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Intransitivity of Consumer Preferences for Privacy

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Abstract

Consumers frequently exchange their private personal data with companies in return for goods and services, such as access to search results or social networks. The authors provide a normative criterion to help assess whether companies compensate consumers adequately for their private data in these exchanges. Across a series of 11 experiments, they find that individuals place a higher price on their private data when they sell them for money than when they barter them for goods. In an application of the compatibility principle in cognitive psychology, the authors also find in two additional experiments that this effect occurs because money is a more compatible medium for valuing private data than goods are, which increases the weight of the data in monetary valuations, raising the prices that participants demand for their private data in money compared with goods. This discrepancy in valuations constitutes a violation of procedure invariance and amounts to an intransitivity of participants' preferences for privacy. The findings raise the question of whether companies are compensating consumers adequately for their data and whether the ubiquitous markets for privacy function efficiently. Accordingly, the authors point to a possible consumer welfare argument for antitrust regulation of technology companies.

Keywords

behavioral economics, compatibility principle, consumer privacy, marketing automation, preference transitivity, privacy preferences, procedure invariance

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> Privacy is something you can sell, but you can't buy it back.
>
> —Bob Dylan

Privacy is considered an essential human privilege in many societies, albeit for different reasons (Whitman 2004). Yet, aside from labor, perhaps the most common asset for a person to trade today is their private data. Companies collect behavioral data such as browsing and purchase histories, geolocation, demographic, social network, and psychographic data, content and product preferences, and much more (Brough and Martin 2021). They use these data to segment their customers (Wedel and Kannan 2016); price discriminate (Dubé and Misra 2021); target individuals with personalized content, programmatic advertising, or promotions (Lambrecht and Tucker 2013); or sell the data to other firms that may use them for similar purposes. In exchange, companies offer consumers "free" goods. These may include search results, video and music streaming, access to social media, and other digital information goods (Shapiro and Varian 1999). These may also include tangible goods, such as offers of free T-shirts or reusable water bottles in exchange for contact and preference data at concerts or other events.

Such exchanges of private data have come under increasing scrutiny by consumers and policy makers, with a growing emphasis on treating consumers equitably in these exchanges. Regulations such as the General Data Protection Regulation (GDPR; Parliament and Council of the European Union 2016) and the California Privacy Act (CCPA 2018) impose constraints on companies by giving consumers rights to privacy as well as control over the data they do share. At the same time, concern for treating consumers equitably may also create strategic opportunities. Companies like Apple are differentiating themselves by increasingly prioritizing transparency and privacy protection in their data collection practices (*The Economist* 2021).

Yet, the way companies commonly collect data may be falling short of these aspirations. We find that consumers demand two prices for their data: a higher one in money and a lower one in goods. Firms almost exclusively pay consumers in goods for their data. Thus, firms that desire and feel the pressure to pay consumers fairly may nonetheless be acquiring data at a discounted price compared with what consumers would

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demand in cash exchanges. Offering less compensation by bartering "free" goods for data could thus be viewed as unfair by consumers and as objectionable by policy makers.

We provide robust experimental evidence that consumers place a greater value on their private data when exchanging them for money than when exchanging them for goods. This systematic discrepancy poses a normative challenge, as consumers cannot simultaneously hold two different valuations for the same good (i.e., their data), all else equal. To the best of our knowledge, our findings are the first to offer a normative criterion to suggest that consumer preferences for privacy are biased by the exchange medium: Consumers are willing to accept less compensation for their private data when firms compensate them with goods than if firms compensated them with money, the standard medium of exchange.

Our participants' valuations systematically violate two essential requirements of rational choice theory. They violate procedure invariance, by which normatively equivalent procedures for measuring preferences should yield the same preference ordering of the choice options (Grether and Plott 1979; Tversky, Slovic, and Kahneman 1990; Tversky and Thaler 1990). The violations of procedure invariance imply that our participants' preferences violate transitivity, an axiomatic condition of utility maximization (Edwards 1954; Von Neumann and Morgenstern 1944). To detect these violations, we measure participants' willingness to accept (WTA) across exchange mediums by eliciting (1) the amount of money they want in exchange for a specific quantity and type of their private data (i.e., a cash equivalent C), (2) the number of units of goods they want in exchange for these data (i.e., a goods equivalent G), and (3) the amount of money at which they are indifferent when choosing between that amount and the goods equivalent of their data (i.e., a cash equivalent G′ of the goods equivalent G).

Consider a consumer who is indifferent between retaining an amount of private data P or receiving an amount of money C in exchange for P (i.e., $P \sim C$), between retaining that amount of private data P or receiving a number of units of a good G in exchange for P (i.e., $P \sim G$), and finally also between receiving the same number of units of the good G or an amount of money G′ (i.e., $G \sim G'$), where $C > G'$. Assuming the consumer monotonically prefers having more money C to having less money G′, these indifference relationships imply that one can construct a cyclic, intransitive preference order such that, for any amount of money ε where $0 < \varepsilon < \frac{C-G'}{2}$,

$$P \succ C - \varepsilon \succ G' + \varepsilon \succ P,$$

and, because $G \sim G'$,

$$P \succ C - \varepsilon \succ G + \varepsilon \succ P.$$

In other words, the consumer would rather keep their private data than exchange them for C minus a small amount ε (i.e., $P \succ C - \varepsilon$). Second, they would also prefer to receive an amount of money $C - \varepsilon$ rather than a number of goods G plus the small amount of money ε (i.e., $C - \varepsilon \succ G + \varepsilon$). Yet, they would prefer to receive $G + \varepsilon$ in exchange for their private data P rather than retain their data (i.e., $G + \varepsilon \succ P$), revealing a preference intransitivity. Close to half the participants in our experiments strictly preferred the amount of money to the number of goods, given their cash valuations of those goods (i.e., $C \succ G \sim G'$).

While prior research shows context effects on how consumers value their private data (Acquisti, John, and Loewenstein 2012, 2013; Winegar and Sunstein 2019), pointing to the malleability of private data valuations, ours is the first to demonstrate the systematic impact of the medium with which buyers compensate consumers selling their own private data. We also provide evidence of the psychological mechanism that predicts these different valuations: a greater compatibility of private data with money than with goods (Slovic, Griffin, and Tversky 1990). The intransitivity of valuations suggests that markets for private data may suffer from inefficiency and points to a possible consumer welfare argument for antitrust regulation of technology firms that derive their market power from such data (Bork 1978), complementing the industry structure–oriented approaches that are currently enjoying a renaissance in antitrust policy (Khan 2017). Thus, our findings may prompt a revision of how firms compensate users for their data.

Theory: How and Why Exchange Mediums Affect Private Data Valuations

Prior research has raised concerns about whether prevailing exchange mechanisms reflect consumers' true valuations of their private data (Acquisti, Taylor, and Wagman 2016). Research on the privacy paradox suggests attitude–behavior inconsistencies between consumers' stated and revealed preferences for privacy (Kokolakis 2017; Norberg, Horne, and Horne 2007; Solove 2021; e.g., a user may object to having their browsing tracked yet not disable cookies). Importantly though, the privacy paradox does *not* imply that companies compensate consumers *in*adequately for their data. It could be argued that consumers' revealed preferences in the marketplace reveal their true valuations of their data because consumers exchange these data subject to actual incentives.

Moreover, consumers are flexible in their data disclosure preferences (Acquisti, Brandimarte, and Loewenstein 2015; Acquisti, John, and Loewenstein 2012, 2013; John, Acquisti, and Loewenstein 2011). For instance, a consumer's willingness to reveal data online depends on the extent to which they trust the firm (Bart et al. 2005; Martin, Borah, and Palmatier 2017; Schlosser, White, and Lloyd 2006) and perceive they have control over future usage of their data (Tucker 2014). Similarly, consumers deem it less acceptable that their data be used for tailored advertising when the data are acquired through a third party rather than explicitly provided by the consumer (Kim et al. 2019). Consumers also vary in their willingness to disclose based on whether privacy concerns have been triggered (John, Acquisti, and Loewenstein 2011), whether the disclosure is seen as part of a fair exchange (Lin 2022; Schumann, Wangenheim, and Groene 2014; White 2004), and whether they think that other consumers are disclosing sensitive data (Acquisti, John, and Loewenstein 2012).

Factors such as these seem reasonable as determinants of data disclosure: willingness to disclose depends on expected psychological and security costs. In contrast, we ask whether the medium with which companies compensate consumers systematically influences the price at which consumers are willing to sell their data. Companies commonly portray exchanges of goods for data as "free." Yet, these are bartering exchanges, which require consumers to value their data in goods. We hypothesize that consumers place a lower value on their private data in such bartering exchanges against goods than in exchanges against money because private data are more compatible with money than with goods. Such a dependency of private data valuations on the medium of exchange is not only unreasonable, it violates procedure invariance and implies an intransitivity of consumer preferences for privacy, a violation of an axiomatic foundation of rational choice theory.

The Compatibility Principle and Procedure Invariance

According to the compatibility principle, "the weight of any input component is enhanced by its compatibility with the output" (Tversky, Sattath, and Slovic 1988, p. 376), which includes how easy or effortful it is to transform the input into the output (Fitts and Seeger 1953; Slovic, Griffin, and Tversky 1990; Tversky, Sattath, and Slovic 1988). In a valuation context, when the output (the valuation scale) is more compatible with the input (the entirety or an aspect of what is being valued), the input receives more weight in the valuation. Slovic, Griffin, and Tversky (1990) explain that *non*compatibility between output and input increases effort and shifts attention and weight away from the noncompatible input, whereas a compatible response mode draws attention and weight to the compatible aspects of the stimulus.

