (completely agree): If the CCPA was in place in my state, then it would give me greater confidence to use online services that require sharing of my personal data.*"

Importantly, only half of the respondents saw the CCPA prompt, and did so directly before they were asked about the required amounts to share their data with the credit card company. Furthermore, those who were shown the CCPA prompt were also shown an altered version of the willingness-to-share question: "*Imagine that the legal framework of the CCPA was in place in your state and imagine you were to sign up for a new credit card. The credit card company has approved your application and is now offering you a sign-up bonus (in the form of money credited to your card account) if you provide the company with access to your full bank transaction history from the past year.*"

This randomization allows us to investigate the extent to which seeing the CCPA prompt and agreeing with the statement about the CCPA correlates with respondents' willingness to share data. Figure 2 shows that among the 554 respondents that were shown the CCPA prompt, about 25% responded 3 or lower, i.e. do not agree with the statement. In contrast, 55% selected a value of 5 or higher, with the remaining 20% selecting the intermediate value of 4. These patterns suggest that, on average, privacy regulation in the spirit of the CCPA gives individuals greater confidence to use online services that require the sharing of personal data. Importantly, the histogram also shows that female respondents tend to agree with the statement more strongly, and the difference in distributions is statistically significant ($p = 0.04$, Wilcoxon–Mann–Whitney test). This suggests that privacy-protecting rules might disproportionately affect women's confidence to use online service that feature data sharing.

In Table 5, we study whether showing the CCPA prompt to a respondent affects their willingness to share data. Column (1) shows that there is no average effect on respondents' willingness to share their bank history data. This regression specification corresponds to the one from column (2) of Table 4.[15]

However, column (2) shows that if respondents agreed with the statement that the CCPA would give them greater confidence, then they require significantly lower amounts to share their data. As noted above, female respondents are more likely to agree with this statement; however, column (3) indicates that the differential effect of the CCPA treatment on female respondents is not statistically significant. The same holds for younger vs. older respondents.[16] The final four columns of the table show that the qualitative patterns are the same for the question on social media and geolocation data sharing.

Taken together, these results suggest that, as long as respondents believe that the

[15] Note that in Table 4 we were also controlling for the CCPA treatment, but without displaying the coefficient. In this section, we opt to use the specification without the controls for concerns about potential risks from sharing data because those questions were asked after the CCPA prompt.

[16] Interaction terms are not straightforward to interpret in nonlinear models in general (Ai and Norton, 2003), and this is particularly true for ordered logit models. However, our conclusions are unchanged if we transform the model into a binary logit as earlier and evaluate marginal effects in the different ways suggested by Dow et al. (2019)—the Female × CCPA and Age × CCPA interaction effects are never close to statistically significant.

CCPA protects their data, the policy has a positive effect on individuals' willingness to share data. However, there is no differential effect between women and men or older and younger respondents.

To provide insights into which subgroups of the population state that privacy regulation would give them more confidence to use online services requiring them to share their data, we regress CCPA agreement measures on various respondent-level characteristics in Table 6. Column (1) estimates an ordered logit regression with the level of agreement with the CCPA statement (on a scale from 1–7) as the outcome variable. It shows that women agree significantly more (in line with the histogram discussed earlier). Married respondents and—to a lesser extent in terms of significance—racial or ethnic minority respondents agree less. Interestingly, neither respondent age nor any of the "behavioral" characteristics like risk aversion, trust, or numeracy are significantly associated with the outcome. Using a dummy for agreement (at least response 4 out of 7) in column (2) provides a qualitatively similar picture.

3.4 Additional tests

Socioeconomic characteristics. We further investigate whether the gender gap in willingness to share data varies with socioeconomic characteristics, namely income, education, or financial literacy. We estimate Equation (1), but interact the female dummy with dummies for respondents with incomes above $100,000, a bachelor degree or higher, or high numeracy (a score of 5 out of 5, achieved by 41% of respondents). Since interaction effects are difficult to interpret in nonlinear models like logits or ordered logits, Table 7 shows results from linear probability models, i.e. ordinary least squares (OLS) regressions, using a dummy for whether a respondent indicated they would not share their data for less than $2,500 as dependent variable.[17] Column (1) shows that the gender gap in the amount required to share data does not significantly change with respondents' income. Column (2) reports a similar picture for education, and column (3) for numeracy. In all three specifications, the coefficient on the interaction term of the female dummy with the measure of socioeconomic status is insignificant. When performing a principal component analysis (PCA) and extracting the first principal component of education, income, and numeracy, and interacting the PCA measure with the gender dummy in column (4), we again obtain an insignificant interaction term. Higher socioeconomic status tends to increase willingness to share, but except for numeracy, this effect is not statistically significant.

Concerns. The survey asked respondents the following question: "What are you specifically concerned about if your personal data were to become publicly available?" The answer options were "My personal safety," "negative effects on my reputation," "identity theft," and "abuse of my data for unintended purposes (in the news or media, for political agenda, targeted ads, ...)." Most respondents are concerned about ID theft (92%), followed by abuse for unintended purposes (64%), personal safety (50%) and reputation (25%). Table 8 investigates to what extent these concerns about sharing data differ across genders or by age. When asked about what they are specifically concerned about (yes or no questions, columns (1)–(4)), women worry significantly more about their personal safety. Older respondents worry less about this aspect. There are no statistically significant differences for reputational concerns, identity theft, or data abuse.[18] Finally, in col-

[17] We obtain qualitatively similar results in binary logit or ordered logit models.

[18] The number of observations varies across columns because some categorical controls perfectly determine the outcome. Also, only respondents who indicated that they were at least somewhat concerned if

umn (5), we study determinants of respondents' agreement with the statement "my data are nobody's business".There are no significant gender differences, but older respondents are more likely to agree more strongly with this statement.

These results suggest that personal safety concerns may be the most distinguishing factor driving differential privacy concerns of men and women in our sample. For older respondents, the aversion to sharing data appears to be more of a matter of principle.

4 Trust in financial intermediaries

Finally, we examine whether data-related trust in different types of financial intermediaries varies systematically across groups, and whether the CCPA may affect this trust.

Specifically, in a later part of the survey, we asked respondents the following question: *"How much do you trust the following entities to safely store your personal data (that is, your bank transaction history, geolocation or social media data)? For each of them, please indicate your trust level on a scale from 1 (no trust at all in ability to safely store personal data) to 7 (complete trust)."* Respondents were asked to indicate their level of trust in four counterparties: traditional financial institutions (henceforth "banks"), technology firms that specialize in financial services ("fintechs"), large technology companies ("big techs"), and a government agency. The order of the counterparties was randomly varied across respondents.[19]

We use these data to estimate the following linear regression at the individual (*i*)–

their personal data were to become public were asked these questions, but this applied to all but 19 respondents.

