



The effect of economic incentives and cooperation messages on user participation in crowdsourced public transport technologies

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Accepted: 5 April 2022

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Abstract

Transport data is crucial for transport planning and operations. Collecting high-quality data has long been challenging due to the difficulty of achieving adequate spatiotemporal coverage within a representative sample. The increasingly integrated use of Information and Communication technologies in transport systems offers an opportunity to collect data using non-traditional methods. Crowdsourcing applications are an example where a community of users shares information about their travel experience. However, crowdsourcing applications depend on a critical mass of users providing feedback. We conducted a large-scale field experiment to examine the effect of economic incentives (a lottery for free trips) and cooperation messages (asking users to help the community) to encourage users to share reports about bus stop conditions using a crowdsourcing app. We found that offering an economic incentive increased the participation rate almost three times compared to a control group, which did not receive any message. This positive effect lasted for several weeks but decreased over time, especially for users who had not made reports prior to the experiment. This incentive also increased the number of reports shared by users. Using a cooperation message, with or without the economic incentive, also increased the participation rate compared to the control group, but adding a cooperation message decreased the effect of a standalone economic incentive.

Keywords Crowdsourcing app · Public transport · Transport data · Field experiment · Contribution

Introduction

A key aspect for planning and operating transport systems is the availability of mobility data, which is essential for network design, operation optimization, coverage assessment, and service quality, among other essential tasks. For many years, both transport planners and transport researchers have relied mainly on traditional survey data to collect

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information about travel patterns and user perceptions, as well as physical inspections to monitor infrastructure. However, these methods are generally expensive, and they do not achieve adequate spatiotemporal coverage, which requires a significant undertaking. To deal with these disadvantages, in recent years, there has been an increased interest in new transport data collection methods based on sources such as GPS devices and smartphone devices (Bonnell and Munizaga 2018). In particular, crowdsourcing applications have become a significant data source based on information shared by users to make transport information available for commuters and transport system planners (Nandan et al. 2014; Hong et al. 2020; Mondschein 2015). These applications typically gather automatic location data to provide bus arrival times (Lau et al. 2011; Zhou et al. 2012; Steinfeld et al. 2011) and add user-reported information about the public transport system (Steinfeld et al. 2011; Faber and Matthes 2016). For example, crowdsourcing mobile applications, such as Moovit, Tiramisu, and Transapp, provide bus arrival times, and request their users to report bus overcrowding levels and whether buses and bus stops are in poor condition and in need of repair.

Crowdsourcing applications, which are voluntary participatory information systems, require a critical mass of users willing to provide information to be useful. However, these applications generally suffer from low participation rates that sometimes hover close to zero (Ling et al. 2005). For example, in 2013, Waze, the worldwide car crowdsourcing app, had 50 million users globally, but only 0.01% sent reports about detours or other traffic information (Weitzenkorn 2013). This is also a problem for public transport crowdsourcing systems, in which planners require widespread active participation (Zimmerman et al. 2011).

The phenomenon of low participation rates in voluntary information systems was summarized by Nielsen (2006), who defined the 90-9-1 rule. This rule states that 90% of users behave as lurkers—they benefit from the contributions of others, but never contribute themselves, 9% contribute occasionally, and 1% actively contribute. This distribution implies that a very small fraction of users not only generates most of the contributions, but also leads to a skewed representation of the users. This is problematic for many voluntary information systems, such as crowdsourcing apps, online communities and online review of products and services. For example, if a crowdsourcing information system for public transport receives user feedback regarding buses and bus stop conditions, and only a small self-selection of users contribute, it is probable that large areas of the city will lack information, making the platform less useful both for users and public transport planners.¹

Due to this problem, a handful of crowdsourcing transport applications have tried to increase participation and contribution rates using elements of gamification, such as avatars and badges (Faber and Matthes 2016). Most of this research has been conducted using survey or lab studies, with very small research samples and with qualitative measures (Hamari et al. 2014), limiting its application to broader information systems. Other studies have used “quid pro quo” techniques to limit app usage to those who contribute. For example, Tomasic et al. (2014) motivated users to share information about bus arrival times and onboard conditions, such as seat availability, by making such information available only