The compatibility principle can explain classic preference reversal effects, which are well-known violations of procedure invariance in judgment and choice (Grether and Plott 1979; Lichtenstein and Slovic 1971; Lindman 1971). In these studies, participants faced with two gambles with financial payoffs—one with a high probability of winning a moderate payoff, the other with a low probability of winning a high payoff—assigned a higher monetary value to the gamble with the higher payoff yet chose the gamble with the higher probability of winning. Because monetary payoffs (the input) are more compatible than probabilities are with assigning monetary values (the output) to the gambles, monetary payoffs weigh more heavily in valuing gambles than in choices among these gambles, a failure of procedure invariance (Slovic, Griffin, and Tversky 1990; Tversky, Sattath, and Slovic 1988; cf. Goldstein and Einhorn 1987; Kim, Seligman, and Kable 2012).

Why Private Data Are More Compatible with Money Than with Goods

Slovic, Griffin, and Tversky (1990) emphasize that the compatibility of different input–output combinations can often be reasonably assumed. Money is the scale with which consumers usually value resources, assets, and other goods in exchanges, which should make it more compatible and thus easier to value these in money than in goods. We propose that this greater compatibility of making valuations in money than in goods causes a compatibility effect of exchange mediums. This should be prominent in valuations of private data because compatibility effects are generally more likely to arise when preferences are not well-articulated and defined (Tversky, Sattath, and Slovic 1988). Consumers are uncertain about the value of their data because the market for private data lacks essential characteristics of other markets. Specifically, we suggest that the key difference that allows us to employ Tversky, Sattath, and Slovic's (1988) compatibility principle is that private data do not have a clearly defined market price, contributing to a lack of certainty in data valuations (Spiekermann et al. 2015). For this reason, we expect the discrepancy between valuations measured in money and in goods to apply to exchanges of private data but not—or less so—to other personal inputs with more clearly defined valuations, such as one's labor or other market goods. We thus predict an attenuation of the discrepancy between valuations across exchange mediums for inputs with well-defined values, a boundary condition we test in Experiments 4 and 5.

The compatibility principle will apply not only valuing private data but also more generally to valuing assets with uncertain value. Our findings on valuations of private data merely provide the first empirical evidence of compatibility effects of exchange mediums (money vs. goods) for such assets. We would thus predict similar effects in other cash versus barter exchanges of assets with uncertain values (e.g., in arts or antiques markets). However, exchanges of private data are arguably more relevant to marketing, the economy, and society than most other exchanges of assets of uncertain value. Our research objective is to identify and explain possible biases in how consumers value and trade their private data, motivated by increasing concerns for privacy protection and regulation among consumers, companies, policy makers, and the media.

Overview of Studies and Experimental Paradigm

We examine the hypothesized intransitivity in private data valuations in 11 preregistered and 2 exploratory online experiments. Throughout, we compare money and goods as exchange mediums. Experiments 1a and 1b use an incentive-compatible procedure to demonstrate that participants systematically value their private data higher in exchange for money than for goods. We replicate this effect for multiple types of private data (Experiment 2a) and trades for a typical information good (Experiment 2b), rule out a potential range effect in our elicitation procedure as an alternative explanation (Experiment 2c), show that the effect is not driven by our exclusion criteria (Experiment 2d), and rule out frequency and order effects as alternative explanations (Experiment 2e). Experiments 3a and 3b provide process evidence for our hypothesis that the intransitivity of private data valuations arises from greater compatibility of private data with money than with goods. Experiments 4 and 5 provide further evidence of the operation of a compatibility effect by showing that certainty about the value of the input variable moderates the intransitivity (Tversky, Sattath, and Slovic 1988). Experiments 5, 6a, and 6b test whether unique features of data markets reduce this certainty. All stimuli, data, Stata do-files, and preregistrations are available at https://osf.io/f2p7u/?view_only=442638c1133142c18a64ba796b15c513.

All studies except Experiments 3a and 3b use the same experimental paradigm, in which each participant provides three valuations: (1) how much money they would demand in exchange for a certain quantity of their private data (C, privacy-to-money), (2) how many units of a good they would demand for that same quantity of data (G, privacy-to-goods), and (3) how much money they would be equally interested in receiving instead of that number of units of the good G (G′, goods-to-money). G′ serves as a subjective monetary valuation of the goods and an indirect monetary valuation of the private data (privacy-to-goods-to-money). The order of these tasks was always randomized (except for Experiment 2e), with the constraint that the privacy-to-goods valuation preceded the goods-to-money valuation because participants needed to establish the value of their data in goods before they could value those goods in money.

To motivate realistic and accurate responses, we allowed participants to choose the type of good they wanted to use in the exchanges from a list of eight goods (observed choice shares across all studies in parentheses): Amazon movie rentals (12.9%), Clif Builder's protein bars (6.3%), Hanes socks (5.2%), Kindle e-books (13.3%), Shell gasoline (27.4%), Yellow Tail wine (7.4%), Keurig K-Cups (3.6%), or Starbucks beverages (23.9%). Experiment 2b offers access to Netflix without a choice of other goods to emulate a typical online exchange of private data. We chose these goods for two reasons. First, we wanted to demonstrate the discrepancy in valuations across different types of barter exchanges, including both digital (e.g., Netflix subscriptions) and physical (e.g., Starbucks beverages) goods to represent the range of offerings participants might receive in exchange for their data (e.g., from digital goods to free samples of products). Second, we wanted to set up a conservative test of our hypothesis by including goods that can be counted so that participants could equate the value of their private data to a specific number of units of a good. While companies often offer goods that are difficult to quantify (e.g., access to a social network) in return for private data, offering our participants goods that can be counted should make them more compatible with money, because both goods and money can be counted. In turn, this greater compatibility should raise participants' monetary valuations of these goods compared with nonquantifiable goods and thus reduce the difference between direct (privacy-to-money) and indirect (privacy-to-goods-to-money) valuations of private data that we hypothesize.

To ensure the normative equivalence of eliciting participants' preferences for their private data that is required for procedure invariance to hold, we measured all valuations using the same multiple price list (MPL) procedure (Andersen et al. 2006; Kahneman, Knetsch, and Thaler 1990; Wertenbroch and Skiera 2002). Participants indicated their WTA in money (i.e., the cash equivalent C) and in goods (i.e., the goods equivalent G) in exchange for their private data in an ordered series of accept–reject questions. For instance, in Experiments 1a and 1b we asked participants whether they were willing to exchange three hours of their GPS location data for £1, £26, £51, and so on, increasing in increments of £25 up to £201, all on the same screen (privacy-to-money). Likewise, we asked whether they would exchange their data for an increasing number of units of the good they had selected in increments of 10 units up to 51 units (101 units in Experiment 2b; privacy-to-goods).[1] We used three price lists for valuations in money and two for valuations in goods to increase the precision of our results. For instance, if a participant was willing to exchange their GPS data for £51 but not for £26, they would see a second, narrower price list. This subsequent list would range from £26 to £51, with smaller increments of £5 between the choices, followed by the third list with a range of £5 and increments of £1. We estimated an indifference value for each participant from their responses to the last price list by taking the midpoint between the lowest amount for which they accepted the exchange and the highest amount for which they rejected it. We treated these indifference values as point estimates of participants' WTA for their private data in money and in goods. Figure 1 illustrates our stimuli.

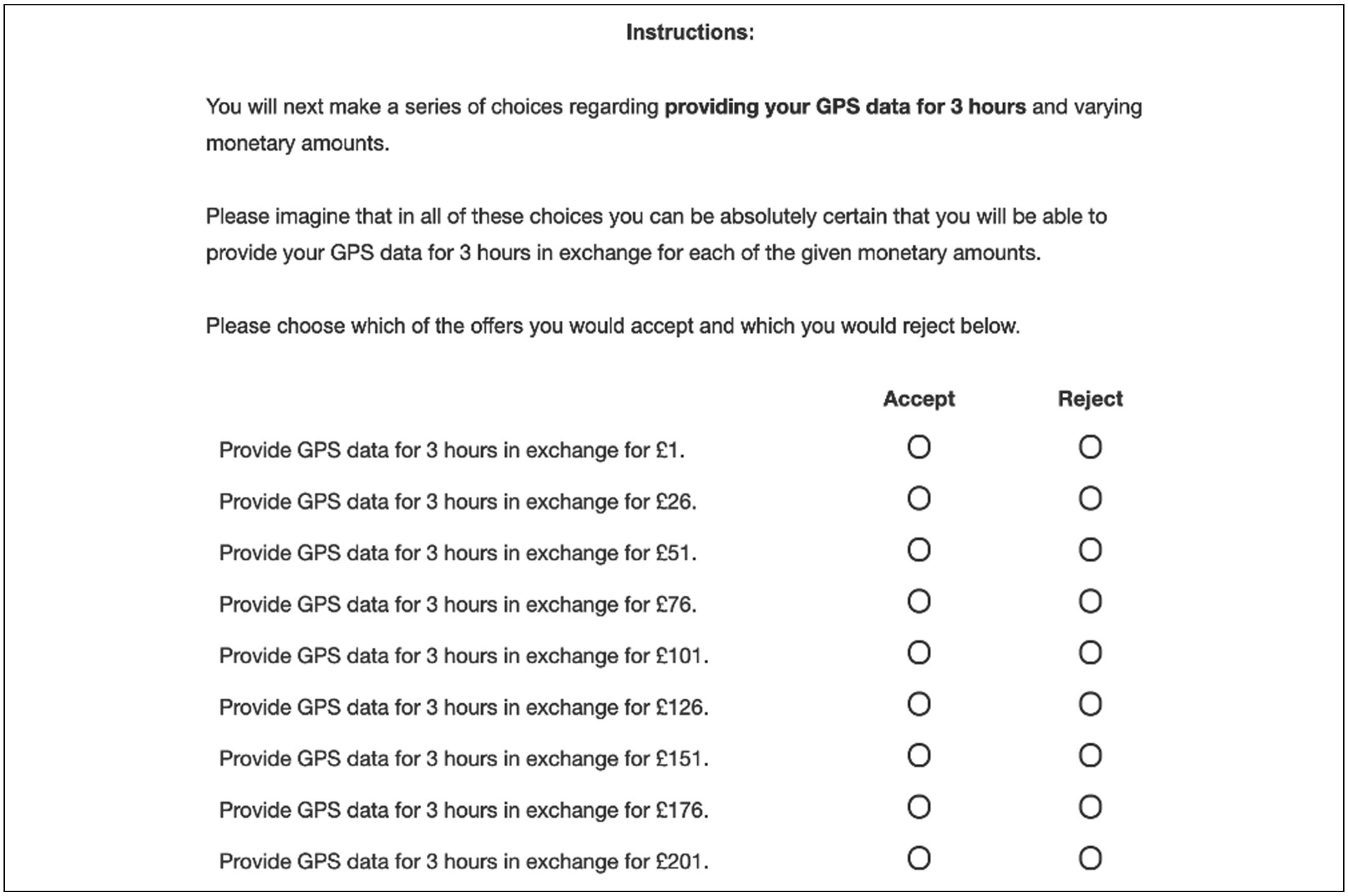
Once we had estimated a participant's goods equivalent G of their private data, they valued these units in money (goods-to-money, i.e., the cash equivalent G′ of the goods equivalent G), using MPLs with the same increments as in the aforementioned privacy-to-money task. For instance, starting at £1 and increasing in increments of £25, participants indicated whether they preferred to receive the amount of money from the price list or the number of units G of the good.[2] The valuation G′ (the midpoint between the lowest acceptable and the highest unacceptable amounts in the final list) of the bundle of goods G serves as an indirectly assessed cash equivalent of the participant's valuation of their data when trading them for goods (privacy-to-goods-to-money). Our means analyses compare G′ with participants' direct WTA in money C (privacy-to-money).