[19] A similar question asked in an earlier wave of the SCE was analyzed descriptively in Armantier et al. (2021).

counterparty (m) level:[20]

$$\begin{aligned} Trust_{i,m} = &\beta_1 \; Fintech_m + \beta_2 \; Big \; tech_m + \\ &\beta_3 \; Fintech_m \times Characteristic_i + \beta_4 \; Big \; tech_m \times Characteristic_i + \theta_i + \varepsilon_{i,m}. \end{aligned} \tag{2}$$

The dependent variable is respondents' trust in banks, fintechs, and big techs, measured on a scale from 1 (no trust at all) to 7 (complete trust).[21] The mean across all counterparties is 3.55, and the standard deviation is 1.83.[22] *Banks* constitute the base category. *Fintech* is a dummy with a value of one if the counterparty asked about is a fintech. *Big tech* is a dummy with a value of one if the counterparty asked about is a big tech. *Characteristic* is either the dummy *Female*, respondent age in years (*Age*), or the dummy *CCPA* that takes on a value of one if the respondent was shown the CCPA statement. All regressions include respondent-level fixed effects (θ_i), meaning we are checking for within-respondent differences across counterparties. Standard errors are clustered at the respondent level.

The coefficients β_1 and β_2 measure trust in fintechs and big techs relative to banks, while coefficients β_3 and β_4 capture how trust in different counterparties varies across groups.

Table 9, column (1) shows that individuals trust fintechs less than banks, and trust big techs less than banks and fintechs. Column (2) shows that female respondents differentially trust fintechs less than banks when compared to their male counterparts. Similarly, column (3) shows that older respondents exhibit differentially lower trust in fintechs as

[20] Even though the outcome is categorical, we prefer linear regressions in this instance because of the large number of fixed effects.

[21] We exclude the response on the government agency from this analysis, since we are most interested in financial counterparties, but including that response leaves the patterns discussed here unaffected.

[22] Average trust is highest for banks (mean = 4.41), compared to fintechs with a mean of 3.42, and big techs with a mean of 2.50.

well as big techs compared to younger respondents. Finally, column (4) shows that respondents that were shown the CCPA statement express significantly higher trust in fintechs and somewhat higher trust in big techs, relative to banks, than those that have not seen the CCPA prompt. Column (5) confirms these patterns when we include all regressors in one regression. Column (6) further shows that results are robust to controlling for the interaction of the trust question order (which was randomized across respondents) and the counterparty.

These results suggest that gender and age differences in trust in "new" financial intermediaries (fintechs and big techs) could inhibit their adoption of new financial products offered by these firms, while privacy regulation holds the potential to increase respondents' willingness to share data as well as trust in non-traditional financial intermediaries.

5 Conclusion

Willingness to share personal data is a prerequisite to access and take advantage of a growing range of services across the digital economy. Yet we find that willingness to share such data differs by gender and age: in our survey of U.S. households, women and older respondents consistently report being more concerned about sharing their data on financial transactions or social media activity and geolocation data. The gender gap is only partially explained by differences in risk aversion and financial literacy. Above all, it is related to specific concerns that data will become publicly available (e.g. in a data breach) and—crucially—to concerns around personal safety. For older individuals, our results point to a reluctance to share data being a matter of principle. In any case, the age and gender gap in willingness to share data remain strongly significant even after controlling for socioeconomic and preference differences.

A key implication of gender and age differences in the willingness to share data is that they could enhance cross-group inequalities. Specifically, women and older consumers may be reluctant to take advantage of new applications in the digital economy that require sharing personal data. While this reflects a potentially rational personal trade-off, over time, the data sets being used by algorithms for digital services may have fewer observations for women or older individuals. This could result in biased samples and outcomes that are not in the interest of the underrepresented groups, e.g. in lending decisions, financial advice, health applications, the use of generative AI, and many more. This requires further care on the part of developers to explicitly test models, including those built on big data, for demographic biases, and to seek out remedies.

Yet our study also holds grounds for hope. Data privacy protections such as the CCPA, which give individuals more control over their data and introduce recourse in the case of data breaches, may increase trust and willingness to share data. Further research will be needed to assess the effectiveness of such rules over time. It will be necessary to assess how they can be designed and communicated to the public in order to bridge to gender and age gap in data sharing.

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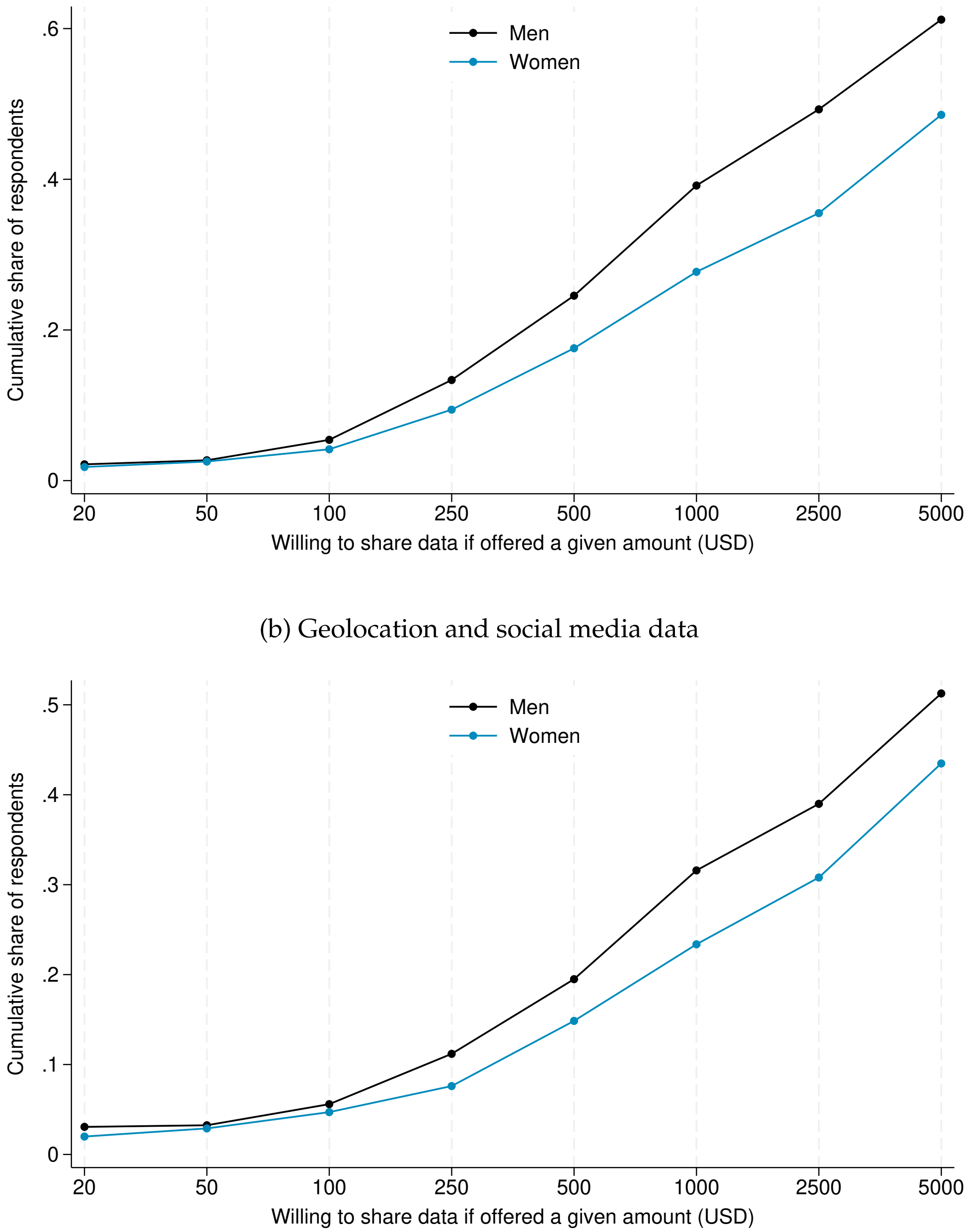
Figures and tables