¹ Other examples include Wikipedia, in which only 0.2% of active US visitors are active contributors (Nielsen 2006). In this case, even though few contributors may provide high-quality information, there is concern about inequality (e.g., gender) (Nielsen 2006; Torres 2016). Similarly, only a small fraction of buyers provide an online review despite the fact that online shoppers highly value online reviews of products from many different consumers (NationMaster 2019).

to contributors. This study found that, despite increasing contribution, a “quid pro quo” approach increased the likelihood of users abandoning the crowdsourcing app altogether. On the other hand, simply asking users to contribute did not increase participation rates. In general, research on transport-oriented crowdsourcing applications has offered little discussion regarding how to encourage new users to participate in these new data collection technologies.

The current research aims to motivate contribution in a transport crowdsourcing technology using economic rewards and cooperation messages. First, economic incentives have been used in many public policy domains in order to motivate socially beneficial behaviors, such as donating blood (Lacetera et al. 2014) or recycling (Schwartz et al. 2021; Córdova et al. 2021). In the field of transportation, economic incentives have been used to promote more sustainable transport modes (Bamberg and Schmidt 2001; Jakobsson et al. 2002; Rosenfield et al. 2020; Thøgersen and Møller 2008), motivate car drivers to avoid rush hours (Ben-Elia and Ettema 2011b, a), and collect mobility data with traditional surveys (Zumkeller et al. 2011; Hoogendoorn-Lanser et al. 2015). However, economic incentives have also been shown to have backfiring effects. For example, Hilton et al. (2014) showed that offering an economic incentive may reduce preferences for taking the most environmentally friendly mode of transportation for an intercity trip.²

Second, previous research has also shown that individuals are willing to cooperate with others even if they could free ride. This can be explained by different types of social preferences such as reciprocity, inequity aversion, and altruism (Fehr and Fischbacher 2002). In particular, people have been shown to have altruistic preferences in order to feel good about themselves (Andreoni 1990, 1993; Andreoni and Miller 2002).³ For example, contributors to Wikipedia have reported that one of the most relevant reasons to cooperate is due to altruistic factors (Nov 2007). In transport, in the context of environmental problems, previous research has evaluated different ways to promote more sustainable transport modes by providing information on carbon dioxide emissions (see e.g., Rose and Ampt (2001), Avineri and Waygood (2013), Waygood and Avineri (2016), Waygood and Avineri (2011)). They seek to increase awareness about the impact on the environment and others, so people can decide to cooperate through more sustainable travel decisions.

Our research contributes to the described literature by assessing the use of economic incentives and cooperation messages to increase participation of users to report bus stop conditions through a crowdsourcing application, and by doing so, contribute to improving the public transport system. Even though bus stops are part of the trip experience and play a key role in customer satisfaction and efficient public transport operations and maintenance (Eboli and Mazzulla 2007), scant research has covered this portion of public transport amenities and conditions. More broadly, with this intervention, we overcome the scarce attention that the use of economic incentives has received in research involved in collecting data for crowdsourcing information systems, and how such incentives have been combined with a cooperation message in this domain.⁴ We also examine how economic

² One reason that economic incentives may backfire is the so-called “crowding-out of intrinsic motivation”, in which economic incentives reduce the chance of a desired behavioral change by undermining people’s intrinsic motivation—i.e., their desire to perform a task for its own sake without any economic reward (Frey and Oberholzer-Gee 1997; Gneezy and Rustichini 2000; Schwartz et al. 2015, 2020).

³ For a further review of the literature on cooperation, see Klein and Ben-Elia (2016).

⁴ The literature on the effect of economic incentives on socially desirable behavior has been mixed, showing that their effect may depend on how incentives are structured and delivered (Gneezy et al. 2011; Kamenica 2012; Schwartz et al. 2019).

incentives and a cooperation message affect different types of users to better represent a larger base of public transport travellers and the transport network they use. The study also offers a methodological contribution as it uses a large randomized field experiment providing internal and ecological validity.