Experiments 1a and 1b: A Higher Price for Privacy in Money Than in Goods

Experiment 1 used the methodology outlined previously. Participants valued their data in money and in goods and then valued those goods in money. As an incentive to respond carefully and truthfully, participants entered a lottery with a chance that one of their choices would be implemented. To test for the hypothesized violation of procedure invariance, we first compared the means of the direct monetary valuations C of the private data with those of the indirect valuations G′ via goods (both valuations were elicited within participants) and then examined the proportion of participants who were intransitive in the predicted direction. To check the reliability of the hypothesized intransitivity, we ran the same experimental design twice.

[1] For the specific price list ranges of money and goods in each experiment, see Web Appendix A.

[2] We had participants choose between these two options rather than indicate a WTA for the goods so as not to impact their valuation through an endowment effect for goods (Kahneman et al. 1990).



Instructions:

You will next make a series of choices regarding **providing your GPS data for 3 hours** and varying monetary amounts.

Please imagine that in all of these choices you can be absolutely certain that you will be able to provide your GPS data for 3 hours in exchange for each of the given monetary amounts.

Please choose which of the offers you would accept and which you would reject below.

	Accept	Reject
Provide GPS data for 3 hours in exchange for £1.	O	O
Provide GPS data for 3 hours in exchange for £26.	O	O
Provide GPS data for 3 hours in exchange for £51.	O	O
Provide GPS data for 3 hours in exchange for £76.	O	O
Provide GPS data for 3 hours in exchange for £101.	O	O
Provide GPS data for 3 hours in exchange for £126.	O	O
Provide GPS data for 3 hours in exchange for £151.	O	O
Provide GPS data for 3 hours in exchange for £176.	O	O
Provide GPS data for 3 hours in exchange for £201.	O	O

Figure 1. Sample Stimulus (the Initial MPL in Privacy-for-Money in Experiments 1a and 1b).

Method

We recruited N = 301 participants (M_{age} = 38.53 years, SD = 10.78; 61.3% female) in Experiment 1a and N = 140 (M_{age} = 38.81 years, SD = 11.36; 59.3% female) participants in Experiment 1b from the United Kingdom and Ireland through Prolific Academic for £.45 each. Participants first indicated whether they owned a smartphone, since this study used smartphone location (GPS) data as the private data under consideration. Those who did not own a smartphone were paid and excluded from the rest of the study (N = 4 in each experiment).

We told the remaining participants that they would be considering various trade-offs between receiving money or goods on the one hand and providing GPS data collected by their smartphone via Google Maps over a three-hour period on the other. These data "would then be given to a company," which we did not name. To induce incentive-compatibility, participants learned that one of them would be randomly selected from all the participants in their respective version of the experiment (301 in Experiment 1a, 140 in Experiment 1b) to have one of the choices they made carried out with real money. This ensured that every single choice that participants made on the MPLs would potentially be binding. We conducted the random selection after the data collection was completed and paid the winners the cash equivalent of a randomly selected choice of theirs without collecting their data.

Participants next selected which of the eight goods listed earlier they would most like to receive. They then started the MPL procedure described previously. Lastly, we collected their Prolific ID and thanked, debriefed, and paid them.

As preregistered, we first excluded participants who provided inconsistent responses. For instance, a participant might have rejected £51 for their data on one screen and then accepted that offer on the subsequent screen, where it was the lower anchor on the price list. This makes it impossible to impute a valuation. Second, also as preregistered, we excluded participants whose valuations fell outside of the initial MPL range, as they accepted the minimum trading amount for their private data or rejected the maximum amount in at least one of the three valuation tasks. In Experiment 1a, 25 participants were excluded for inconsistencies, 71 for falling outside the range, and 23 for both, yielding a final sample of N = 178. In Experiment 1b, 9 participants were excluded for inconsistencies, 25 for falling outside the range, and 18 for both, yielding a final sample of N = 84. Experiment 2d tests whether these exclusion criteria impact our findings.[3]

[3] Prior research shows similar rates of inconsistencies (Charness, Gneezy, and Imas 2013; Dave et al. 2010; Holt and Laury 2002) and of participants exceeding list ranges (Charness and Viceisza 2011; Jacobson and Petrie 2009).

Results

Results of Experiments 1a and 1b are presented in Table 1. Unless otherwise noted, all comparisons of mean valuations across exchange mediums were done using paired-sample t-tests throughout this article. Likewise, unless stated otherwise, all comparisons of proportions were done using proportions tests. For each test, we set the null hypothesis as the proportion of interest being equal to the observed proportion of comparison. For instance, to test whether the proportion of participants who were intransitive in the direction our hypothesis predicted was equal to the proportion of participants who were intransitive in the opposite direction, the null hypothesis in Experiment 1a was that the proportion of participants intransitive in the predicted direction equaled 29.8%. Because the tests involved multiple comparisons, we also applied the more conservative Holm–Bonferroni significance (alpha) levels to these proportions tests (Holm 1979); all relevant proportion results remain significant.

As predicted, mean valuations of private data in both Experiments 1a and 1b were higher when measured in money than when measured in goods. Likewise, as predicted, in both Experiments 1a and 1b a greater proportion of participants exhibited intransitive preferences in the direction predicted by our hypothesis (i.e., they valued their data higher in money than in goods, $C > G'$) than the proportion who exhibited intransitive preferences in the opposite direction ($C < G'$). Also as predicted, the proportion of participants whose privacy preferences were intransitive in the predicted direction ($C > G'$) exceeded the proportion of participants whose preferences were transitive ($C = G'$). Lastly, a greater proportion of participants were intransitive in the opposite direction than were transitive.

Discussion

As we hypothesized, participants valued their private geolocation data higher when they considered exchanging the data for money than for goods in incentive-compatible choices. This effect held when comparing participants' mean valuations and when examining the proportion of participants who exhibited the intransitive pattern of preferences that our theory predicts. The effect occurs reliably, with identical pattern of results in both Experiments 1a and 1b.

Experiments 2a, 2b, 2c, 2d, and 2e: Checks of External and Internal Validity

Experiments 2a–2e tested the external and internal validity of our findings in Experiment 1 by varying our methodological approach.

In Experiment 2a, participants evaluated ten types of private data to show that the discrepancy in valuations generalizes to other types of private data beyond geolocation data.

Experiment 2b was designed to further establish the external validity of our findings by emulating a typical online data exchange. In contrast to our other experiments, where we offered participants a choice of which from a set of physical and digital goods to consider in trading their GPS data, Experiment 2b tested whether the effect holds when all participants consider exchanging their data for the same information good: weeks of access to Netflix streaming, a prominent online digital service with which consumers provide private data to the company.[4]

Experiment 2c addressed a potential limitation of the MPL value elicitation method. MPLs may constrain participants' valuations, because the experimenter sets the range of possible values participants can choose (Bohm, Lindén, and Sonnegård 1997; Poulton 1975). For example, in Experiment 1 participants could not indicate a specific WTA for their private data above 51 units of their chosen good. Even though we had pretested acceptable ranges of MPL values for Experiment 1, the maximum value in the MPLs may have limited the number of goods that some participants demanded for their data, biasing their valuations in goods downward, which might have artifactually enabled the effect we had hypothesized. Experiment 2c varied the range of maximum MPL values to address this concern. One condition featured the same privacy-to-goods price list range as Experiment 1, while the other almost doubled the range to 101 units. If the range of the number of goods contributed to the effect, we would expect a moderation of the effect in the latter condition. We would also expect fewer participants to reject the maximum privacy-to-goods offer when the range of goods offered is wider.

Experiment 2d addressed a second potential concern with MPL elicitations: the number of participants excluded from the analyses due to unimputable, missing valuations. Experiment 1 excluded a large number of participants from the analyses because they accepted the minimum valuation or rejected the maximum valuation in a price list, which made it impossible to calculate an indifference point (see the "Method" subsection, Experiment 1). Likewise, we excluded participants who had made inconsistent choices. To check whether the intransitive preference pattern we found in Experiment 1 is sensitive to exclusions, Experiment 2d prescreened participants to yield an experimental sample of individuals who were more likely to provide usable observations. Experiment 2d also accounted for participants who would give up their data without compensation to test the impact of including them in our analyses on our results.

