Individual willingness to provide geospatial global positioning system (GPS) data from their smartphone during the COVID-19 pandemic[1]

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Abstract

This study aims to evaluate people's willingness to provide their geospatial global positioning system (GPS) data from their smartphone during the COVID-19 pandemic. Based on the self-determination theory, the addition of monetary incentives to encourage data provision may have an adverse effect on spontaneous donation. Therefore, we tested if a crowding out effect exists between financial and altruistic motivations. Participants were randomized to different frames of motivational messages regarding the provision of their GPS data based on 1) self-interest, 2) pro-social benefit and 3) monetary compensation. We also sought to examine the use of a negative versus positive valence in the framing of the different armed messages. 1055 participants were recruited from 41 countries with a mean age of 34 years on Amazon Mechanical Turk (MTurk), an online crowdsourcing platform. Participants living in India or in Brazil were more willing to provide their GPS data compared to those living in the United States. No significant differences were seen between positive and negative valence framing messages. Monetary incentives of $5 significantly increased participants' willingness to provide GPS data. Half of participants in the self-interest and pro-social arms agreed to provide their GPS data and almost two-thirds of participants were willing to provide their data in exchange for $5. If participants refused the first framing proposal, they were followed up with a "Vickrey auction" a sealed-bid second-priced auction (SPSBA). An average of a $17 bid was accepted in the self-interest condition to provide their GPS data, and the average "bid" of $21 was for the pro-social benefit experimental condition. These results demonstrate that a crowding-out effect between intrinsic and extrinsic motivations does not take place. Framing and incentivization can be used in combination to influence the acquisition of private GPS smartphone data. Financial incentives can increase data provision to a greater degree with no losses on these intrinsic motivations, to fight the COVID-19 pandemic.

Keyword: global positioning system, GPS, geospatial data, auction, health communication, human mobility, behavioral economics, COVID-19, intrinsic, extrinsic, framing, donation

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Introduction

During the COVID-19 pandemic, human mobility collected from geospatial global positioning system data (GPS) on smartphones has been used to support efforts to understand the transmission patterns of COVID-19 and to control the effectiveness of public health interventions like contact tracing (Parra, 2021; Beria and Lunkar, 2021; Grantz et al. 2020). GPS data provided by users' smartphones can be analyzed to obtain a verifiable record of individuals' human mobility patterns and help predict the future disease trajectory of COVID-19 such as the identification of hotspots and the social and environmental factors that contribute to the further spread of COVID-19.

However, large concerns have been brought up about how users may not readily release their personal data and if so they will only do it under specific conditions (Acquisti et al., 2016; Posner 1981). This "privacy concern" (Posner 1981) must be compensated by an additional means that would drive people to give access to their data. For social scientists, one of the key points in the data donation behavior is the motivational mechanism that can be activated to incentivize people to donate their private data. During the COVID-19 pandemic, disclosing personal data can generate social benefits, and so, "data altruism" – data donated for the common good[2] – may act as a major motivational mechanism. However, "data altruism" by itself may not be able to counteract the strong obstacle of a concern for privacy, at least to be able obtain a sufficient acceptance rates level (estimated at 60%, in Ferreti et al. 2020). Evidence had also emerged in the field of behavioral economic framing (e.g. Oullier et al. 2010), that the form of the message may have an impact, depending on the salience of the social motive for the data donation.

As there is collective benefit of data donation, the decision involves more than the individual balance between privacy concern and the participant's personal willingness to give access to their data. Thus, the public authority may consider another motivational mechanism: a monetary reward, with the aim to trigger people to internalize the collective benefit of their decision. It has already been shown that a monetary reward can bias the self-interest calculation toward data donation decision (Gefen et al., (2020)). However, in the behavioral economic literature, individuals seem to be more sensitive to the loss aversion effort – greater fear of losses than to a symmetric gain. In addition, a strong complication could also come from the "crowding-out effect" of extrinsic incentives. Deci, the founder of the "self-determination theory" was the first to detect this kind of unexpected effects in professional behaviors (Deci, 1972). Economists then progressively developed a reflection on professional motivations (Kreps, 1997) and more generally in prosocial motivations (Frey, 1997, Gneezi and Rustichini, 2000). Since the end of 1990's, several studies on pro-social behavior, particularly in the health domain, have confirmed the concerns that monetary payments may crowd-out intrinsic and altruistic motives, thus ultimately reducing the overall social contribution. For instance, it has been documented that blood donation behavior, initially studied by Titmuss, is above all motivated by a sense of altruism, with a (generally) unanticipated crowding-out effect of monetary incentives (Mellström, Johannesson, 2008). In other words, offering a monetary reward may deter users from donating for altruistic means. Which leads us to the research question of this study, what is the effectiveness of monetary incentives

[2] In this Act, the commission aimed at fostering populations to trust the facilitation of voluntary data disclosure: *Official Journal of the European Union*, 560th plenary session of the European Economic and Social Committee (JDE) – INTERACTIO, 27.4.2021-28.4.2021, part III Preparatory acts European Economic and Social Committee. 16.7.2021.

compared to other extrinsic, and intrinsic, motivations in health donation behaviors. We also sought study the reality of a loss aversion phenomenon in the data donation domain by examining the use of a negative versus positive valence in the framing of the message.