Figure 1: **Women are less willing than men to share their data**

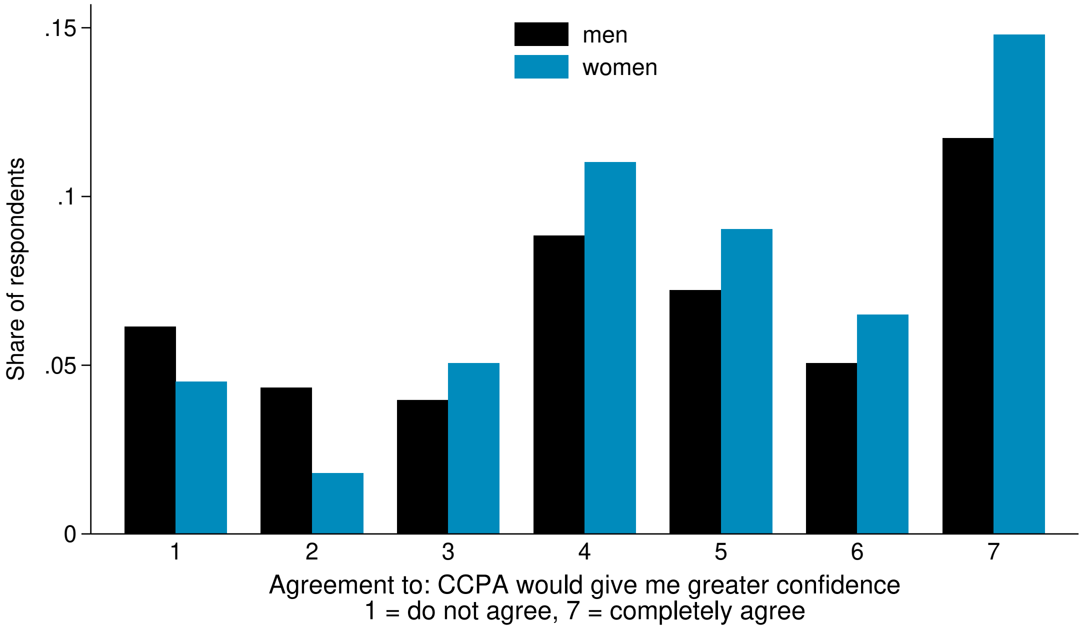


(a) Bank transaction history

(b) Geolocation and social media data

Note: This figure shows the share of male and female respondents that indicated that they would be willing to share their bank transaction history (panel a) or geolocation and social media data (panel b) with a credit card company if offered the USD amount shown on the x-axis.

Figure 2: **Agreement with the CCPA statement**



Note: This figure shows the share of male and female respondents for each level of agreement with the statement "To what extent do you agree with the following statement? Please indicate your level of agreement on a scale from 1 (do not agree at all) to 7 (completely agree): If the CCPA was in place in my state, then it would give me greater confidence to use online services that require sharing of my personal data."

Table 1: **Summary statistics – covariates**

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
Age (years)	1106	49.967	15.382	18	94	37	49.5	62
White (0/1)	1106	.847	.36	0	1	1	1	1
Hispanic (0/1)	1106	.07	.255	0	1	0	0	0
Black (0/1)	1106	.095	.293	0	1	0	0	0
Asian (0/1)	1106	.041	.198	0	1	0	0	0
Education: bachelor or more (0/1)	1106	.571	.495	0	1	0	1	1
Income above 100k (0/1)	1106	.346	.476	0	1	0	0	1
Working full-time (0/1)	1106	.58	.494	0	1	0	1	1
Working part-time (0/1)	1106	.112	.316	0	1	0	0	0
Owner of primary residence (0/1)	1106	.709	.454	0	1	0	1	1
Married (0/1)	1106	.609	.488	0	1	0	1	1
Lives alone (0/1)	1106	.262	.44	0	1	0	0	1
Has been subject to data breach (0/1)	1106	.612	.487	0	1	0	1	1
Willingness to take financial risks (1-7)	1104	3.611	1.549	1	7	2	4	5
Willingness to take daily risks (1-7)	1105	3.746	1.448	1	7	3	4	5
General trust in people (1-7)	1106	3.14	1.528	1	7	2	3	4
Numeracy score (0-5)	1106	3.938	1.16	0	5	3	4	5
Makes financial decisions in household (0/1)	1106	.576	.494	0	1	0	1	1
Concern: negative personal conseq. (1-7)	1106	5.38	1.678	1	7	4	6	7
Concern: higher costs (1-7)	1106	5.105	1.724	1	7	4	5	7
Concern: publicly available (1-7)	1105	5.695	1.497	1	7	5	6	7
Valuation online banking (USD)	1106	24.421	90.355	0	2500	0	10	20
Valuation social media (USD)	1106	11.347	81.623	0	2500	0	0	10
Valuation payments app (USD)	1106	13.201	107.983	0	2500	0	0	10

Note: This table shows summary statistics (observations, mean, standard deviation, minimum, maxmimum, as well 25th, 50th and 75th percentile) of the main variables. Sample weights are not applied.