Experiment 2e helped rule out potential order effects. In our standard experimental paradigm, participants always value their data in goods (G) before they can value these goods in money (G′). To show that this sequence does not impact our findings simply by allowing the valuation of the goods (G′) to reflect additional deliberation by participants, Experiment 2e gave

[4] Experiment 2b also enables us to assess any unforeseen impact of differences in the marginal utility of goods and money over the ranges provided in our MPLs. Theoretically, such differences should not impact our results, because participants should demand a relatively larger number of goods in exchange for their data if the marginal utility of these goods declines faster than that of money. Furthermore, if no quantity of goods offered in our MPLs were sufficiently valuable for a participant to exchange their data, then they would simply reject all offers and be excluded from our analyzed sample. Nonetheless, we designed Experiment 2b to equate the marginal utility of goods and money, based on a pretest that had shown that Netflix and money provide equivalent marginal utilities over our MPL range (Web Appendix C; we thank an anonymous reviewer for suggesting this study).

Table 1. Results of All Experiments (Except Experiments 3a and 3b).

Experiment	Mean Valuations			Proportions			Proportions Tests		
	Money	Goods	Test Statistics from Analysis	Intransitive Predicted ($C > G'$)	Intransitive Opposite ($C < G'$)	Transitive ($C = G'$)	Intransitive Predicted Versus Opposite	Intransitive Predicted Versus Transitive	Intransitive Opposite Versus Transitive
1a Prolific, UK/Ireland N = 178	£49.45 (£42.94)	£40.70 (£37.28)	$t(177) = 3.49$ $p < .001$	.545 (N = 97)	.298 (N = 53)	.157 (N = 28)	$z = 7.21$ $p < .001$	$z = 14.20$ $p < .001$	$z = 5.15$ $p < .001$
1b Prolific, UK/Ireland N = 84	£47.67 (£39.29)	£41.43 (£34.73)	$t(83) = 3.08$ $p = .003$	.583 (N = 49)	.250 (N = 21)	.167 (N = 14)	$z = 7.06$ $p < .001$	$z = 10.25$ $p < .001$	$z = 2.05$ $p = .040$
2a Prolific, UK N = 146	£52.23 (£63.34)	£36.14 (£39.81)	$F(1, 136) = 9.14$ $p = .003$	.500 (N = 73)	.370 (N = 54)	.130 (N = 19)	$z = 3.26$ $p = .001$	$z = 13.28$ $p < .001$	$z = 8.61$ $p < .001$
2b Prolific, USA N = 168	$54.78 ($48.91)	$46.31 ($39.16)	$t(167) = 2.64$ $p = .009$	.488 (N = 82)	.363 (N = 61)	.149 (N = 25)	$z = 3.37$ $p < .001$	$z = 12.36$ $p < .001$	$z = 7.80$ $p < .001$
2c (narrow condition) Prolific, UK N = 100	£39.71 (£43.77)	£30.02 (£28.07)	$F(1, 193) = 9.80$ $p = .002$	.550 (N = 55)	.310 (N = 31)	.140 (N = 14)	$z = 5.19$ $p < .001$	$z = 11.82$ $p < .001$	$z = 4.90$ $p < .001$
2c (wide condition) Prolific, UK N = 95	£43.87 (£43.53)	£37.17 (£33.90)	$F(1, 193) = 4.46$ $p = .036$	.463 (N = 44)	.358 (N = 34)	.179 (N = 17)	$z = 2.14$ $p = .032$	$z = 7.23$ $p < .001$	$z = 4.55$ $p < .001$
2d Prolific, USA N = 275	$34.80 ($45.01)	$29.46 ($40.05)	$t(274) = 3.96$ $p < .001$	.338 (N = 93)	.182 (N = 50)	.480 (N = 132)	$z = 6.72$ $p < .001$	$z = 4.71$ $p < .001$	$z = 9.90$ $p < .001$
2e (B/S first evaluation) Prolific, USA N = 299	$71.80 ($55.46)	$52.58 ($42.87)	$t(297) = 3.31$ $p = .001$	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
2e (B/S second evaluation) Prolific, USA N = 299	$72.70 ($55.80)	$54.89 ($44.97)	$t(297) = 3.00$ $p = .003$	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
2e (W/S) Prolific, USA N = 129	$62.37 ($46.19)	$49.37 ($38.89)	$t(128) = 3.58$ $p < .001$	.566 (N = 73)	.279 (N = 36)	.155 (N = 20)	$z = 7.26$ $p < .001$	$z = 12.89$ $p < .001$	$z = 3.89$ $p < .001$
4 (data) MTurk, USA N = 176	$57.89 ($62.84)	$48.15 ($47.87)	$F(1, 417) = 15.16$ $p < .001$	.494 (N = 87)	.352 (N = 62)	.153 (N = 27)	$z = 3.95$ $p < .001$	$z = 12.55$ $p < .001$	$z = 7.32$ $p < .001$

(continued)

Table 1. (continued)

	Mean Valuations			Proportions			Proportions Tests		
Experiment	**Money**	**Goods**	**Test Statistics from Analysis**	**Intransitive Predicted (C > G′)**	**Intransitive Opposite (C < G′)**	**Transitive (C = G′)**	**Intransitive Predicted Versus Opposite**	**Intransitive Predicted Versus Transitive**	**Intransitive Opposite Versus Transitive**
4 (labor) MTurk, USA N = 243	\$46.09 (\$40.49)	\$45.24 (\$36.79)	$F(1, 417) = .16$ $p = .691$	.403 (N = 98)	.432 (N = 105)	.165 (N = 40)	z = .91 $p = .365$	z = 10.03 $p < .001$	z = 11.24 $p < .001$
5 (price absent) Prolific, USA N = 299	\$50.11 (\$47.20)	\$44.72 (\$41.98)	$F(1, 632) = 9.74$ $p = .002$	.502 (N = 150)	.371 (N = 111)	.127 (N = 38)	z = 4.67 $p < .001$	z = 19.45 $p < .001$	z = 12.67 $p < .001$
5 (price present) Prolific, USA N = 335	\$51.15 (\$33.27)	\$50.66 (\$32.49)	$F(1, 632) = .09$ $p = .766$	.436 (N = 146)	.442 (N = 148)	.122 (N = 41)	z = .22 $p = .826$	z = 17.50 $p < .001$	z = 17.84 $p < .001$
6a (neutral impact) MTurk, USA (N = 202)	\$55.74 (\$53.81)	\$46.03 (\$43.45)	$F(1, 386) =$ 10.47, $p = .001$	.450 (N = 91)	.351 (N = 71)	.198 (N = 40)	z = .295 $p = .003$	z = 9.00 $p < .001$	z = 5.47 $p < .001$
6a (unfavorable impact) MTurk, USA (N = 186)	\$68.59 (\$67.91)	\$55.38 (\$56.83)	$F(1, 386) =$ 17.83, $p < .001$	.519 (N = 97)	.332 (N = 62)	.150 (N = 28)	z = 5.44 $p < .001$	z = 14.14 $p < .001$	z = 6.97 $p < .001$
6b (resale) Prolific, USA N = 289	\$55.11 (\$49.43)	\$49.49 (\$44.07)	$F(1, 597) = 7.62$ $p = .006$	.460 (N = 133)	.356 (N = 103)	.183 (N = 53)	z = 3.68 $p < .001$	z = 12.16 $p < .001$	z = 7.60 $p < .001$
6b (no resale) Prolific, USA N = 310	\$59.77 (\$51.19)	\$50.27 (\$43.88)	$F(1, 597) =$ 23.37 $p < .001$	.481 (N = 149)	.348 (N = 108)	.171 (N = 53)	z = 4.89 $p < .001$	z = 14.48 $p < .001$	z = 8.30 $p < .001$

Notes: N.A. = not applicable; B/S = between subjects; W/S = within subjects. Standard deviations, degrees of freedom, and number of participants in parentheses. We did not preregister proportion analyses for Experiments 1a, 1b, 4, 5, 6a, and 6b. However, preregistered replications of these proportions results are reported in Experiments 2a, 2b, 2c, and 2d. In Experiment 2a, participants valued ten types of private data that had different magnitudes of value (see Web Appendix B). For Experiment 2e, between-subjects comparisons of the first and second valuations of private data in money versus in goods are reported in this table. For the differences in valuations, we report t-tests instead of the regression results reported in the description of Experiment 2e. Only the within-subjects condition in this experiment was designed to test for proportion differences.

some participants further opportunities to deliberate.[5] As in Experiment 1, there was a condition in which participants valued their data in money (C) and in goods (G) and also placed a cash value on their goods valuation of their data (G′). In contrast to Experiment 1, there were two additional conditions, one in which participants valued their data in money twice (C, the direct monetary valuation of their data) and another in which they valued their data in goods twice (G) and then valued those goods in money twice (G′, the indirect monetary valuation of their data). If additional deliberation impacted participants' valuations, we would expect valuations to be affected by where in these sequences a given valuation occurs. In contrast, we predicted that participants' valuations would reveal a difference between mediums (i.e., C > G′), measured within and also between participants, but would not vary with their position in these sequences.

Method

Experiments 2a–2e each added design variations to the base design of Experiment 1.

Experiment 2a. We recruited N = 350 participants (M_{age} = 36.86 years, SD = 12.30; 67.4% female) from the United Kingdom through Prolific Academic to participate for £.40 each. In a mixed experimental design, we randomly assigned each participant to one of ten types of private data (between participants) of varying degrees of personal sensitivity that we asked them to value both in money and in goods (within participants): (1) three hours of their GPS geolocation data; (2) 10 hours of browsing history; (3) details of the last two purchases they had made online; (4) the titles of the last ten songs they had listened to through any medium; (5) a list of the last 20 online studies they had participated in; (6) their height and weight measurements; (7) a list of all the apps on their phone; (8) the last five messages they had sent on any platform; (9) a sample of their saliva; and (10) their phone number, email address, and mailing address. As preregistered, we excluded participants who made consistency errors (N = 20), accepted the minimum or rejected the maximum values in any of the three MPL assessments (N = 124), or did both (N = 60; N = 204 total exclusions; see the "Method" subsection, Experiment 1, for why these participants were excluded). Thus, our final sample comprised N = 146 observations.