Specifically, we aimed to evaluate people's willingness to provide their geospatial global positioning system (GPS) data from their Smartphone during the COVID-19 pandemic based on different methods of framing and incentives. In this randomized experimental design, we test the suitability of various messages that could increase smartphone users' willingness to provide their personal information on human mobility.

Methods

Participants were recruited via *Amazon Mechanical Turk* (MTurk), an online crowdsourcing platform that is one of the suites of *Amazon.com Web Services*. In recent years MTurk had been extensively used in social science research. MTurk enables researchers to recruit participants to perform tasks such as filling out surveys, opinion polls, cognitive psychological studies, and other research services. MTurk rules state that participants can terminate the study by returning the task at any time, without any penalty. Participants on MTurk have a unique Worker ID, which is semi-random alphanumeric string. Participants' Worker IDs is associated with the study results making participant **anonymous**, as no identifying information including their names or address can be collected. Additionally, MTurk has several mechanisms in place to protect unauthorized access including protecting the security of information during transmission by using Secure Socket Layer (SSL) software to keep users' privacy protected.

Users on MTurk are presented list of potential task or Human Intelligence Jobs (referred to as HITs) when they log into their MTurk account. Our research study was listed on MTurk as a HIT and potential participant were proposed a compensated ($0.05 – standard compensation for a HIT) to complete the HIT questionnaire (5 minutes). Once users clicked on the HIT they were directed to the online consent which provided further information about the study. If the user agreed to the consent they were directed to complete the study that was hosted on the Qualtrics platform. The first portion of the study questionnaire included questions on demographics, COVID-19 testing history and whether they know anyone who has tested positive. Inclusion criteria included 18 years or older and owned a smartphone and what type of operating system they used (Android-Google, IOS-Apple).

Users were then randomly assigned to equal arms whereby they were provided messages that related to 1) self-interest; 2) pro-social; 3) monetary motivations for contributing their GPS data from their smartphone to understand the COVID-19 pandemic. Within each arm, participants received either a message framed with either positive or negative valence (creating 6 questions or "groups" in total), and asked if they would be willing to contribute their GPS data from their smartphone.

- *Arm 1, self-interest (+ valence)*: We will provide you feedback on how to navigate your daily schedule in a safe way with COVID-19.
- *Arm 2, self-interest (- valence)*: We will provide you feedback on if you have been in contact with someone who has been tested positive for COVID-19.
- *Arm 3, pro-social (+ valence)*: It will help us identify how to re-open your community safely
- *Arm 4, pro-social (- valence)*: It will help us identify hotspots that need to be sheltered-in-place in your community.

- *Arm 5, monetary (+ valence)*: You will receive a $5 bonus payment if you give your GPS data.
- *Arm 6, monetary incentive (- valence)*: You will not receive a $5 bonus payment if you renounce giving your GPS data.

The monetary incentive arm offered a $5 payment for their willingness to provide their GPS data. Participants in this arm that indicated that they were willing to provide their data received a $5 bonus payment, on top of the base $0.05 HIT payment. Assignment to the monetary arm was completely random and equally likely for all participants. The test of the crowding-out effect due to monetary incentives stands in the comparison between arms 5&6 with arms 1 to 4. The test of the positive vs negative valence framing effect stands in the comparison of arms 1, 3, 5 to arms 2, 4, 6 respectively.

Individuals in all groups that mark that they were not willing to contribute their GPS data received a Vickrey auction. A Vickrey auction or sealed-bid second-price auction (SPSBA) is a type of auction where a "bidder" submits a bid without knowing the bid of the other users in the auction. This auction method has been shown to elicit more truthful values for data provision of personal internet data (Gefen et al. (2020)). Thus, in our study, users were asked if they would like to place a "bid" of a selected monetary value of their choosing in exchange for their GPS data. In our study, users were blinded to other user's bids as well as the maximum threshold bid that was deem a payout. They were prompted with this message for the Vickrey auction if they declined to provide their data in first step:

- "*You have declined to give your data. Others have refused to be paid $5 to give their location history data. However, we are very interested in capturing your location history data from your Smartphone. We will be asking 1000 people to give their location history data. We will only be paying the people with the lowest 100 bids and bids that are under our threshold*."

Users were able to select a sliding scale of monetary compensation they would take in exchange for their data. The recap of the value $5 was made to anchor participants in all arms to be in the same context (including those who were not prompted with the monetary condition at the first step). If they bid higher than our threshold of $10 they were immediately told that their bid was not accepted. If the user's bid was lower than our threshold of $10 and their bid under the top 100 other bidders, they were paid their bid price.