Table 2: **Compensation required to share bank history and social media data**

	(1)	(2)	(3)	(4)	(5)	(6)
	ord log	ord log	ord log	logit	ord log	logit
VARIABLES	BH amount	BH amount	BH amount	BH > 2.5k	SM amount	SM > 2.5k
Female (0/1)	0.617***	0.679***	0.652***	0.716***	0.390***	0.400**
	(0.141)	(0.142)	(0.144)	(0.161)	(0.142)	(0.162)
Age (years)	0.042***	0.040***	0.037***	0.035***	0.028***	0.028***
	(0.005)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)
Observations	1,106	1,106	1,106	1,106	1,106	1,106
Demographic Controls	-	✓	✓	✓	✓	✓
Socioeconomic Controls	-	-	✓	✓	✓	✓
Pseudo R2	0.0451	0.0491	0.0582	0.105	0.0385	0.0596

Note: This table reports results for Equation (1). Columns (1)–(3) and (5) report results from ordered logit regressions, columns (4) and (6) from logistic regressions. Columns (1)–(3) use the dollar amount respondents require to share their bank history (BH) as the dependent variable. Column (4) uses a dummy as the dependent variable that takes on a value of one if the amount of money required to share bank history data is at least $2,500. Columns (5) uses the dollar amount respondents require to share their social media data as dependent variable. Column (6) uses as the dependent variable a dummy that takes on a value of one if the amount of money required to share social media/geolocation data is at least $2,500. *Female* is a dummy with a value of one if the respondent is female. *Age* is the respondent's age in years. Demographic controls include dummies for whether the respondent owns their primary residence, whether they are married, whether they belong to a racial or ethnic minority, whether they are working (with separate dummies for full-time and part-time work), and whether they are living alone. Socioeconomic controls include the respondent's educational attainment, a quadratic function of the household's income category, and whether they have been subject to a data breach in the past. All regressions control for whether the respondent was randomly subject to the CCPA treatment. All regressions are weighted and use robust standard errors. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: **Individual characteristics and the correlation with gender**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	ord log	ord log	ord log	ord log	ord log	ord log	ord log	ord log	ord log	ord log
VARIABLES	fin risk	gen risk	trust	numeracy	neg cons	costs	publ avail	onl bank amt	pay app amt	soc med amt
Female (0/1)	-0.407***	-0.281**	-0.129	-0.663***	0.287**	0.231*	0.351**	0.006	0.100	0.492***
	(0.136)	(0.137)	(0.134)	(0.146)	(0.138)	(0.132)	(0.140)	(0.138)	(0.158)	(0.176)
Age (years)	-0.014**	-0.022***	-0.005	0.005	0.010*	0.007	0.017***	0.002	-0.021***	-0.021***
	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)
Observations	1,104	1,105	1,106	1,106	1,106	1,106	1,106	1,106	1,106	1,106
Demographic Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Socioeconomic Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Pseudo R2	0.0325	0.0152	0.0317	0.106	0.0250	0.0212	0.0315	0.0256	0.0360	0.0351

Note: This table reports results for Equation (1), estimated with ordered logit regressions. Columns (1) uses respondents' willingness to take financial risks as the dependent variable. Columns (2) uses respondents' willingness to take risks in general as the dependent variable. Columns (3) uses respondents' level of general trust as the dependent variable. Columns (4) uses respondents' numeracy level as the dependent variable. Columns (5) uses respondents' level of concern about negative consequences from sharing data as the dependent variable. Columns (6) uses respondents' level of concern about higher monetary costs from sharing data as the dependent variable. Columns (7) uses respondents' level of concern about data becoming publicly available as the dependent variable. Columns (8) uses the dollar amount respondents are willing to pay to use online banking as the dependent variable. Columns (9) uses the dollar amount respondents are willing to pay for access to digital payments technologies as the dependent variable. Columns (10) uses the dollar amount respondents are willing to pay to use social media as the dependent variable. *Female* is a dummy with a value of one if the respondent is female. *Age* is the respondent's age in years. Demographic controls include dummies for whether the respondent owns their primary residence, whether they are married, whether they belong to a racial or ethnic minority, whether they are working (with separate dummies for full-time and part-time work), and whether they are living alone. Socioeconomic controls include the respondent's educational attainment, a quadratic function of the household's income category, and whether they have been subject to a data breach in the past. All regressions control for whether the respondent was randomly subject to the CCPA treatment. All regressions are weighted and use robust standard errors. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: **Required compensation to share data, controlling for further factors**

	(1)	(2)	(3)	(4)	(5)	(6)
	ord log	ord log	ord log	ord log	ord log	ord log
VARIABLES	BH amount	BH amount	BH amount	BH amount	SM amount	SM amount
Female (0/1)	0.640***	0.560***	0.452***	0.465***	0.372***	0.283*
	(0.144)	(0.149)	(0.157)	(0.159)	(0.142)	(0.160)
Age (years)	0.035***	0.036***	0.035***	0.035***	0.027***	0.024***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
Observations	1,104	1,104	1,104	1,104	1,104	1,104
Demographic Controls	✓	✓	✓	✓	✓	✓
Socioeconomic Controls	✓	✓	✓	✓	✓	✓
Risk av. & trust	✓	✓	✓	✓	✓	✓
Fin. literacy	-	✓	✓	✓	-	✓
Concerns	-	-	✓	✓	-	✓
Use benefit	-	-	-	✓	-	✓
Pseudo R2	0.0637	0.0716	0.0964	0.105	0.0453	0.0846

Note: This table reports results for Equation (1), estimated with ordered logit regressions. Columns (1)–(4) use the dollar amount respondents require to share their bank history (BH) as dependent variable. Columns (5)–(6) use the dollar amount respondents require to share their social media/geolocation data as dependent variable. *Female* is a dummy with a value of one if the respondent is female. *Age* is the respondent's age in years. Demographic controls include dummies for whether the respondent owns their primary residence, whether they are married, whether they belong to a racial or ethnic minority, whether they are working (with separate dummies for full-time and part-time work), and whether they are living alone. Socioeconomic controls include the respondent's educational attainment, a quadratic function of the household's income category, and whether they have been subject to a data breach in the past. All regressions control for whether the respondent was randomly subject to the CCPA treatment. All regressions are weighted and use robust standard errors. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: **Required compensation to share data given privacy legislation by gender**