The remainder of this paper is organized as follows. "[Background information and method](#)" section describes the experiment developed using a public transport-oriented crowdsourcing smartphone app. "[Results](#)" section describes the results. Finally, "[Discussion and conclusions](#)" section discusses the results and relates them to the existing literature.

Background information and method

Background information

We collaborated with a widely-used crowdsourcing smartphone application, Transapp (Arriagada and Munizaga 2017), based in Santiago (Chile). Santiago is a large and congested city, with an integrated public transport system that serves over 4.5 million trips per day. In a typical week, 3 million passengers use the system to make 25.5 million trips. Transapp allows users to easily access real-time information about bus arrival times, driver behavior, overcrowding, bus conditions, bus stop conditions, and bus bunching, among other factors. This information is publicly available to all users that have downloaded the application. In addition, the app allows users to indicate whether certain information is true or false, creating a self-regulated environment. As of September 2019, Transapp was downloaded 144,917 times since launching and had 47,320 active users who used the application at least once during September 2019 and accessed the app 719,545 times, mainly to check wait times.

The reporting feature, in which users can share information about buses and bus stops, requires a critical mass and widespread contribution from users. However, it suffers from the low participation problem described above. In fact, when studying the contributions of active users who used the app at least once in the year before this study, only 16.73% sent at least one report; the remaining 83.27% did not share any reports (i.e., they would be considered *lurkers*). Even more, 48.32% of all reports were contributed by only 1% of users, and the remaining 51.68% of reports were contributed by 15.73% of users, following Nielsen's Rule reasonably closely. Since reports are verified by the user community, if more users validate the veracity of reports, the data is more reliable, and users will consider it so. In addition, higher rates of user participation can capture a broader set of information both spatially and temporally, making the data on user experience, system operations, and infrastructure status more efficient and complete. For example, users' reports can detect problems in the maintenance of bus stops. As a reference, Santiago's public transport system has more than 11,000 bus stops, making it practically impossible for dedicated inspectors to routinely carry out a thorough visual inspection of all assets.

Participants

Transapp provided a database that contained all users and reports sent in the app. We selected all active users during September 2019, considered as those who used the app to at least look at some information about bus time arrivals, resulting in a database of 46,516

Table 1 Classification of users before the campaign

Users	Reports sent	N	Percentage
Previous contributors	1 or more	8136	17.5%
Previous lurkers	None	38,380	82.5%
Total	–	46,516	100%

users.⁵ Then, we classified these users into two categories according to the number of reports they had shared in the previous two months: “*Previous Contributors*” and “*Previous Lurkers*”. Table 1 shows that those users who sent at least one report represented 17.5% of all active users, and those who never sent a report represented the remaining 82.5%. This classification was made in order to evaluate if messages and incentives had different effects depending on a user’s past behavior.

Experimental design and procedure

We sent smartphone push notifications inviting users to participate in a three-day campaign to provide information on bus stops (e.g., if they need repair). We sent out one notification reminder once a day during the campaign at specific times, using historical data on periods of high user activity.⁶ To examine the effect of incentives and messages on participation rates, we randomly assigned users ($N = 46,516$) into four experimental conditions using a block randomization procedure based on users’ previous reporting behavior prior to the experiment, such that each condition had the exact same proportion of Previous Contributors. The experimental conditions were: (1) Economic incentive condition, (2) Cooperation message, (3) Both economic incentive and cooperation message condition, and (4) Control.

For the economic incentive condition, the message indicated that users who shared a report about bus stop conditions would be participating in a drawing for three-\$13.95 reloads on their public transport smart-card.⁷ In other words, those users who received a message with the economic incentive and shared a report about a bus stop could gain one of the three rewards distributed as a lottery. The fare structure in Santiago’s public transport system requires users to use a smart card to pay for every trip made in the system (there is no multiple-ride pass or monthly ticket available). The economic incentive represents 4.81 times the value of the average smart card reload, and allows users to make up to 13 one-way trips in non-peak hours. While the economic incentive is high for public transport users, it is a low expenditure for public transport authorities. For the cooperation message condition, users were reminded that sending reports about bus stops would help other passengers and contribute to improving the public transport system. The third condition combined the economic incentive and the cooperation message. Users assigned to the control group did not receive any notification, representing the baseline scenario. If users opened the push notification, they accessed the message section of the app, which repeated

⁵ We used almost the entire database of active users at the time of the experiment, and excluded only a few hundred users who participated in a pilot test.