To remove the possibility of deception, we indicated to participants that we would be providing a debriefing message after the survey. They were told that the full objective of this study was to investigate the effectiveness of different messaging in encouraging individuals to contribute their GPS data to COVID-19 and the need to initially withhold some of this information due to the nature of randomized scheme. This study was approved by the IRB at the University of California San Francisco.

Economic Model

Providing access to GPS data from a user's smartphone is an effort.

Let call V_{cm}^{i} and V_{fi}^{i} the valuation of the participant i for their effort, under the different experimental conditions (self-interest, pro-social, monetary), and let's call $V_{tot}^{i} = V_{cm}^{i} + V_{fi}^{i}$ the total value for participant i to their data. Let denote V_{cost}^{i} the cost for the participant i in revealing their valuation. The total valuation of participant P^{i} is given by $P^{i} = V_{tot}^{i} - V_{cost}^{i}$. P^{i} is value to be reported if the individual participates in a truth-revealing Vickrey auction. In an experiment where the participant is asked to provide personal data, the decision to provide the data will be taken when P^i would be positive and refused when P^i will be negative.

As highlighted by Gefen et al. (2020), under the assumption that V_{cm} and V_{fi} are independent and that P is a linear combination of thereof, all transaction can be represented using a linear model where P is the dependent variable and the independent variables are dummies that indicate the type of experimental conditions submitted to the participant. Therefore, each transaction will be represented by the following equation:

$$P^i = V_{cm}^i X_{cm}^i + V_{fi}^i X_{fi}^i - V_{cost}^i$$

where X_{fi}^i, and X_{cm}^i are indicators reflecting the experimental condition that participant was shown. The linear coefficients obtained as solution of the econometric equation (V_{cm}^i, V_{fi}^i) represents the average participant valuation associated to each condition (cm, fi).

When P^i is not observable, the above linear equation is equivalent to the probit model $y^i = V_{cm}^i X_{cm}^i + V_{fi}^i X_{fi}^i - V_{cost}^i$ where y^i is the observable response dummy variable of whether the participate decides to provide his personal data. y^i satisfies $y^i = 1$ if $P^i > 0$ and $y^i = 0$ otherwise

Testable assumption

An appropriate framing message can modify the value that subjects attach to their personal data and, therefore, the willingness to transfer their GPS-data from their Smartphones, as well as the asked compensation to do it (P^i) when subjects will be confronted to a monetary compensation. We test whether:

1/ …experimental conditions change the willingness to provide access to data ($V_{cm}^i \neq 0, V_{fi}^i \neq 0$)

2/ …experimental conditions change the amount of money requested to provide GPS-data (check of $P^i(V_{cm}^i = 0;\ V_{fi}^i) \neq P^i(V_{cm}^i; V_{fi}^i = 0)$ when P^i is observed)

Results

Descriptive statistics

1055 participants were recruited from 41 countries. 445 (42.18%) of them were located in the US, 308 (29.2%) in India, 151 (14.3%) in Europe, 94 (8.9%) in Brazil, and 57 (5.4%) in other countries around the World. The average age of the participants was 34 (s.d. 10) years. The proportion of males was 57.3% (604) whereas the proportion of female was 42.7% (448), and less than 0.3% (3) of the participants did not report their gender or have chosen to not disclose.

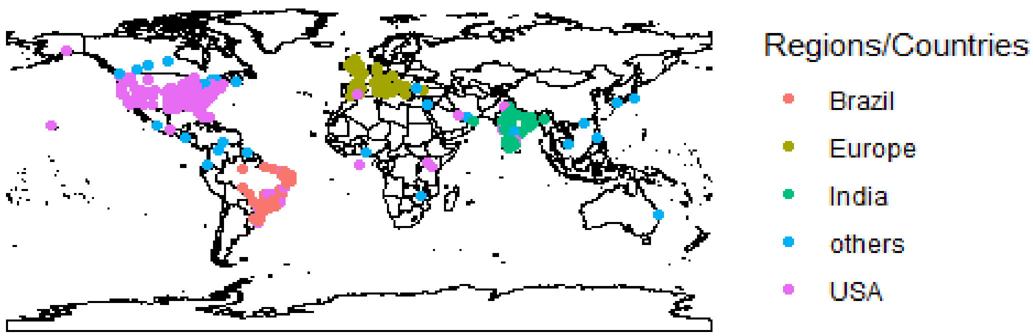

Figure 1: map the location of the participants

1017 (96.4%) participants were owner of a smartphone. 742 (73.01%) of the participants reported using an Android phone operating system whereas 26.98% (274) reported using a IOS operating system. 77.3% (786) of the participants reported knowing somebody who tested positive for COVID-19. (106) 10.48% of the participants reported having a positive COVID-19 status, (416) 40.94% a negative status, (452) 44.46% did not do the test, and (42) 4.11% did not know that status.