VARIABLES	(1) ord log BH amount	(2) ord log BH amount	(3) ord log BH amount	(4) ord log BH amount	(5) ord log SM amount	(6) ord log SM amount	(7) ord log SM amount	(8) ord log SM amount
Female (0/1)	0.560***	0.601***	0.598***	0.561***	0.318**	0.334**	0.310	0.319**
	(0.149)	(0.148)	(0.207)	(0.148)	(0.146)	(0.145)	(0.195)	(0.146)
Age (years)	0.036***	0.036***	0.036***	0.034***	0.028***	0.027***	0.028***	0.027***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.006)	(0.006)	(0.006)	(0.008)
CCPA treatment	0.022	0.407**	0.057	-0.136	0.218	0.444**	0.211	0.137
	(0.148)	(0.195)	(0.194)	(0.505)	(0.147)	(0.193)	(0.200)	(0.502)
CCPA treatment and agrees		-0.689***				-0.410*		
		(0.201)				(0.210)		
Female × CCPA			-0.074				0.015	
			(0.279)				(0.290)	
Age × CCPA				0.003				0.002
				(0.010)				(0.010)
Observations	1,104	1,104	1,104	1,104	1,104	1,104	1,104	1,104
Demographic Controls	✓	✓	✓	✓	✓	✓	✓	✓
Socioeconomic Controls	✓	✓	✓	✓	✓	✓	✓	✓
Risk av. & trust	✓	✓	✓	✓	✓	✓	✓	✓
Fin. literacy	✓	✓	✓	✓	✓	✓	✓	✓
Pseudo R2	0.0717	0.0765	0.0717	0.0717	0.0479	0.0497	0.0479	0.0480

Note: This table reports results for Equation (1), estimated with ordered logit regressions. Columns (1)–(4) use the dollar amount respondents require to share their bank history as dependent variable. Columns (4)–(8) use the dollar amount respondents require to share their social media/geolocation data as dependent variable. *Female* is a dummy with a value of one if the respondent is female. *Age* is the respondent's age in years. *CCPA treatment* is a dummy with a value of one if the respondent was shown the CCPA statement. *CCPA treatment and agrees* is a dummy with a value of one if the respondent was shown the CCPA statement and agrees with it (4 or higher). Demographic controls include dummies for whether the respondent owns their primary residence, whether they are married, whether they belong to a racial or ethnic minority, whether they are working (with separate dummies for full-time and part-time work), and whether they are living alone. Socioeconomic controls include the respondent's educational attainment, a quadratic function of the household's income category, and whether they have been subject to a data breach in the past. All regressions control for whether the respondent was randomly subject to the CCPA treatment. All regressions are weighted and use robust standard errors. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: **CCPA correlations**

VARIABLES	(1) ord log CCPA agreement (1-7)	(2) logit CCPA agrees (>4)
Female (0/1)	0.430***	0.520**
	(0.163)	(0.221)
Age (years)	-0.003	-0.000
	(0.006)	(0.009)
Minority racial or ethnic group (0/1)	-0.374*	-0.327
	(0.207)	(0.273)
Owner of primary residence (0/1)	-0.113	0.036
	(0.189)	(0.258)
Working full-time (0/1)	-0.082	-0.087
	(0.203)	(0.264)
Working part-time (0/1)	-0.196	-0.339
	(0.270)	(0.368)
Married (0/1)	-0.560**	-0.767**
	(0.248)	(0.371)
Income above 100k (0/1)	0.216	0.243
	(0.202)	(0.258)
Education: bachelor or more (0/1)	0.052	0.114
	(0.180)	(0.210)
Lives alone (0/1)	-0.092	-0.248
	(0.263)	(0.373)
Willingness to take financial risks (1-7)	-0.025	-0.041
	(0.060)	(0.079)
Willingness to take daily risks (1-7)	0.076	0.061
	(0.060)	(0.082)
General trust in people (1-7)	0.016	-0.006
	(0.052)	(0.071)
Numeracy score (0-5)	0.088	0.137
	(0.072)	(0.101)
Makes financial decisions in household (0/1)	0.053	-0.106
	(0.191)	(0.266)
Has been subject to data breach (0/1)	0.088	0.263
	(0.157)	(0.213)
Lives in California (0/1)	0.014	-0.089
	(0.293)	(0.405)
Observations	552	552
Pseudo R2	0.0127	0.0323

Note: This table reports conditional correlations between the level of agreement with the CCPA statement and respondent characteristics (columns 1), or whether respondents strongly agree with the CCPA statement and respondent characteristics (column 2). Columns (1) estimates an ordered logit regression, while column (2) estimates a logistic regressions. All regressions are weighted and use robust standard errors. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: **Gender differences and socioeconomic characteristics**

	(1)	(2)	(3)	(4)
	income	education	numeracy	PCA
VARIABLES	BH $>$ 2.5k	BH $>$ 2.5k	BH $>$ 2.5k	BH $>$ 2.5k
Female (0/1)	0.145***	0.138***	0.063	0.153***
	(0.040)	(0.046)	(0.060)	(0.033)
Socio indicator	0.027	-0.042	-0.144**	-0.027
	(0.052)	(0.046)	(0.060)	(0.031)
Female × socio indicator	-0.027	-0.001	0.115	0.029
	(0.068)	(0.060)	(0.072)	(0.023)
Observations	1,104	1,104	1,104	1,104
R-squared	0.149	0.149	0.152	0.151
Demographic Controls	✓	✓	✓	✓

Note: This table reports variations of Equation (1) estimated with OLS regressions. Columns (1)–(4) use a dummy as the dependent variable that takes on a value of one if the amount of money required to share bank history (BH) data is at least $2,500. *Female* is a dummy with a value of one if the respondent is female. In column (1) *socio indicator* is a dummy that takes on a value of one for respondents with incomes above $100,000. In column (1) it is a dummy that takes on a value of one for respondents with a bachelor's degree or higher. In column (3) it is a dummy that takes on a value of one for respondents with high numeracy (a score of 5 out of 5). In column (4) it is first principal component of education, income, and numeracy. Demographic controls include dummies for whether the respondent owns their primary residence, whether they are married, whether they belong to a racial or ethnic minority, whether they are working (with separate dummies for full-time and part-time work), and whether they are living alone. Socioeconomic controls include the respondent's educational attainment, a quadratic function of the household's income category, and whether they have been subject to a data breach in the past. All regressions control for whether the respondent was randomly subject to the CCPA treatment. All regressions are weighted and use robust standard errors. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: **Concerns**