⁶ Even though push notifications could be received even if the app was not being used, sending them when users were more likely to use the app increased the chance that they had some information to share.

⁷ The messages showed the amounts in Chilean pesos (CLP), but we show them here in U.S. dollars (USD) using the prevailing conversion rate at the time of the experiment.

the text from the push notification and included instructions on how to share a report about a bus stop. Users could also see the notification and report later on (see “Appendix 1” for all materials used in the experiment).⁸

Empirical strategy

In this section we describe the empirical strategy to evaluate the participation rate and the level of contribution.

To examine the effect of each experimental condition on the participation rate, we estimate a logit model for the probability of participating using:

$$Y_i = B_0 + \sum_j B_j * D_{ij} + e_i \quad (1)$$

where Y_i indicates whether user i sent at least one report during the three-day campaign (=1, 0 if the user did not engage), D_{ij} is a dummy variable indicating whether user i was assigned to condition $j \in \{Economic, Cooperation, Both\}$ (=1, 0 if not). Therefore, all estimates use the control condition as the baseline. ϵ_i is the error term. Because users were randomly assigned, β_j will provide an unbiased estimate of the average treatment effects (Rubin 1974). Additionally, we estimated a linear regression model (see “Appendix 3”) to facilitate the interpretation of results.

To examine users’ contribution levels, i.e. the number of reports shared by users, we ran a zero-inflated negative binomial model. This model is well-suited for data distributions with an excess of zeros. Its central idea is that participation and report counts are generated by separate processes. In this case, the excess of zeros is attributable to users who did not receive or see the notification (e.g., push notifications were not allowed, or were deactivated, on some phones), and to users who may have automatically disregarded the push notification without reading it, or saw it but decided not to report. Across conditions, 96% of participants did not report during the campaign. This model is shown in equations 2 and 3:

$$Pr(Y_i = j) = \begin{cases} \pi_i + (1 - \pi_i)g(y_i = 0 | \mu_i) & \text{if } j = 0 \\ (1 - \pi_i)g(y_i | \mu_i) & \text{if } j > 0 \end{cases} \quad (2)$$

$$\log(E(y_i) = \mu_i) = B_0 + \sum_j B_j * D_{ij} + e_i \quad (3)$$

where π_i is the logistic function, which associates individuals who do not participate with probability π_i , and users who contribute with probability $1 - \pi_i$. Therefore, π_i can be interpreted as the probability of observing users not reporting. $g(y_i)$ is the negative binomial distribution, since the assumption is that the report count is generated according to this distribution with μ_i as the expected value of the negative binomial component. Its regression equation is presented in Equation 3, where y_i indicates the number of reports made by user i , D_{ij} is a dummy variable indicating whether user i was assigned to condition $j \in \{Economic, Cooperation, Both\}$ (=1, and 0 if not) and ϵ_i is the error term.

⁸ We oversampled the experimental conditions with an economic incentive based on the results from a pilot (“Appendix 2” provides information about the sample size and the statistical power analysis).

Results

In this section, we show the results of the randomized experiment. In particular, we focus on the participation rate (both overall and disaggregated by type of user), level of contribution, and the effect over time.