Participants were successfully randomized into one of each of the experimental condition in our study *(*Table 1, chi^2 *test, p-value = 0.48).* 329 (32.4%) received the self-interest condition (14.9 % arm-1, 17.4% arm 2), 340 (33.4%) received the pro-social condition (16.0% arm 3, 17.4% arm 4), and 348 (34,2%) received the monetary condition (16.3% arm 5, 17.9% arm 6). After receiving one of the 6 experimental conditions, 55.95% (566) of the participants accepted to provide their GPS data (16.42% in the self-interest condition (7.17% arm-1, 9.24% arm-2), 17.60% accepted the pro-social condition (8.45% arm-3, 9.14% arm-4), 21.93% the monetary condition (10.22% arm-5, 11.70% arm-6). Among those who refused one of the 6 conditions, upon being given the Vickrey auction - told they would receive a monetary incentive for their GPS data, 16.96% (76) accepted to submit a bid.

Table 1: Test for equality of proportions in the arms

Test for equality of proportions without continuity				
Alternative hypothesis: two sided				
	Proportions	X - squared	df	p-value
Arm 1	0.1494	4.4566	5	0.4857
Arm 2	0.1748			
Arm 3	0.1602			
Arm 4	0.174			
Arm 5	0.1632			
Arm 6	0.1789			