	(1)	(2)	(3)	(4)	(5)
	logit	logit	logit	logit	ord logit
VARIABLES	pers safe	reput	ID theft	abuse	nobody's bus
Female (0/1)	0.313**	-0.153	-0.211	-0.024	0.106
	(0.153)	(0.167)	(0.293)	(0.164)	(0.149)
Age (years)	-0.022***	-0.008	0.019*	-0.009	0.018***
	(0.006)	(0.008)	(0.011)	(0.006)	(0.006)
Observations	1,086	1,077	1,071	1,086	1,106
Demographic Controls	✓	✓	✓	✓	✓
Socioeconomic Controls	✓	✓	✓	✓	✓
Pseudo R2	0.0461	0.0240	0.0901	0.0449	0.0598

Note: This table reports results for Equation (1). Columns (1)–(4) reports results from logistic regressions, while column (5) reports results from an ordered logit regression. Columns (1) uses respondents' concern about their personal safety when data become publicly available as the dependent variable. Columns (2) uses respondents' concern about negative effects on their reputation when data become publicly available as the dependent variable. Columns (3) uses respondents' concern about identity theft when data become publicly available as the dependent variable. Columns (4) uses respondents' concern about abuse my data for unintended purpose when data become publicly available as the dependent variable. Columns (5) uses respondents' agreement with the statement "my data are nobody's business" as the dependent variable. *Female* is a dummy with a value of one if the respondent is female. *Age* is respondents age in years. Demographic controls include dummies for whether the respondent owns their primary residence, whether they are married, whether they belong to a racial or ethnic minority, whether they are working (with separate dummies for full-time and part-time work), and whether they are living alone. Socioeconomic controls include the respondent's educational attainment, a quadratic function of the household's income category, and whether they have been subject to a data breach in the past. All regressions control for whether the respondent was randomly subject to the CCPA treatment. All regressions are weighted and use robust standard errors. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: **Privacy legislation and trust in financial institutions**

VARIABLES	(1) Trust	(2) Trust	(3) Trust	(4) Trust	(5) Trust	(6) Trust
Fintech (0/1)	-0.994***	-0.890***	0.067	-1.108***	0.091	
	(0.059)	(0.074)	(0.195)	(0.087)	(0.217)	
Big tech (0/1)	-1.908***	-1.861***	-0.994***	-1.983***	-0.998***	
	(0.070)	(0.094)	(0.246)	(0.101)	(0.252)	
Female × fintech		-0.201*			-0.247**	-0.242**
		(0.117)			(0.113)	(0.111)
Female × big tech		-0.091			-0.127	-0.149
		(0.140)			(0.137)	(0.134)
Age × fintech			-0.020***		-0.021***	-0.020***
			(0.004)		(0.004)	(0.004)
Age × big tech			-0.018***		-0.018***	-0.017***
			(0.005)		(0.005)	(0.004)
CCPA × fintech				0.220*	0.233**	0.213*
				(0.118)	(0.114)	(0.113)
CCPA × big tech				0.145	0.151	0.144
				(0.140)	(0.138)	(0.138)
Observations	3,318	3,318	3,318	3,318	3,318	3,318
R-squared	0.738	0.738	0.744	0.738	0.745	0.753
Individual FE	✓	✓	✓	✓	✓	✓
Order FE	-	-	-	-	-	✓

Note: This table reports results for Equation (2). The dependent variable is respondents' trust in banks, fintechs, and big techs (on a scale of 1 to 7 where higher values mean more trust; the mean is 3.55, the st.dev. 1.83). *Banks* constitute the base category. *Fintech* is a dummy with a value of one if the counterparty asked about is a fintech. *Big tech* is a dummy with a value of one if the counterparty asked about is a big tech. *Female* is a dummy with a value of one if the respondent is female. *Age* is the respondent's age in years. *CCPA* is a dummy with a value of one if the respondent was shown the CCPA statement. All regressions include individual-level fixed effects. The last specification further controls for the interaction of the trust question order (which was randomized across respondents) and the intermediary type. All regressions are weighted and use standard errors clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

A Online appendix

Table 10: **Summary statistics – covariates (weighted)**

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
Age (years)	1106	51.807	15.984	18	94	38	53	64
White (0/1)	1106	.842	.365	0	1	1	1	1
Hispanic (0/1)	1106	.086	.281	0	1	0	0	0
Black (0/1)	1106	.101	.302	0	1	0	0	0
Asian (0/1)	1106	.028	.166	0	1	0	0	0
Education: bachelor or more (0/1)	1106	.347	.476	0	1	0	0	1
Income above 100k (0/1)	1106	.284	.451	0	1	0	0	1
Working full-time (0/1)	1106	.506	.5	0	1	0	1	1
Working part-time (0/1)	1106	.114	.318	0	1	0	0	0
Owner of primary residence (0/1)	1106	.659	.474	0	1	0	1	1
Married (0/1)	1106	.576	.494	0	1	0	1	1
Lives alone (0/1)	1106	.28	.449	0	1	0	0	1
Has been subject to data breach (0/1)	1106	.549	.498	0	1	0	1	1
Willingness to take financial risks (1-7)	1104	3.481	1.613	1	7	2	3	5
Willingness to take daily risks (1-7)	1105	3.72	1.541	1	7	3	4	5
General trust in people (1-7)	1106	3.005	1.569	1	7	2	3	4
Numeracy score (0-5)	1106	3.706	1.246	0	5	3	4	5
Makes financial decisions in household (0/1)	1106	.575	.495	0	1	0	1	1
Concern: negative personal conseq. (1-7)	1106	5.417	1.712	1	7	5	6	7
Concern: higher costs (1-7)	1106	5.199	1.726	1	7	4	6	7
Concern: publicly available (1-7)	1105	5.734	1.533	1	7	5	6	7
Valuation online banking (USD)	1106	21.591	81.73	0	2500	0	10	20
Valuation social media (USD)	1106	11.176	95.008	0	2500	0	0	0
Valuation payments app (USD)	1106	15.195	136.458	0	2500	0	0	10

Note: This table shows summary statistics (observations, mean, standard deviation, minimum, maxmimum, as well 25th, 50th and 75th percentile) of the main variables. Observations are weighted to correspond to target values from the American Community Survey. WTP = willingness to pay.

QUESTIONAIRE

DSQInfo - DSQInfo

Finally, we would like to ask you some questions to better understand your views about using social media and online technology providers.