Participation rate

Figure 1 shows the participation rate across groups during the campaign, and the first column of Table 2 shows the results using Equation 1. Only 1.34% of users in the control condition reported (this is the baseline, as these users did not receive any type of message). The likelihood of reporting substantially increased to 5.26% when users were offered an economic incentive ($OR = 4.10$; $p < 0.001$), which represents a relative increase of 294%. Similarly, users who were sent a cooperation message or a combined economic incentive and cooperation message also increased their likelihood of reporting to 2.30% ($OR = 1.74$; $p < 0.001$; a relative increase of 72%) and 4.02% ($OR = 3.10$; $p < 0.001$; a relative increase of 201%), respectively. A pairwise comparison indicates that participation rates between treatments are all statistically different (all $ps < 0.001$). This means that there is a detrimental effect when a cooperation message is included with the economic incentive.⁹ In comparison, a demanding “quid pro quo” approach (Tomasic et al. 2014) increased the participation rate in a transport crowdsourcing app in the US by 3.6 percentage points (a 23% relative increase from their baseline). In addition, in Transapp, the natural proportion of contributors in the 2 weeks previous to the experiment were 1.55% and 1.53%, respectively, a relative reduction of 1.3% in the number of contributors between the 2 weeks. Compared with the increase in the participation rate during the campaign (up to 3.92

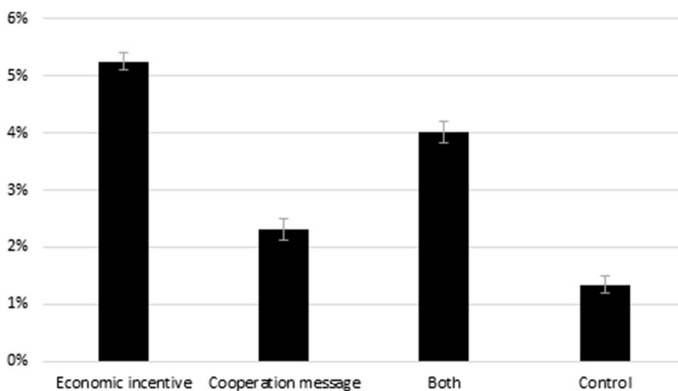


Fig. 1 Percentage of users that sent a bus stop report during the campaign. Error bars represent ± 1 standard error

⁹ We also found that the percentage of users who uninstalled the app during the campaign was small and very similar across conditions: economic incentive (0.58%), cooperation message (0.54%), both (0.47%), and control (0.57%).

percentage points, more than 200% in relative terms), this shows that an economic incentive can strongly boost participation rates, despite being a low-cost tool for the system.

A similar analysis by user type, shown in the last two columns of Table 2, demonstrates that users who had reported prior to the experiment (Previous Contributors) increased their participation rate. They increased their participation from 4.4%, in the control group, to 12.3% when they were offered an economic incentive alone ($OR = 3.05$; $p < 0.001$), to 10.6% when the message also included the cooperation message ($OR = 2.58$; $p < 0.001$). In relative terms, this is an increase of 180% and 141%, respectively. Previous Contributors' participation rate was 7.9% when only a cooperation message was used (a relative increase of 80%; $OR = 1.87$; $p < 0.001$).

However, the largest relative effect was found for the Previous Lurkers group (those who had never reported in the app prior to the experiment). For these users, the baseline control is 0.7%, implying that only a tiny fraction of users would have reported without the campaign. Users' participation in the economic incentive condition was 3.8% ($OR = 5.65$; $p < 0.001$), a 447% relative increase. For the both condition, Previous Lurkers' participation rate was 2.6% ($OR = 3.89$; $p < 0.001$), a relative increase of 280%. Finally, the cooperation message condition had a participation rate for this group of 1.1% ($OR = 1.63$;

Table 2 Estimation of the effect of each experimental condition on participation rate using a logit model

	All	Previous contributors	Previous lurkers
Economic incentive	1.411*** (0.112) [4.099] < 0.001	1.115*** (0.153) [3.049] < 0.001	1.731*** (0.169) [5.647] < 0.001
Cooperation message	0.555*** (0.136) [1.741] < 0.001	0.624*** (0.182) [1.867] < 0.001	0.488* (0.210) [1.629] <i>0.019</i>
Both	1.130*** (0.118) [3.095] < 0.001	0.948*** (0.162) [2.580] < 0.001	1.359*** (0.177) [3.892] < 0.001
Constant	-4.302*** (0.108) [0.014] < 0.001	-3.080*** (0.145) [0.046] < 0.001	-4.972*** (0.165) [0.007] < 0.001
<i>p values for pairwise comparisons</i>			
Economic incentive versus cooperation message	< 0.001	< 0.001	< 0.001
Economic incentive versus both	< 0.001	<i>0.058</i>	< 0.001
Cooperation message versus both	< 0.001	<i>0.014</i>	< 0.001
Log-likelihood	-7658.923	-2635.653	-4626.176
Observations	46,516	8136	38,380