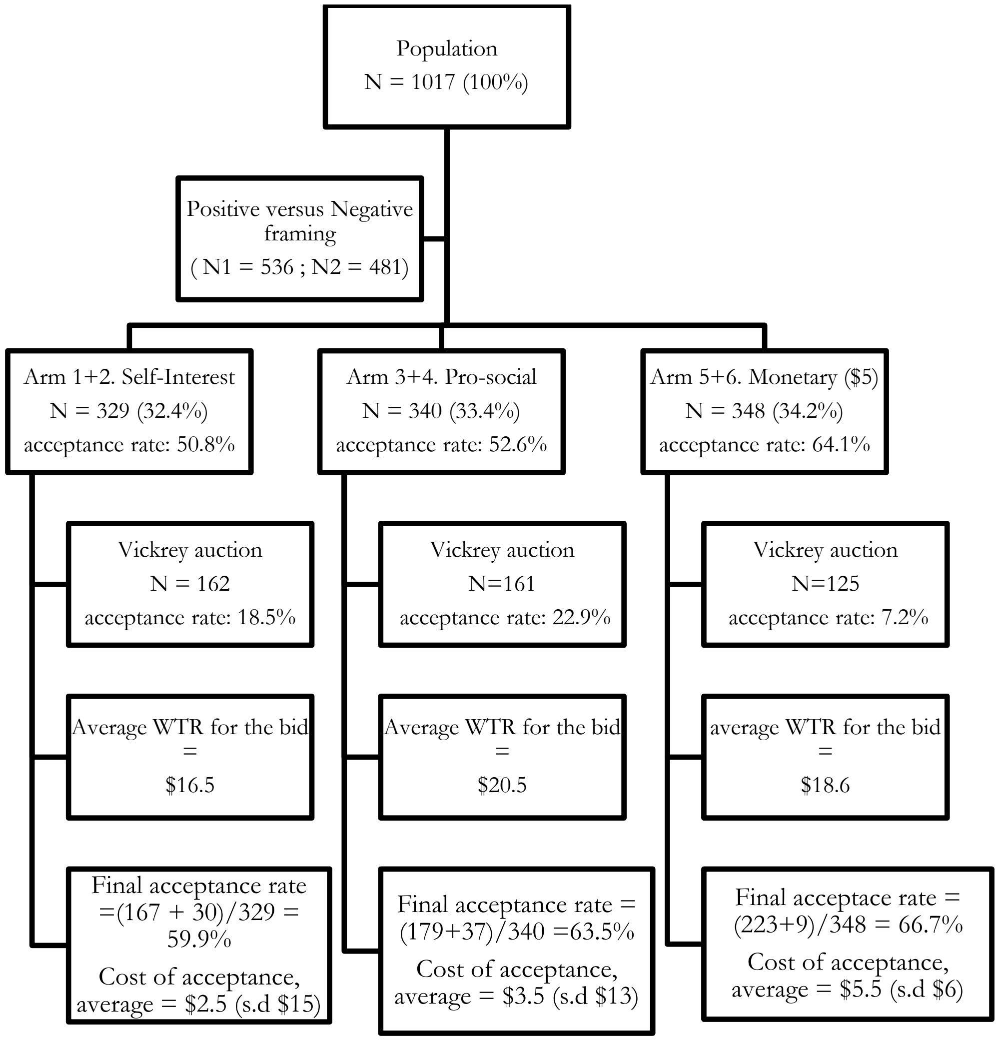

Figure 2: Flow chart describing the results of the experiment

Econometric results

For the demographic and health determinants, there was a significant negative association between the type of mobile operating system and participants' decision to provide their GPS data. Participants using an IOS (Apple) operating system were significantly less willing to provide their GPS data compared to those who use an Android (Google) operating system. Additionally, we found a significant association between the region or country of where the participant was located and their willingness to provide their GPS data. Participants living in India or in Brazil were more willing to provide their GPS data compared to those living in the United States. Finally, we found a significant association between the testing COVID-19 status of the participant and their decision to provide their GPS data. Participants who were tested for COVID-19 (positive or negative) were more willing to provide their GPS data. Participants that tested positive for COVID-19 were significantly more likely to provide their GPS data compared to those who tested negative for COVID-19.

The results after receiving one of 6 experimental conditions are provided in Table 2. For the first proposal, with all 6 experimental conditions, we found no significant difference between a positive valence and a negative valence on the willingness to provide a user's GPS data (columns 1 and 3,

Table 2). Based on this result and to increase the number of observations, a second stage model was employed where the conditional arms were grouped into 3 simplified arms: self-interest (arms 1+2), pro-social (arms 3+4), and monetary (arms 5+6).

Columns 2, and 4 of Table 2 show a significant association between the monetary condition (arms 5+6) and the decision to provide a user's GPS data. Based on this result participants are more willing to provide their GPS data if they were told they would receive a $5 monetary compensation. Columns 5 and 6 allow studying the results by groups of countries (classed by GDP per capita); the monetary incentivization is more effective in low-income countries (+0.481***), but still slightly positive in richer contexts (+0.195, not significant, but not negative in any cases).

Table 2: determinants of the willingness to provide GPS data

	Dependent variable: willingness to donate GPS data					
	Whole sample	Whole sample	Whole sample	Whole sample	High income Countries	Middle income Countries
	1	2	3	4	5	6
Arm conditions (ref: *Negative valence*)						
Positive[#]	-0.061		-0.061			
	(0.079)		(0.083)			
Arm conditions (ref: *Personal gain*)						
Social benefit		0.047		0.035	0.025	0.067
		(0.097)		(0.102)	(0.134)	(0.155)
Monetary gain		0.342***		0.310***	0.195	0.481***
		(0.098)		(0.102)	(0.134)	(0.159)
Control variables						
Gender (ref: *Female*)			-0.045	-0.042	-0.132	0.059
			(0.085)	(0.085)	(0.110)	(0.134)
Age			-0.006	-0.005	-0.005	-0.003
			(0.004)	(0.004)	(0.005)	(0.007)
IOS operating system (ref *Android*)			-0.240**	-0.227**	-0.217**	-0.235
			(0.100)	(0.100)	(0.114)	(0.192)
Knowing covid-19 positive (ref: *No*)			0.004	-0.011	-0.167	0.232
			(0.101)	(0.101)	(0.128)	(0.165)
Personal COVID-19 status (ref: *Not tested*)						
Positive			0.697***	0.692***	0.934***	0.545***
			(0.152)	(0.152)	(0.231)	(0.201)

Negative			0.389***	0.383***	0.419***	0.386***
			(0.091)	(0.091)	(0.117)	(0.146)
Do not know			0.147	0.164	0.135	0.176
			(0.220)	(0.220)	(0.306)	(0.318)
Location (ref : *US*)						
Brazil			0.411**	0.425***		
			(0.164)	(0.165)		
India			0.410***	0.416***		
			(0.109)	(0.109)		
Europe			-0.077	-0.079		
			(0.127)	(0.127)		
Other countries			0.108	0.138		
			(0.187)	(0.188)		
Constant	0.179***	0.019	0.093	-0.069	0.100	-0.047
	(0.054)	(0.069)	(0.203)	(0.215)	(0.252)	(0.326)
Observations	1017	1017	990	990	557	433
Log Likelihood	-697.416	-690.429	-637.232	-631.840	-366.594	-262.248
Akaike Inf, Criteria	1398.833	1386.857	1300.464	1291.681	753.15	544.31

Note: *p<0.1; **p<0.05; ***p<0.01

In this Table 2, we reported the aggregated test for positive versus negative valence, with grouped arms (self interest + prosocial + monetary). We tested also positive versus negative valence arm by arm, separately. Tests were nor significant.

Vickrey Auction

Participants who refused to provide their GPS data after the first request were followed up with a Vickrey auction whereby users were presented with an option to place a monetary bid to be paid for their GPS data, as in Gefen et al. (2020). To analyze the acceptance of this Vickrey Auction (see flow chart (Figure 2) for a recap of the process), we ran a second step regression on the acceptance of the Vickrey auction process. The results show a significant negative association between the monetary condition (arms 5+6) to provide GPS data from their smartphone by using the auction procedure. Thus, among participants who initially refuse to share their GPS data, the type of exposure to the first request influences their decision to bid a price for their GPS data. In addition, Figure 3 shows the distribution of the monetary bid by the participants who initially (first proposal) refused to provide their GPS data. For those who had received the monetary condition as a first proposal, they were less willing to give their data for a bidding price in the Vickrey auction (Table 3).