DSQ1_1 - DSQ1_1

Please indicate how often you use social media (such as Facebook, Instagram, Twitter, Snapchat, TikTok, LinkedIn, Pinterest, ...).

○ Never (1)
○ Less than once a month (2)
○ More than once a month but less than once a week (3)
○ A couple of times a week (4)
○ Once a day (5)
○ More than once a day (6)

DSQ1_2 - DSQ1_2

Please indicate how often you use online banking (via your bank(s)' website or app).

○ Never (1)
○ Less than once a month (2)
○ More than once a month but less than once a week (3)
○ A couple of times a week (4)
○ Once a day (5)
○ More than once a day (6)

DSQ1_3 - DSQ1_3

Please indicate how often you use digital payment technologies (such as Apple Pay, Google Pay, PayPal, Venmo, Zelle, ...)

○ Never (1)
○ Less than once a month (2)
○ More than once a month but less than once a week (3)
○ A couple of times a week (4)
○ Once a day (5)
○ More than once a day (6)

DSQ2_1 - DSQ2_1

We will now ask you about data breaches. By "data breach" we mean the unauthorized leakage of your personal data, for instance as a result of a cyber-attack on a company. Examples include the breach of personal credit score information, or the theft of social media account data.

Have you ever been subject to a data breach?

○ Yes (1)
○ No (2)
○ Unsure (3)

DSQ2_1a - DSQ2_1a

Have you suffered any negative consequences from the data breach?

○ Yes (1)

❍ No (2)
❍ Unsure (3)

DSQ2_2 - DSQ2_2

Do you know of a family member, friend, or colleague who has experienced a data breach?

❍ Yes (1)
❍ No (2)

DSQ2_2a – DSQ2_2a

Have they suffered any negative consequences from the data breach?

❍ Yes (1)
❍ No (2)
❍ Unsure (3)

[Programmer Note: Create two random groups of equal size, A and B. **Group A sees DSQ3_info_NEW and DSQ3_a_NEW. Group B DOES NOT SEE DSQ3_info_NEW and DSQ3_a_NEW.** For questions **DSQ3_1** and **DSQ3_2**, Group A sees [**Imagine that the legal framework of the CCPA was in place in your state** and imagine you…], while group B sees [Imagine you..]. Group A also sees in a box at the top of the screen the text provided in **DSQ3_info** when they are shown **DSQ3_1** and **DSQ3_2**. **DSQ3_1** and **DSQ3_2** should be shown on separate screens.]

DSQ3_info_NEW

The California Consumer Privacy Act (CCPA) ensures privacy rights for consumers in California. The law is widely considered to provide the strongest consumer data protection in the US. The law provides consumers with the right to know the personal information that a business collects about them, and the right to delete such personal information. The law also provides consumers with the right to opt out of the sale of personal information to third parties. In addition, if there is a data breach and personal information is stolen (e.g. a consumer's name or driver's license number), then the consumer can sue the business for damages up to $750.

DSQ3_a_NEW

To what extent do you agree with the following statement? Please indicate your level of agreement on a scale from **1 (do not agree at all)** to **7 (completely agree)**.

	Do not agree at all 1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	Completely agree 7 (7)
If the CCPA was in place in my state, then it would give me greater confidence to use online services that require sharing of my personal data.	❍	❍	❍	❍	❍	❍	❍

DSQ3_1 – DSQ3_1

In the next questions, we are interested in your willingness to share your personal data with companies.

[Imagine that the legal framework of the CCPA was in place in your state and imagine]/[Imagine] you were to sign up for a new credit card. The credit card company has approved your application and is now offering you a sign-up bonus (in the form of money credited to your card account) if you provide the company with access to your full bank transaction history from the past year.

Please select for each of the following amounts whether you'd be willing to share this data:

	No, do not share data (2)	Yes, share the data (1)
if the sign-up bonus you'd receive is $20 (1)	○	○
if the sign-up bonus you'd receive is $50 (2)	○	○
if the sign-up bonus you'd receive is $100 (3)	○	○
if the sign-up bonus you'd receive is $250 (4)	○	○
if the sign-up bonus you'd receive is $500 (5)	○	○
if the sign-up bonus you'd receive is $1000 (6)	○	○
if the sign-up bonus you'd receive is $2500 (7)	○	○
if the sign-up bonus you'd receive is $5000 (8)	○	○

DSQ3_2 – DSQ3_2

[Imagine that the legal framework of the CCPA was in place in your state and imagine]/[Imagine] now that the credit card company is offering you a sign-up bonus (in the form of money credited to your card account) if you provide the company with access to your geolocation and social media data from the past year.

("Geolocation data" is information relating to your movements, usually gathered from your mobile phone. Social media data refers to your posts, likes, contacts and friends, messages)

Please select for each of the following amounts whether you'd be willing to share this data:

	No, do not share data (2)	Yes, share the data (1)
if the sign-up bonus you'd receive is $20 (1)	○	○
if the sign-up bonus you'd receive is $50 (2)	○	○
if the sign-up bonus you'd receive is $100 (3)	○	○
if the sign-up bonus you'd receive is $250 (4)	○	○
if the sign-up bonus you'd receive is $500 (5)	○	○
if the sign-up bonus you'd receive is $1000 (6)	○	○
if the sign-up bonus you'd receive is $2500 (7)	○	○
if the sign-up bonus you'd receive is $5000 (8)	○	○

DSQ4_1 – DSQ4_1

In the next questions, we are interested in knowing if you have concerns about sharing your personal data.

(Note: "personal data" here means your bank transaction history, geolocation or social media data; it does NOT include your social security number, credit card info, or passwords.)

Are you concerned that sharing your personal data could have negative consequences for you?
Please indicate your level of concern on a scale from 1 (not at all concerned) to 7 (extremely concerned).

	Not at all concerned (h1)	1 (1)		2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	Extremely concerned (h2)	7 (7)	
&nbsp; (1)	○	○	○	○	○	○	○	○	○	○	○

DSQ4_2 – DSQ4_2

Are you concerned about companies using this information to charge you more money for other goods or services?
Please indicate your level of concern on a scale from 1 (not at all concerned) to 7 (extremely concerned).

	Not at all concerned (h1)	1 (1)		2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	Extremely concerned (h2)	7 (7)	
&nbsp; (1)	○	○	○	○	○	○	○	○	○	○	○

DSQ4_3 – DSQ4_3

Are you concerned that your personal data might become publicly available?
Please indicate your level of concern on a scale from 1 (not at all concerned) to 7 (extremely concerned).