Experiment 2b. We recruited N = 350 U.S. participants (M_{age} = 37.56 years, SD = 13.02; 50.0% female) through Prolific Academic for £.40 each.[6] We asked participants to consider various trade-offs between receiving money or months of access to Netflix streaming on the one hand and providing three hours of their GPS data to Netflix on the other. After they had completed the MPL tasks, we collected their Prolific IDs and thanked, debriefed, and paid them. As preregistered, we excluded participants who provided inconsistent responses. Also as preregistered, we excluded participants whose valuations fell outside of the initial MPL range as they accepted the minimum trading amount for their private data or rejected the maximum amount in at least one of the three valuation tasks. We excluded 17 participants for inconsistency errors, 149 for falling outside the range, and 16 for both, yielding a final sample of N = 168.

Experiment 2c. We recruited N = 362 participants (M_{age} = 36.63 years, SD = 11.88; 66.8% female) from the United Kingdom via Prolific Academic to participate for £.45 each. In a mixed experimental design, we randomly assigned participants to one of two initial price list conditions (between participants), a narrow-range or a wide-range condition, with which they began valuing their private data in money and in goods (within participants). In the narrow-range condition, we presented participants with an MPL ranging from one to 51 units of their preferred goods type when assessing whether they would trade their data for goods. In the wide-range condition, the range was from 1 to 101 units. All other price lists were identical across conditions. After excluding participants who made consistency errors (N = 44), accepted the minimum or rejected the maximum values in any of the three MPL assessments (N = 81), or did both (N = 42; N = 167 total exclusions), our final sample comprised N = 195 observations.

Experiment 2d. This experiment replicated Experiment 1 with a more vetted sample of participants to include not only those who would exchange their data for a price but also those who would give up their data for free and those who could successfully complete an MPL task. At a screening stage, we recruited N = 603 U.S. participants on Prolific Academic to participate for £.15. We screened out participants who would never trade their data and those who failed at least one of two attention checks. We invited only the remaining participants to the experiment. Full details of the preregistered screening procedure are in Web Appendix D.

Two hundred seventy-one participants were eligible to continue to the experiment, 234 of whom returned and completed it for £.40 each (M_{age} = 31.42 years, SD = 11.33; 47.0% female). From these, we excluded participants who made repeated consistency errors (N = 20), rejected the maximum value in any of the three MPL assessments (N = 18), and/or did not complete the experiment (N = 1).[7] If a participant accepted the minimum valuation in goods but not money, or vice versa, we excluded them from analyses (N = 16). This is because such participants would require nothing in exchange for their data in one medium but implausibly not in the other. This left 186 observations with 48 participants excluded based on meeting at least one exclusion criterion during the main

[5] We thank an anonymous reviewer for suggesting this test of an order effect.

[6] We used samples from different countries across experiments to ensure that the effect was robust.

[7] In Experiment 2d, we gave participants a chance to recomplete an MPL task if they made a consistency error. Eleven participants in our final sample received, and successfully used, this second chance.

experiment. After adding 89 observations with WTAs of \$0 and 0 units for those participants who had indicated at the screening stage that they would give their data away for free, our final sample included 275 observations.

Experiment 2e. We recruited N = 599 U.S. participants through Prolific. We allocated them to one of three conditions: a base condition, where they performed the same choice tasks as in Experiments 1a and 1b (i.e., privacy-to-money valuations C, privacy-to-goods valuations G, and goods-to-money valuations G′ in a random order, subject to privacy-to-goods coming before goods-to-money); a money condition, where participants provided two back-to-back privacy-to-money valuations C of their data; or a goods condition, where participants provided two back-to-back privacy-to-goods valuations G of their data and then provided two back-to-back goods-to-money valuations G′ of the resulting units of goods.

As preregistered, we excluded observations from participants who were inconsistent when using a price list (N = 45), accepted the minimum or rejected the maximum valuation in a price list (N = 114), or did both (N = 12). In addition, we employed the same incentive-compatible approach as in Experiments 1a and 1b.

Results

Table 1 shows results of Experiments 2a–2e.

Experiment 2a. As predicted, participants valued their private data higher when considering exchanging them for money, and this effect generalized across different data types. Eight of the ten data types show directionally greater valuations in money than in goods. A 2 (exchange medium, within-participants) × 10 (type of private data, between-participants) mixed-design analysis of variance (ANOVA) revealed the predicted within-participants main effect of exchange medium on valuations (Table 1).[8] There was also a between-participants main effect of data type ($F(9, 136) = 3.11$, $p = .002$) but, consistent with our prediction, no interaction effect ($F(9, 136) = 1.15$, $p = .333$). Also as predicted, proportions tests showed that more participants exhibited preferences that were intransitive in the predicted direction ($C > G'$) than intransitive in the opposite direction ($C < G'$) or transitive ($C = G'$) across the different data types (Table 1).[9]

Experiment 2b. As predicted, mean valuations of private data were higher when measured in money than in weeks of access to Netflix (Table 1). Moreover, and again as predicted, a greater proportion of participants exhibited preferences that were intransitive in the predicted direction ($C > G'$) than intransitive in the opposite direction ($C < G'$) or transitive ($C = G'$; Table 1).

Experiment 2c. We conducted a repeated-measures ANOVA to test for the basic effect of exchange mediums and whether there was any attenuation of this effect across MPL ranges. The dependent variable was the value participants placed on their data. A 2 (MPL range, between-participants) × 2 (exchange medium, within-participants) mixed-design ANOVA revealed no significant interaction between range and exchange medium ($F(1, 193) = .45$, $p = .502$). As predicted, a main effect of exchange medium showed that participants valued their data higher in money than in goods ($F(1, 193) = 13.66$, $p < .001$), without a main effect of range ($F(1, 193) = 1.30$, $p = .255$). Planned contrasts revealed that participants valued their private data significantly higher in money than in goods in both the narrow- and the wide-range conditions (Table 1). Also as predicted, proportions tests showed that in both conditions more participants exhibited preferences that were intransitive in the predicted direction ($C > G'$) than intransitive in the opposite direction ($C < G'$) or transitive ($C = G'$; Table 1). To corroborate this result, we ran a multinomial logistic regression, which detected no difference in these proportions between the narrow- and wide-range conditions (Web Appendix F).

In addition to our preregistered analyses, we also tested whether a greater proportion of participants rejected the maximum privacy-to-goods offer in the narrow-range condition than in the wide-range condition. This test included the subsample of participants who met our inclusion criteria (see the "Method" subsection, Experiment 1), minus the requirement that they not reject the maximum number of goods offered. There was no difference in the proportion of participants who rejected the maximum number of goods in the narrow-range condition (4.8% of 105 participants) and the wide-range conditions (4.0% of 99 participants; $z = .25$, $p = .802$), further suggesting that the exchange medium effect is not an artifact of a narrow MPL range of goods.

Experiment 2d. Replicating our main effect again, participants valued their data higher in money than in goods (Table 1). In addition, and again as predicted, more participants were intransitive in the predicted direction ($C > G'$) than were intransitive in the opposite direction ($C < G'$; Table 1). One hundred one participants (36.7%) stated that they would give their data away for free. Because they valued their data at \$0 and 0 units, they were transitive by design. Despite this, 33.8% of our sample was intransitive in the predicted direction, which is viewed as a notable level of intransitivity in the literature (Kivetz and Simonson 2000).

Experiment 2e. We analyzed two observations from each participant: C and G′ in the base condition, two repeated observations of C in the money condition, and two repeated observations of G′ in the goods condition. Each of these observations were coded on two factors. The first factor (exchange medium) was whether the observation was a privacy-to-money valuation (C) or a goods-to-money valuation (G′). Privacy-to-goods valuations (G) were not included as observations because they are not directly comparable to privacy-to-money valuations (C).

The second factor (position) was the position of a valuation in the sequence of valuations. In the money and goods

[8] We also conducted a regression analysis, which we had preregistered instead of the mixed-design ANOVA. This analysis yielded similar results (Web Appendix E).

[9] Means and proportions for individual data types can be found in Web Appendix B.

conditions, an observation was coded by whether it was the first or second time a participant provided that valuation. In the base condition, the relative ordering of privacy-to-money (C) and privacy-to-goods (G) determined the position coding. The positions of privacy-to-money valuations (C) were coded as follows: If the privacy-to-money valuation (C) came before the privacy-to-goods valuation (G), that participant's privacy-to-money valuation (C) was coded as coming first. If the privacy-to-money valuation (C) came after, the corresponding valuation was coded as coming second. The positions of goods-to-money valuations (G′) (i.e., the indirect monetary measure of a participant's valuation of their data in goods) were coded as follows: If the privacy-to-goods valuation (G) came before the privacy-to-money valuation (C), that participant's goods-to-money valuation (G′) was coded as coming first. If the privacy-to-goods valuation (G) came after, the participant's goods-to-money valuation (G′) was coded as coming second.

We then regressed the value a participant placed on their data on exchange medium (0 if goods-to-money [G′], 1 if privacy-to-money [C]) and the position of a valuation in the study (0 if first, 1 if second), while clustering standard errors by participant. As predicted, we found an effect of exchange medium, indicating a higher price for data in money than goods ($b = 17.02$, 95% confidence interval [CI] = [8.79, 25.24], $p < .001$), but no effect of valuation order ($b = .77$, 95% CI = [−1.74, 3.28], $p = .548$). This indicates that the position of a valuation did not impact the value a participant placed on their data, whereas the exchange medium did. In particular, this analysis suggests that, on average, participants valued their data $17.02 more in money than in goods.

Discussion

Experiments 2a–2e showed that the intransitivity in participants' valuations of their private data generalizes across different types of data and goods and is robust to methodological variations. In Experiment 2a, participants placed a higher value on their data when exchanging them for money as opposed to goods across diverse types of private data. In Experiment 2b, participants were intransitive when valuing their data in money and in weeks of access to Netflix streaming, which is representative of typical online exchanges of digital services and private data. In Experiment 2c, participants again valued their data higher in money than in goods, regardless of the range of the number of goods offered in the MPLs. In Experiment 2d, the effect persisted in a select sample of prescreened participants, showing robustness to our exclusion criteria. In Experiment 2e, valuations were impacted only by the medium, not by valuation frequency or order.