Table 3: 3- Determinants of the acceptance of the Vickrey auction procedure

	Dependent variable: Follow up, willingness to provide GPS data

	1	2
Arm conditions (ref: *Self-interest*)		
Pro-social benefit	0.156	0.134
	(0.158)	(0.168)
Monetary incentive	-0.565***	-0.645***
	(0.204)	(0.215)
Control variables		
Gender (ref: *Female*)		0.066
		(0.154)
Age		0.0003
		(0.007)
IOS operating system (ref *Android*)		-0.280
		(0.179)
Know someone with COVID-19 (ref: *No*)		0.238
		(0.191)
Tested for COVID-19 (ref: *Not tested*)		
Positive		0.413
		(0.305)
Negative		0.181
		(0.160)
Do not know		-4.582
		(138.864)
Location (ref : *US*)		
Brazil		0.302
		(0.321)
India		-0.023
		(0.205)
Europe		-0.088
		(0.218)
Other countries		-0.153
		(0.360)
Constant	-0.896***	-1.062***
	(0.114)	(0.398)
Observations	448	432
Log Likelihood	-196.760	-183.577
Akaike Inf, Criteria	399.520	395.154

Note: *p<0.1; **p<0.05; ***p<0.01

Note: before estimating this second step regression, we first conduct a test for the selection bias using a two steps model, considering a possible self-selection behavior of participants (only those who refused were proposed the auction procedure). The non-significance of the Inverse Mill Ratio (p-value of the lambda = 0. 21) suggests that our second-step econometric equation is not biased by the self-selection process at the first proposal.

After refusing to provide their GPS data and being provided with the Vickrey auction to receive monetary compensation in exchange for their GPS data, the average compensation (monetary value) they will exchange their GPS data in the self-interest experimental condition (arms 1+2) is on average

$17 and for the pro-social experimental condition (arms 3+4) it is *$21*. If participants received the monetary incentive experimental condition (arms 5+6), the average compensation (monetary value) they will exchange their GPS data *$19,* however, the latter is non-significantly different from 0 (Table 4).

Table 4: Average monetary value of the GPS data among the 'follow up proposal' branch

Monetary value of GPS data		
	coefficients	s.e
Experimental conditions		
Self-interest	16.483***	(5.988)
Pro-social	20.446***	(5.374)
Monetary incentive	18.571	(12.188)
Observations	72	
R-square	0,261	
Adjusted R-square	0,229	
Residual Std. Error	32,245	
F-Statistic	8.125***	

Figure 3 The distribution of the monetary value of the GPS data of participants who are confronted to the Vickrey auction procedure (bid price).

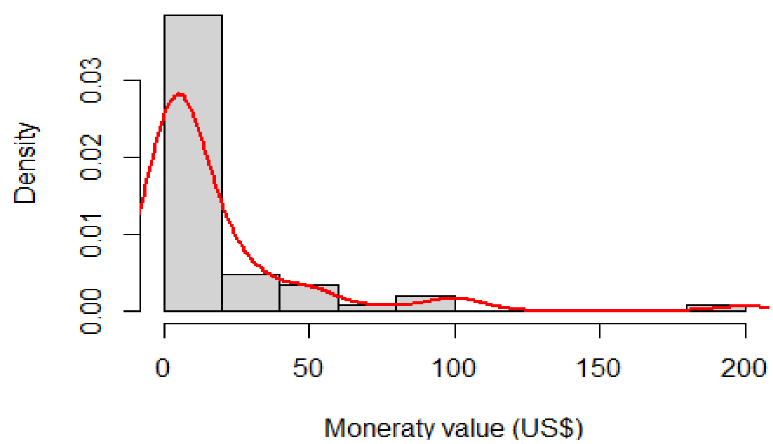

Figure 3: Distribution of the Vickrey auction bid value of participants GPS data

Discussion

This study was made to assess persons' willingness to provide their GPS data stored on their smartphone and to better understand how to frame messages that will encourage the provision of such human mobility data. Two specific questions were addressed, i) the effectiveness of monetary incentives, compared to other motivations, and ii) the effectiveness of a negative versus positive valence in the framing of the message.

Based on our logistic model, our result suggests that framing the use of users' GPS data into a positive or negative incentive was not significant. A simple positive or negative framing without additional information does not significantly change the approbation rates for giving access to GPS data. In fact, a strong source of privacy behavior arises from incomplete and asymmetric information (Acquisti et al., 2015). It appears that the positive vs negative valence framing is not enough to push away people's concern for providing private data on their mobility patterns.