	Not at all concerned (h1)	1 (1)		2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	Extremely concerned (h2)	7 (7)	
&nbsp; (1)	○	○	○	○	○	○	○	○	○	○	○

DSQ4_3x1 – DSQ4_3x1

What are you specifically concerned about if your personal data were to become publicly available?

□ My personal safety (1)
□ Negative effects on my reputation (2)
□ Identity theft (3)
□ Abuse of my data for unintended purposes (in the news or media, for political agenda, targeted ads, ...) (4)
□ Other (please specify) (9)____________

DSQ4_3x2 – DSQ4_3x2

Which is the most important concern?

○ My personal safety (1)
○ Negative effects on my reputation (2)
○ Identity theft (3)
○ Abuse of my data for unintended purposes (in the news or media, for political agenda, targeted ads, ...) (4)
○ Other: ^f('DSQ4_3x1_9_other')^ (9)

DSQ4_5 _NEW – DSQ4_5_NEW

To what extent do you agree with the following statement? "Even if I have no immediate concerns about my reputation or safety, I do not want to share my data because 'my data are nobody's business'."

Please indicate your level of agreement on a scale from **1 (do not agree at all)** to **7 (completely agree)**.

.

	Do not agree at all (h1)	1 (1)		2 (2)	3 (3)	4 (4)		5 (5)	6 (6)	Completely agree (h2)	7 (7)	
&nbsp; (1)	○	○	○	○	○	○		○	○	○	○	○

DSQ5_1_NEW – DSQ5_1_NEW

In the next questions, we are interested in knowing how you value products that use digital financial technology in the areas of online banking, digital payments, or social media.

[ONLY ASKED IF DSQ1_2 IS NOT "NEVER"]

Imagine you now had to pay an annual fee in order to keep using online banking. How much would you be willing to pay for the coming year?

[PN: If "2" No, would not pay selected for any row, then all rows that follow should "2". : If "1" Yes, would pay selected for any row, then all rows before that should also be "1".]:

	No, would not pay (2)	Yes, would pay (1)
$10 (1)	❍	❍
$20 (2)	❍	❍
$50 (3)	❍	❍
$100 (4)	❍	❍
$250 (5)	❍	❍
$500 (6)	❍	❍
$1000 (7)	❍	❍
$2500 (8)	❍	❍

DSQ5_2_NEW - DSQ5_2_NEW

[*ONLY ASKED IF DSQ1_3 IS NOT "NEVER"*]

Imagine you now had to pay <u>an annual fee</u> in order to keep using <u>any</u> digital payment technologies (such as Apple Pay, Google Pay, PayPal, Venmo, Zelle, …). How much would you be willing to pay for the coming year?

[PN: If "2" No, would not pay selected for any row, then all rows that follow should "2". : If "1" Yes, would pay selected for any row, then all rows before that should also be "1]

	No, would not pay (2)	Yes, would pay (1)
$10 (1)	❍	❍
$20 (2)	❍	❍
$50 (3)	❍	❍
$100 (4)	❍	❍
$250 (5)	❍	❍
$500 (6)	❍	❍
$1000 (7)	❍	❍
$2500 (8)	❍	❍

SQ5_3_NEW

[*ONLY ASKED IF DSQ1_1 IS NOT "NEVER"*]

Imagine you now had to pay <u>an annual fee</u> in order to keep using <u>any</u> social media (such as such as Facebook, Instagram, Twitter, Snapchat, TikTok, LinkedIn, Pinterest, ...). How much would you be willing to pay for the coming year?

[PN: If "2" No, would not pay selected for any row, then all rows that follow should "2". If "1" Yes, would pay selected for any row, then all rows before that should also be "1".]

	No, would not pay (2)	Yes, would pay (1)
$10 (1)	○	○
$20 (2)	○	○
$50 (3)	○	○
$100 (4)	○	○
$250 (5)	○	○
$500 (6)	○	○
$1000 (7)	○	○
$2500 (8)	○	○

DSQ5_1 - DSQ5_1

[PN: *Randomized answer list and record order that rows are shown*]

How much do you trust the following entities to safely store your personal data (that is, your bank transaction history, geolocation or social media data)? For each of them, please indicate your trust level on a scale from 1 (no trust at all in ability to safely store personal data) to 7 (complete trust).

	No trust at all 1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	Complete trust 7 (7)
A government agency (1)	○	○	○	○	○	○	○
Traditional financial institutions (such as banks, insurers, ...) (2)	○	○	○	○	○	○	○
Large technology companies (such as Facebook, Google, Apple, ...) (3)	○	○	○	○	○	○	○
Technology firms that specialize in financial services (such as PayPal, Venmo, Quicken Loans, ...) (4)	○	○	○	○	○	○	○

DSQ5_4 - DSQ5_4

Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?
Please indicate your level of trust on a scale from 1 (can be trusted) to 7 (must be very careful).

	Can be trusted (h1)	1 (1)		2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	Must be very careful (h2)	7 (7)	
&nbsp; (1)	○	○	○	○	○	○	○	○	○	○	○

DSQ6_1 - DSQ6_1

We would like to ask some questions with relevance to gender.

If personal information (bank transaction history, geolocation or social media data) is leaked, do you think the consequences are more severe for women or for men?

○ More severe for women (1)
○ More severe for men (2)
○ No difference (3)

DSQ6_2 - DSQ6_2

Do you agree with the following: "Managing personal finances is important for a woman to be an independent person."

Please indicate your level of agreement on a scale from 1 (do not agree at all) to 7 (completely agree).

	Do not agree at all (h1)	1 (1)		2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	Completely agree (h2)	7 (7)	
&nbsp; (1)	○	○	○	○	○	○	○	○	○	○	○

DSQ6_3 - DSQ6_3

Do you agree with the following: "Discrimination against women or girls is an important problem in the world as a whole."

Please indicate your level of agreement on a scale from 1 (do not agree at all) to 7 (completely agree).

	Do not agree at all (h1)	1 (1)		2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	Completely agree (h2)	7 (7)	
&nbsp; (1)	○	○	○	○	○	○	○	○	○	○	○

DSQ6_4 - DSQ6_4

Do you agree with the following: "Discrimination against women or girls is an important problem in the part of the country where I live."

Please indicate your level of agreement on a scale from 1 (do not agree at all) to 7 (completely agree).

	Do not agree at all (h1)	1 (1)		2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	Completely agree (h2)	7 (7)	
&nbsp; (1)	○	○	○	○	○	○	○	○	○	○	○

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