Experiments 3a and 3b: Private Data Are More Compatible with Money Than with Goods

So far, we have shown that consumers value their private data higher in money than in goods, revealing an intransitivity of valuations of private data. We hypothesized that this effect arises because valuations of private data are more compatible with money than with goods. Consistent with Slovic, Griffin, and Tversky (1990) and Tversky, Sattath, and Slovic (1988), consumers should thus find it easier to value their data in money than in goods, causing them to place a greater weight and higher value on their data in monetary valuations.

To test this psychological process explanation, Experiment 3 employed an established experimental paradigm to demonstrate compatibility effects in preference reversals (Carmon and Simonson 1998; Fischer et al. 1999; Fischer and Hawkins 1993; Lichtenstein and Slovic 1971; Tversky, Sattath, and Slovic 1988). In this paradigm, an input variable (e.g., units of private data) is found to be compatible with an output scale (e.g., units of money or goods) if participants weigh the input more when they directly *match* its equivalent on the output scale than when they *choose* between different combinations of levels of the input and the output scale (i.e., when they implicitly value the input in a choice rather than explicitly matching its value on the output scale).

We adapted this paradigm such that participants in a choice condition chose between exchanging a small amount of private data for a small amount of compensation ($-P_L$, $+C_L$) and exchanging a larger amount of private data for a larger amount of compensation ($-P_H$, $+C_H$). Participants in a matching condition considered the same trades as those in the choice condition. However, for the trade of the larger amount of data $-P_H$, the value of the larger amount of compensation $+C_H$ was missing. Participants filled in this missing value by providing a matching amount of compensation $+C_X$ that would make them indifferent between the two trades. From these responses we can determine whether data are more compatible with money or with goods.

We predicted that participants' responses would reveal a greater compatibility of their data with money than with goods. Specifically, we predicted that participants would place greater weight on their private data—and thus demand a higher value for them—in matching than in choice when data are exchanged for money but not when data are exchanged for goods.

Method

To ensure the robustness of our findings, we ran the same experiment twice. For Experiment 3a, we recruited $N = 499$ U.S. participants ($M_{age} = 37.49$ years, $SD = 12.68$; 44.8% female) through Prolific Academic to participate for £.10 each. For Experiment 3b, we recruited $N = 500$ participants ($M_{age} = 36.73$ years, $SD = 13.15$; 72.4% female) from the United Kingdom. We paid participants £.12 each. We allocated them randomly to four experimental conditions in a 2 (money vs. goods) × 2 (choice vs. matching) between-participants design in each experiment.

The first factor manipulated whether participants considered trading their private data for money or for goods (Starbucks beverages; we chose these due to their popularity in our previous studies). The second factor, choice versus matching, implemented the standard scale compatibility test described previously. Participants in the choice conditions were presented with a choice between two trades: an exchange of three hours of their private GPS data for a small amount of compensation

Table 2. Stimuli for Experiments 3a and 3b.

	Choice Conditions	**Matching Conditions**
Prompt	You will consider two exchanges and be asked to indicate your preference for which one you would rather make. Even if you dislike both exchanges, please choose the option which you dislike the least between the two. If you truly have no preference between the two, please indicate that you are indifferent between them. Between the two exchanges below, which one would you rather make, if you had to choose between them?	Please provide a value for **X**, such that you would be indifferent between the following two exchanges. Even if you dislike both exchanges, please provide a value for **X** so that you would consider these two exchanges equivalent.
Money conditions	**($-P_L$, $+C_L$)**: Exchange three hours of your GPS data for $60 **($-P_H$, $+C_H$)**: Exchange 10 hours of your GPS data for $180 I am indifferent between these two options	**($-P_L$, $+C_L$)**: Exchange three hours of your GPS data for $60 **($-P_H$, $+C_X$)**: Exchange 10 hours of your GPS data for $**X** The value of **X** that would make me equally likely to make either exchange is $[____].
Goods conditions	**($-P_L$, $+C_L$)**: Exchange three hours of your GPS data for 18 medium Starbucks beverages **($-P_H$, $+C_H$)**: Exchange 10 hours of your GPS data for 54[a] (100[b]) medium Starbucks beverages I am indifferent between these two options	**($-P_L$, $+C_L$)**: Exchange three hours of your GPS data for 18 medium Starbucks beverages **($-P_H$, $+C_X$)**: Exchange 10 hours of your GPS data for **X** medium Starbucks beverages The value of **X** that would make me equally likely to make either exchange is [____] beverages.

[a]In Experiment 3a.
[b]In Experiment 3b.

($-P_L$, $+C_L$) or an exchange of ten hours of their private GPS data for higher compensation ($-P_H$, $+C_H$). In the money condition, $+C_L$ was $60 and $+C_H$ was $180. In the goods condition, $+C_L$ was 18 medium Starbucks beverages and $+C_H$ was 54 medium Starbucks beverages. That is, in both the money and the goods conditions, we tripled $+C_L$ to determine the compensation $+C_H$ offered in return for the large amount of private data in Experiment 3a. In Experiment 3b, we more than tripled it in the goods condition, raising $+C_H$ to 100 medium Starbucks beverages, to ensure that the proportion of participants who preferred ($-P_H$, $+C_H$) in the goods-choice condition would be comparable to that in the money-choice condition and be high enough in both the money and the goods conditions to allow for a difference between choice and matching. We asked participants "Between the two exchanges below, which one would you rather make, if you had to choose between them?" Participants could also express indifference. Participants in the matching conditions were shown the ($-P_L$, $+C_L$) exchange from the choice conditions (i.e., exchange three hours of their private GPS data for $60 or for 18 medium Starbucks beverages). They were also shown an exchange ($-P_H$, $+C_X$) of ten hours of GPS data for $X (money condition) or X Starbucks beverages (goods condition) and asked to indicate a value of X such that they would be indifferent between the two exchanges. Table 2 provides the stimuli, experimental design, and dependent measures.

Suppose a participant in the matching condition indicates an indifference value $+C_X$ that is higher than the corresponding fixed value in the choice condition $+C_H$. This implies that the participant would prefer the trade that involves exchanging only a small amount of private data for the small amount of compensation if they were in the choice condition. Put differently, matching values of $+C_X > +C_H$ imply a strict preference to exchange the small amount of data for the small amount of compensation ($-P_L$, $+C_L$) in choice. Conversely, matching values of $+C_X < +C_H$ imply a strict preference to exchange the large amount of data for the large amount of compensation ($-P_H$, $+C_H$) in choice.

Our key dependent measure is the proportion of participants who state in the choice conditions, or imply in the matching conditions, a preference for ($-P_H$, $+C_H$) over ($-P_L$, $+C_L$). If private data are compatible with money but not with goods, this proportion will be lower in the money-matching condition than in the money-choice condition, implying a greater weight on data in money-matching than in money-choice, while this difference will be attenuated between the goods-matching and the goods-choice conditions.

Results

Table 3 shows the proportions of participants in Experiments 3a and 3b with a preference for ($-P_L$, $+C_L$), for ($-P_H$, $+C_H$), or who were indifferent. We ran logistic regression analyses to evaluate whether the task type had an impact on preference distributions within both the money and goods conditions.[10] The dependent variable was whether a participant preferred to give up a large amount of data (1 if [$-P_H$, $+C_H$], 0 if otherwise). We combined a preference for ($-P_L$, $+C_L$) and being indifferent between the two trade-offs into one outcome since they both mean that a participant did not prefer ($-P_H$, $+C_H$). The independent variables were task (0 if choice, 1 if matching), medium (0 if goods, 1 if money), and their interaction. The regression coefficients show how the independent variables impact the likelihood

[10] We had preregistered the use of ANOVA in our analyses; given the binary nature of the dependent variable, we present a logistic regression model here. An ANOVA shows similar results.

Table 3. Proportions of Preferred Choices in Experiments 3a and 3b.

Experiment 3a

	($-P_L$, $+C_L$): 3 Hours of GPS Data for $60 (18 Beverages)	($-P_H$, $+C_H$): 10 hours of GPS Data for $180 (54 Beverages)	Indifferent
Money choice	.250	.645	.105
Money matching	.680	.288	.032
Goods choice	.357	.381	.262
Goods matching	.626	.366	.008

Experiment 3b

	($-P_L$, $+C_L$): 3 Hours of GPS Data for $60 (18 Beverages)	($-P_H$, $+C_H$): 10 Hours of GPS Data for $180 (100 Beverages)	Indifferent
Money choice	.405	.492	.103
Money matching	.648	.320	.032
Goods choice	.366	.463	.171
Goods matching	.048	.895	.057

of a preference for ($-P_H$, $+C_H$). We observed significant interaction effects in both Experiment 3a ($b = -1.45$, 95% CI = [−2.19, −.71], $p < .001$) and Experiment 3b ($b = -3.04$, 95% CI = [−3.89, −2.20], $p < .001$). We then ran a series of contrast analyses in Stata. As predicted, participants in Experiment 3a were less likely to prefer ($-P_H$, $+C_H$) in matching than in choice in the money conditions ($b = -1.50$, 95% CI = [−2.04, −097], $p <$ .001) but not in the goods conditions ($b = -.05$, 95% CI = [−.56, .46], $p = .843$). In Experiment 3b, participants were also less likely to prefer ($-P_H$, $+C_H$) in matching than in choice in the money conditions ($b = -.72$, 95% CI = [−1.24, −.21], $p =$ .006), while they were more likely to prefer ($-P_H$, $+C_H$) in matching than in choice in the goods conditions ($b = 2.32$, 95% CI = [1.65, 2.99], $p < .001$).