When designing the experimental condition into different types of motivational messages to provide private data, the self-interest motivation, pro-social benefit or monetary benefit, we found that monetizing access to GPS data increased the proportion of participants willing to share their human mobility data. The perspective of a small $5 monetary compensation seems first to generate the higher proportion of acceptance rate (64%). These results parallel previous study conducted by Munzert et al., (2021) whereby the addition of a small monetary value up to $5 significantly increased the likelihood of users to download a contact tracing application to fight COVID-19. However, this study did not offer a monetary incentive in the first proposal, whereas our study provided a first (fixed amount) and a secondary proposal (sealed bid) in the form of a Vickrey auction, allowing users to have an additional opportunity to bid for a greater monetary value for their private smartphone data. In our study, offering to indicate a monetary value for their GPS data after the first framing message, we found that proposing a payment through an auction mechanism could be also fruitful, with a significant additional increase in acceptance rates, varying between 23% to 7%, depending on the previous framing (self-interest, pro-social), with the monetary arms (5 and 6) having the lower additional acceptance rates at the step of the Vickey option. Munzert et al., (2021) did not evaluate this secondary effect of two monetary incentives and our study gives evidence that individuals who rejected a first monetary incentive are less likely to give up their private data. These findings show that some users estimate that their mobility data as "priceless", as they reject both the first and the second financial incentives; making it clear that their data is not for sale at any price.

When using the result of the elicitation of the monetary value obtained from the bid, the average monetary valuation given by participants was US$17 when they are told their human mobility data will be used for a self-interest purpose. This value is similar as the value given by participants for public use of their internet health data (Gefen et al., 2020). The valuation of participants when the motivational message was the use of their GPS data for a collective purpose was US$21. This valuation, although a little bit higher, is not significantly different from the self-interest condition. At the end of the survey (taking into account that spontaneous data donation exists, for free), we evaluate the average cost of acceptance, per sharing accepted, US$3 for the self-interest framing to US$4 for the pro-social benefit framing, and US$6 for the monetary incentive framing. This means that, in return for a small compensation to users, it is possible for a service provider to obtain the needed GPS data. In addition, the significant difference between these average costs (p-value = 0.0104) suggests that an efficient approach to encourage smartphone users to provide their historical location data is to start with a self-interest incentive framing for the request of private smartphone data, and, for those who remain resistant, that a follow-up of a small monetary incentive will be effective. However, certain individuals, who initially rejected to provide their data, may still reject both the first framing messages and a secondary monetary incentive.

On a theoretical point of view, the findings of the study tend to invalidate the preconception of a crowding-out effect, at least for the specific domain of data donation behavior. To the contrary, the financial motivation appears to be "crowding-in", since the arms (5 and 6), with a monetary reward, are tested much more fruitful in terms of average adhesion to personal data access. We rather validate previous research in monetary incentives for the adoption of contact-tracing apps (Munzert et al. 2021) and the general statement that crowding theory can be either "in" or "out", depending on the precise context (Frey et al., 2012; Gneezy et al., 2011). Our results build on these previous researches as we demonstrate that there is no crowding-out effect between intrinsic and extrinsic motivations for the provision of private smartphone data. Methods of framing and of incentivization can be used in conjunction to influence the user's willingness to provide their private human mobility data from their smartphone. No loss for the public authority was found when a mixed strategy was selected. On the contrary, this dual strategy had the best cost-effectiveness ratio to incentivize data provision.

Lastly, our results indicate that participants who knew their COVID-19 serology status are more willing to share their GPS data than those who have not been tested. The same was seen for participants who knew someone who had COIVD-19. This may indicate that "empathic" response was taking place whereby if participants have a personal health experience with the disease of study they are more likely to exhibit altruistic or pro-social behaviors and has also been seen in previous data donation studies. (Gefen et al., 2019; Papachristou et al. 2004). Our results also suggest that participants living in Brazil or in India are more willing to provide their mobile phone GPS data compare to those living in the US. The latter result may reflect a local context behavior (Eggo et al. 2021). Indeed, during the period of study, those two countries (Brazil and India) were some of the countries with the highest prevalence rate of COVID-19, again perhaps eliciting an empathetic response that stimulates a pro-social behavior. Finally, we found that the type of operating system of the user smartphone may play a role in the willingness to provide location data. Users of IOS (Apple) operating system are less willing to share their mobile phone GPS data compare to users of Android (Google) operating system which may indicate a selection bias that those who opt to use an IOS system have greater privacy concerns than the others.

This paper has some limitations that should be recognized. One of the first is the conceivable sensitivity of our results to the population surveyed. Recruitment on Amazon Mechanical Turk permits large and costless sample, but may create biases. Tests on the reliability, for behavioral researches, of data collected through the Amazon-Turk platform are reassuring (Crump et al., 2013; Arechar et al., 2018). However, they may be insufficient to be sure that in part the response we have in our own experiment was not biased by the profile of the Amazon-Turk users, who may be more likely to accept data transfers. Note that, during the COVID-19 pandemic, this method of data collection was a necessary measure, as lockdowns prohibited in-person data collection. The RCT design was also assuring that the observed differences between arms were not biased in relative terms (measurement of the effect), although the absolute rates could be. Another limitation may lie in the way we introduced and studied the loss-aversion effect. Generally, this has to be associated with a first "endowment", which, in turn, allows to put people in a loss context. This was not possible for the arms 1 to 4 (self-interest / pro-social), so for a reason of parallelism we did not do it for the monetary arms (5 and 6).

Conclusion:

Country of origin and COVID-19 testing status influences the behavioral response to sharing private GPS smartphone data. Self-interest and pro-social motivations for data donation are sufficient to encourage donation, if the target is around a 50% acceptance rate. However, supplementing prior intrinsic motivations with monetary incentives regarding the provision of private human mobility mobile data has an additive effect at influencing users' decisions, that could help to reach the 60% acceptance rates level needed to fight the epidemic efficiently. Communications that promote altruistic donation with the addition of financial compensation will encourage the most active participation of users to provide private location data.

References

Acquisti, A., L. Brandimarte, and G. Loewenstein (2015). Privacy and human behavior in the age of information. *Science 347* (6221), 509-514.

Acquisti, A., C. Taylor, and L. Wagman (2016). The economics of privacy. *Journal of economic literature 54* (2), 442-92.

Arechar, A. A., S. Gächter, and L. Molleman (2018). Conducting interactive experiments online. *Experimental economics 21 (*1), 99-131.

Beria, P. and V. Lunkar (2021). Presence and mobility of the population during the first wave of covid-19 outbreak and lockdown in italy. *Sustainable Cities and Society 65*, 102616.

Crump, M. J., J. V. McDonnell, and T. M. Gureckis (2013). Evaluating amazon's mechanical turk as a tool for experimental behavioral research. *PloS one 8* (3), e57410.

Deci, E. L. (1972). Intrinsic motivation, extrinsic reinforcement, and inequity. *Journal of personality and social psychology 22* (1), 113.

Eggo, R. M., J. Dawa, A. J. Kucharski, and Z. M. Cucunuba (2021). The importance of local context in covid-19 models. *Nature computational science 1* (1), 6-8.

Ferretti, L. et al. (2020). Quantifying SARS-CoV-2 transmission suggests epidemic control with digital contact tracing. *Science* 368, eabb6936.

Frey, B. S. et al. (1997). Not just for the money. Cheltenham: Edward Elgar Publishing. ISBN 1-85898-509-9.

Frey, B. S. et al. (2012). Crowding out and crowding in of intrinsic preferences. *Reflexive governance for global public goods 75*, 78.

Gefen, G., O. Ben-Porat, M. Tennenholtz, and E. Yom-Tov (2020). Privacy, altruism, and experience: Estimating the perceived value of internet data for medical uses. In *Companion Proceedings of the Web Conference 2020*, pp. 552-556.

Gneezy, U., S. Meier, and P. Rey-Biel (2011). When and why incentives (don't) work to modify behavior. *Journal of economic perspectives 25* (4), 191-210.

Gneezy, U. and A. Rustichini (2000). A fine is a price. *The journal of legal studies 29* (1), 1-17.

Grantz, K. H., H. R. Meredith, D. A. Cummings, C. J. E. Metcalf, B. T. Grenfell, J. R. Giles, S. Mehta, S. Solomon, A. Labrique, N. Kishore, et al. (2020). The use of mobile phone data to inform analysis of covid-19 pandemic epidemiology. *Nature communications 11* (1), 1-8.

Kreps, D. M. (1997). Intrinsic motivation and extrinsic incentives. *The American economic review 87* (2), 359-364.

Mellström, C. and M. Johannesson (2008). Crowding out in blood donation: was Titmuss right? *Journal of the European Economic Association 6* (4), 845-863.

Munzert, S., P. Selb, A. Gohdes, L. F. Stoetzer, and W. Lowe (2021). Tracking and promoting the usage of a covid-19 contact tracing app. *Nature human behaviour 5* (2), 247-255.

Oullier, O., R. Cialdini, R. H. Thaler, and S. Mullainathan (2010). Improving public health prevention with a nudge. *Economic perspectives 6* (2), 117-36.

Papachristou, G. I. and D. C. Whitcomb (2004). Predictors of severity and necrosis in acute pancreatitis. *gastroenterology clinics 33* (4), 871-890.

Perra, N. (2021). Non-pharmaceutical interventions during the covid-19 pandemic: A review. *Physics Reports* 913: 1–52.

Posner, R. A. (1981). The economics of privacy. *The American economic review 71* (2), 405-409.