Discussion

Employing Tversky, Sattath, and Slovic's (1988) experimental paradigm to demonstrate compatibility effects, Experiments 3a and 3b show that participants place a greater value on their private data in matching than in choice in exchanges with money but not in exchanges with goods. Thus, private data are more compatible with money than with goods. The stronger preference for trading in a large amount of data for a large number of goods in matching than in choice in Experiment 3b even suggests that private data may be "incompatible" with goods, lowering their weight when traded against goods. Supplemental Experiment 1 (Web Appendix G) provides a further test of the robustness of this effect of compatibility of private data with money but not with goods to variations in the trade-off ranges of the data and compensation used here.

Experiment 4: Preference Intransitivity Is Unique to Private Data

Experiment 3 showed that consumers' private data are more compatible with money than with goods, which accounts for the violations of procedure invariance and transitivity observed in Experiments 1 and 2. Compatibility effects arise when preferences for the input variable—in this case, private data—are uncertain (Tversky, Sattath, and Slovic 1988). There are multiple unique features of markets in which consumers exchange private data that may contribute to this uncertainty (Spiekermann et al. 2015), allowing for the greater compatibility of data with money than with goods that Experiment 3 demonstrated. One of these features is the absence of well-defined market prices for private data. We therefore predicted an attenuation of the violation of procedure invariance and implied preference intransitivity when consumers exchange assets with well-defined market prices compared with when they exchange their private data. To test this prediction, Experiment 4 asked Amazon Mechanical Turk (MTurk) workers to value their private data or to value their MTurk labor, again based on MPLs. MTurk labor has a well-established wage rate band that is familiar to MTurk workers because they repeatedly choose to work for rates within that band.

Method

We recruited N = 603 U.S. participants (53.0% female) through MTurk to participate for $.40 each. We randomly assigned participants to one of two conditions, in which we asked them to state their WTA in money and in goods either in exchange for three hours of their GPS data (data condition, corresponding to our base design) or for completing a three-hour-long MTurk image coding task (labor condition) in a mixed 2 (exchange medium, within-participants) × 2 (data versus labor, between-participants) design. The procedure followed the standard MPL paradigm described in the "Overview of Studies and Experimental Paradigm" section. As in Experiments 2a and 2d, the initial price lists ranged from $1 to $276 and from 1 unit to 51 units of goods. After excluding participants who made consistency errors (N = 52), accepted the minimum or rejected the maximum MPL value in one of three valuations

(N = 88), or did both (N = 44; N = 184 total exclusions), the final sample comprised N = 419 observations for the different analyses.

Results

First, we conducted a (nonpreregistered) manipulation check of the greater preference uncertainty for data than for labor implied by the lack of a well-established market price for private data. Uncertainty is often measured as variation around the mean (Soll and Klayman 2004). We averaged each participant's valuations in money (C) and in goods (G′) and compared the standard deviations of these averages in the data and labor conditions as proxies for preference uncertainty. The mean of these average valuations in the data condition exceeded the corresponding mean in the labor condition by a factor of 1.16, so we multiplied each observation in the labor condition by 1.16 to make both standard deviations comparable in scale. A two-sample standard deviations test revealed a higher standard deviation around the mean of the average valuations in the data condition (SD = \$53.02) than in the labor condition (SD = \$40.97; F = 1.67, $p < .001$), confirming that participants were less certain of the value of their data than that of their labor, consistent with the absence of a well-established market price for private data.

Next, we ran a repeated-measures ANOVA where the dependent variable was the value participants placed on their data and the independent variable was condition (data or labor) with the exchange medium (money C or goods G′) as the repeated factor. As predicted, there was a significant interaction effect of condition and exchange medium ($F(1, 417) = 7.33$, $p = .007$), showing that the discrepancy in valuations that reflects the underlying intransitivity was attenuated in the labor condition compared with the data condition. Planned contrasts revealed that, as predicted, participants in the data condition valued their data higher in money, whereas participants in the labor condition exhibited no difference in valuations across money (Table 1). In addition, there was a significant main effect of the exchange medium, showing that valuations in money exceeded those in goods ($F(1, 417) = 10.39$, $p = .001$). Unrelated to testing our theory, a marginally significant main effect showed that participants valued providing three hours of their GPS data higher than providing three hours of MTurk labor ($F(1, 417) = 2.90$, $p = .090$). Crucially and also as predicted, proportions tests and a preregistered multinomial regression analysis confirmed a corresponding attenuation of the underlying preference intransitivity among participants (Table 1 and Web Appendix H).

Discussion

Consistent with our theorizing, Experiment 4 demonstrated that the discrepancy between participants' valuations of private data in money and in goods does not arise for inputs such as labor, which are characterized by more well-defined prices. Participants exhibited systematically intransitive preferences in the predicted direction only when they valued their private data, not when they valued their labor. Consistent with Tversky, Sattath, and Slovic's (1988) assertion that compatibility effects arise when preferences are not well-defined, the intransitivity attenuates when participants exchange assets of whose value they are less uncertain (e.g., their labor) than of the value of their private data. The preference uncertainty for private data triggers the effect of the greater compatibility of private data with money than with goods.

The results of Experiment 4 are also further evidence that our findings do not arise as an artifact of the MPL methodology. Otherwise, participants in the labor condition would have exhibited the same systematic preference intransitivity.

Experiment 5: A Market Price Attenuates Preference Intransitivity

Experiment 4 examined the effect of preference uncertainty on the intransitivity of valuations of private data by comparing valuations of data and of labor. Our findings suggested that uncertainty about how to value their data causes intransitive preferences among consumers. Experiment 5 tests this proposition by manipulating uncertainty about the value of private data directly. In contrast to most other markets, demand and supply in data markets do not yield a well-defined market price (Spiekermann et al. 2015). Because the lack of such a reference price likely contributes to consumers' uncertainty about the value of their data, we predicted that informing participants of a clear market price would attenuate the systematic intransitivity we observe throughout, by serving as a reference price on which to base their own data valuations.

Method

We recruited N = 902 U.S. participants ($M_{age} = 36.62$ years, SD = 13.64; 50.1% female) through Prolific Academic to participate for £.40 each. The methodology again employed the base design of Experiments 1a and 1b, but without the incentive compatibility. We randomly assigned participants to one of two conditions, in which we either did (price present) or did not (price absent, corresponding to our base design) present them with the following message:

> Please note that our research group has established a market price for GPS data based on our past research. The going market price is \$51.50 for 3 hours of GPS data from people such as yourself. This is the amount we have paid in the past and the amount we plan to pay in the future for this type of data. This pay corresponds well to the median price at which our past participants have been willing to sell this data, which is also \$51.50.

This manipulation was designed to establish a market price for the data participants are exchanging in our experiment. While the mechanism by which the market price was generated should be immaterial to participants, we derived it from participants' median WTA in Experiment 2e and noted this to participants to lend it further plausibility. After the manipulation in the price-present condition, we asked participants to report back this price before they could proceed. Two participants were unable to do so after three attempts but were allowed to proceed nonetheless. We also reminded them of the market price at the beginning of each valuation. After excluding participants who made consistency errors (N = 77), accepted the minimum or rejected the maximum MPL value in one of the three valuations (N = 143), or did both (N = 48; N = 184 total exclusions), the final sample comprised N = 634 observations for the different analyses.

Results

First, we conducted a (nonpreregistered) manipulation check of the greater preference uncertainty in the absence compared with the presence of a clear market price for private data. As in Experiment 4, we averaged each participant's data valuations in money (C) and in goods (G′) and compared the standard deviations around the means of these averages in the price-absent and price-present conditions. The means were similar (participants placed an average 1.07 times greater valuation on their data in the price-present condition; $p = .222$), so no rescaling was needed. A two-sample standard deviations test revealed a higher standard deviation around the mean of the average data valuations in the price-absent condition (SD = \$41.71) than in the price-present condition (SD = \$29.79; $F = 1.96$, $p < .001$). This suggests that participants were less certain of the value of their data in the price-absent condition than in the price-present condition.

Next, we ran a repeated-measures ANOVA where the dependent variable was the value participants placed on their data (C or G′) and the independent variables were the condition (price present or price absent, between-participants) and the exchange medium (money or goods, within participants). As predicted, there was a significant interaction effect of condition and exchange medium ($F(1, 632) = 4.26$, $p = .040$), showing that the discrepancy in valuations that reflects the underlying intransitivity was attenuated when participants were aware of a well-defined market price for their data. Planned contrasts revealed that, as predicted, participants in the price-absent condition valued their data higher in money, whereas participants in the price-present condition exhibited no difference in their valuations across money and goods (Table 1). In addition, there was a significant main effect of the exchange medium, showing that valuations in money exceeded those in goods ($F(1, 632) = 6.12$, $p = .014$). There was no main effect of the presence of a market price on data valuations ($F(1, 632) = 1.49$, $p = .222$). Crucially, and also as predicted, proportions tests and a multinomial regression analysis confirmed a corresponding attenuation of the underlying preference intransitivity among participants (Table 1 and Web Appendix I).[11]

Discussion

Consistent with our theorizing, Experiment 5 demonstrated that the discrepancy between participants' valuations of their private data in money and in goods—as shown throughout—did not arise in the presence of a well-defined market price for such data. Participants exhibited systematically intransitive preferences in the predicted direction only in the absence of a market price. The presence of the market price reduced participants' uncertainty about the value of their data and thus limited the extent to which a greater compatibility of private data with money than with goods could affect their valuations. The absence of established market prices in actual exchanges of private data may thus be a key driver of consumers' uncertainty about how to value their private data.

Experiments 6a and 6b: Tests of Additional Unique Features of Data Markets

Experiments 4 and 5 showed that a key feature of markets for private data that contributes to consumers' preference uncertainty about how to value their data and thus enables the compatibility effect we have hypothesized—the absence of well-defined market prices—moderates the intransitivity of these valuations. In the exploratory Experiments 6a and 6b (not preregistered), we aimed to demarcate this effect by showing that two other unique features of markets for private data fail to moderate the exchange medium effect.[12] We summarize these studies here (see Web Appendices J and K).

Experiment 6a

Another unique feature of markets for private data is that consumers may face different consequences of providing personal data depending on how they are used by a third party that obtains them. In Experiment 6a, we examined whether changes in the perceived consequences of what will happen with one's data after an exchange can explain our effect. Using our standard experimental paradigm, we told participants either that "The GPS data you would provide would be collected and stored by a company" (neutral impact condition) or that "The GPS data you would provide would be sold to multiple marketing companies. It would be used to send you ads and market to you based on where you spend your time" (unfavorable impact condition). A posttest confirmed that participants felt that exchanging their data would pose a greater risk of an unfavorable impact on them personally in the unfavorable impact condition than in the neutral impact condition (Web Appendix L). Participants' uncertainty about the value of their data did not differ across conditions, measured by the variance in valuations (Web Appendix J). A repeated-measures ANOVA where the dependent variable was the value a participant placed on their data and the independent variable was condition (neutral vs. unfavorable impact), with the exchange medium (money or goods) as the repeated factor, revealed no interaction effect of condition and exchange medium ($F(1, 386) = .65$, $p = .420$). Furthermore, planned contrasts revealed that participants valued their data higher in

[11] We did not preregister the proportions analyses in this experiment.

[12] We thank an anonymous reviewer for suggesting these tests.

money than in goods in both the neutral and the unfavorable impact conditions (Table 1).

Experiment 6b

Yet another unique feature of markets for private data is that consumers often provide the same personal data to multiple companies (e.g., via third-party cookies, by providing the same email address to multiple websites to gain access to these sites). Experiment 6b tested whether participants' ability to sell a given data set multiple times or only once impacts the intransitivity of data valuations. Using our standard experimental paradigm involving the exchange of GPS data, participants in a resale condition read, "Specifically, you would download an app that would track and analyze your location for 3 hours. The company that collects your data would then sell this data. The company would return this data to you, such that you would be able to resell it to other companies." Participants in a no-resale condition read, "Specifically, you would download an app that would track and analyze your location for 3 hours. The company that collects your data would then sell this data. The company would not return this data to you, such that you would not be able to resell it to other companies." Participants' uncertainty about the value of their data did not differ across conditions, measured by the variance in valuations (Web Appendix K). A repeated-measures ANOVA where the dependent variable was the value a participant placed on their data and the independent variable was condition (resale or no resale) with the exchange medium (money or goods) as the repeated factor revealed no interaction effect of condition and exchange medium ($F(1, 597) = 1.88$, $p = .170$). Furthermore, planned contrasts revealed that participants valued their data higher in money than in goods in both the resale condition and in the no-resale condition (Table 1).

Discussion

Experiments 6a and 6b tested whether two other unique features of markets for private data moderate the effect of exchange mediums on privacy valuations. We found no significant effect of perceptions of a negative personal impact of data sharing (Experiment 6a) or of the ability to sell the same data multiple times (Experiment 6b) on the exchange medium effect, further increasing our confidence that the primary driver of the intransitivity of consumer privacy valuations is a greater compatibility of private data with being valued in money than in goods.

General Discussion

A series of 11 experiments documented a robust violation of procedure invariance and an intransitivity of consumer preferences for privacy: participants valued the same private personal data higher in money than in goods. Experiments 1a and 1b demonstrated this exchange medium effect in an incentive-compatible setting. In tests of external validity, Experiment 2a demonstrated the generalizability of the effect across multiple types of private data, while Experiment 2b demonstrated the effect by comparing data exchanges for money and for access to Netflix, a proxy for the types of information goods for which data are commonly exchanged (online video streaming). In tests of internal validity, Experiments 2c, 2d, and 2e (the latter again in an incentive-compatible setting) showed that the intransitivity is robust to technical characteristics of the MPL methodology (ranges, exclusion criteria, and sequencing).

We hypothesized that this effect occurs because private data are more compatible with being valued in money than with being valued in goods. Experiments 3a and 3b confirmed this hypothesis by adapting an established experimental design for demonstrating compatibility effects, comparing preferences elicited in matching and in choice tasks. Experiments 4 and 5 again replicated the basic discrepancy in valuations and demonstrated—consistent with the compatibility principle—that preference (un)certainty provides a boundary condition that moderates the effect: the intransitivity of valuations that arises from the greater compatibility of private data with money than with goods is driven by participants' uncertainty about how to value their data. Experiments 4 and 5 tested the effect of such preference uncertainty by varying the presence or absence of a well-defined market price. The absence of such a price is a key characteristic of markets for private data that contributes to consumers' uncertainty. The lack of significant effects of two other key characteristics of these markets in Experiments 6a and 6b lends further support to our hypothesis that the intransitivity of consumer privacy valuations arises from a greater compatibility of private data with valuations in money than in goods.

Limitations and Future Directions

While Experiment 2a showed the external validity of our results by replicating the intransitivity of privacy preferences across several types of private data, it also suggests that the extent of the intransitivity may vary for some types of data. Future research could focus on whether, how, and why the discrepancy between private data valuations in money and in goods systematically depends on the type of private data that consumers give up. More generally, it may also be interesting to examine how this discrepancy might be affected by contextual factors, such as the salience of giving up one's data.

A limitation of our research is that we show the difference between private data valuations in money and in goods with experimental data. As we discuss next, our findings of an intransitivity of preferences for privacy call into question whether markets for private data (e.g., online platforms) function efficiently. Therefore, future research should aim to devise methods to detect intransitive valuations of private data in naturalistic settings to confirm our experimental findings in the field and test whether markets for privacy are functioning correctly.

Theoretical and Practical Implications

Our contribution to the literature is twofold. First, our findings complement research on effects of the medium of exchange, usually card versus cash, on consumer willingness to pay (Hirschman 1979; Prelec and Simester 2001). Whereas this line of research generally attributes differences in willingness to pay across payment mediums to differences in the salience of parting with money (Raghubir and Srivastava 2008; Soman 2003), Experiments 3, 4, and 5 instead provide evidence of a compatibility effect that differentially impacts WTAs across money and goods. Experiments 4 and 5 varied participants' certainty about how to value what was exchanged, which moderates compatibility effects but not the salience of what is exchanged.

Our other primary contribution is to provide experimental evidence of the intransitivity of consumers' valuations of their own private data, going beyond descriptions of the privacy paradox, to offer a normative criterion to suggest a possible market failure for private data. While compatibility effects of exchange mediums on consumer preferences may not be limited to exchanges of consumers' private data, studying them in this context is pertinent and urgent. A systematic discrepancy between consumer valuations in money and in goods and the implied violation of preference transitivity suggests that consumer preferences for privacy are biased, and thus market exchanges for data may be inefficient (Grether and Plott 1979; Kahneman, Knetsch, and Thaler 1990). Consequently, our findings suggest a new interpretation of the privacy paradox: consumers reveal privacy preferences that are specific to bartering exchanges of private data in return for information goods, whereas their stated preferences may be more representative of their (equally true) monetary valuations.

The practical significance of this finding arises from how technology companies compensate consumers for their private data in online interactions, such as searches, targeted advertising, purchases, social network participation, streaming, and news consumption. Such companies typically offer consumers information goods while collecting consumer data, portraying these goods as "free." Our analysis offers a normative (i.e., axiomatic; Von Neumann and Morgenstern 1944) criterion to raise the question of whether companies are compensating consumers adequately. Our findings imply that consumers would demand higher prices for the same data if companies paid them in money rather than in goods. While we cannot identify a normatively correct price for data, a case of normative ambiguity in welfare analysis (Bernheim and Rangel 2007), we can highlight that consumer-facing data markets differ from most other markets in that they entail payment in goods rather than money and that our results show consumers would demand more value for their data if companies paid them in cash.

Furthermore, applying a normative (i.e., axiomatic) criterion to our analysis of individual consumer choices suggests that a behavioral bias—a violation of procedure invariance implying an intransitivity of consumer preferences for privacy—may enable technology companies to build market power from collecting private consumer data without (inadvertently or deliberately) adequately compensating consumers. To protect consumer welfare and remedy the possible inefficiencies in markets for private data that our findings suggest, policy makers might explore methods by which consumers could sell, rather than barter, their private data to technology companies. This approach would be in line with two major objectives of antitrust policy: protecting consumer welfare (Bork 1978) while also fostering competition among firms that collect consumer data (Khan 2017).

A possible step in addressing these inefficiencies could be to assign explicit property rights to consumers' private data (Coase 1960; Hazel 2020; Spiekermann et al. 2015). This should help consumers treat their personal data as tradeable assets and foster competition among firms for this data. The rights to be forgotten and to data portability under GDPR and CCPA already provide consumers with a degree of control over their data and separate data exchanges and goods exchanges (Ke and Sudhir 2020), but they stop short of granting explicit legal ownership. A better ability of larger firms to bear compliance costs may even increase industry concentration under such privacy regulation (Johnson, Shriver, and Goldberg 2021). Giving consumers more control but not legal and commercial ownership of their data may constrain data access by firms and thus, in fact, hamper competition (Wertenbroch 2021). To illustrate, Apple's iOS now asks consumers for explicit consent to allow other firms to track their behavior across apps and share their data, while Google Chrome and other browsers are phasing out third-party cookies, which will also limit tracking of consumers (Brodherson et al. 2021). Apple frames the iOS feature as a tool to protect consumers' privacy, whereas firms like Meta, whose business models are based on advertising, protest that it limits their ability to target advertising and thus to compete (*The Economist* 2021). In contrast, various private enterprises have attempted to enable consumers to sell their data for cash, using pricing as a tool to foster competition (Harrison 2018).

Our findings support a pricing approach, the technical challenges (e.g., transaction costs) of implementing it notwithstanding. They suggest that allowing, or perhaps requiring, consumers to sell or license their data for monetary compensation might dampen the market power that companies can amass from obtaining consumers' private data in barter exchanges. Enabling consumers to sell their own data for money would force companies to compete for the data at more clearly defined market prices, much like they compete for labor (Arrieta-Ibarra et al. 2018). Such an approach should allow consumers to better protect their privacy and welfare, while using market-clearing pricing to enhance competition and innovation in markets that treat privacy as a tradeable asset.

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