⁺ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All columns show standard errors between parentheses, p values in italics, and odd-ratios between brackets

$p = 0.019$), a relative increase of 62%. These results demonstrate a small effect of cooperation messaging for Previous Lurkers, which is consistent with this group's lack of previous (intrinsic) motivation to send reports. The results with Previous Lurkers are also notable as they indicate a potential expansion of the contributor base of the crowdsourcing app. "Appendix 3" shows these results using a linear probability model.

Level of user contribution

The previous sub-section focused on participation rates (i.e., an extensive margin analysis). In the following analysis, we examine the number of reports shared by users (i.e., intensive margin). Figure 2 shows the average number of shared reports per user and per day, conditional on participation. Users who were offered an economic incentive, with or without a cooperation message, made 19.5% more reports when compared to users in the control group, from 0.80 to 0.96 daily reports per user (both significant only at the 10% significance level; $d = 0.2$ for the both condition).¹⁰ This means that in the economic incentive group, users who reported sent almost three reports, on average, during the campaign. There is a much smaller difference for users who were sent a cooperation message; they made 0.86 average reports, on average, which represents an increase of 6.7% from the control group, and is not sizably different from the daily reports shared by the control group ($p = 0.54$; $d = 0.1$). These results suggest that the economic incentive not only increased the active user base, but incentivized that user base to interact (i.e., share reports) slightly more frequently. While all treatments showed a positive effect regarding both extensive and intensive margins, the economic incentive was the most successful treatment with regards to both margins.

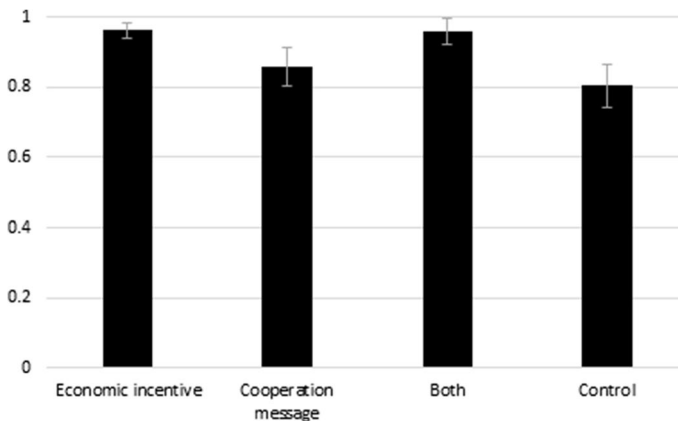


Fig. 2 Average number of daily reports shared by users who participated during the campaign. Error bars represent ± 1 standard error

¹⁰ We excluded outlier observations with an extremely high number of reports—over the 99.5th percentile—to avoid a strong influence from very few observations. For completeness, in the "Appendix 4", we show an analysis that includes these observations.

The contribution-level analysis by user type shows that Previous Contributors increased the number of shared reports conditional on participation. They increased their contribution from 0.82 average daily reports, in the control group, to 1.12 average daily reports when they were offered an economic incentive with or without the cooperation message, a relative increase of 36% ($p = 0.013$ for the economic incentive and $p = 0.03$ for both, $d = 0.4$). Previous Contributors' contribution level was 0.99 daily average reports when only a cooperation message was used (a relative increase of 20.6%; $p = 0.18$; $d = 0.3$). For the Previous Lurkers group, there were no sizably significant differences in shared reports compared to the control group—these were users who started to report for the first time, so it is hard to expect that their intensive margin was any greater than those in the control group. Overall, these results indicate that economic incentives, mainly, but also cooperation messaging, increased the likelihood of participation for all users, with a larger increase for users who never reported before, and also increased the number of reports shared by those who had experience reporting with the app.

The previous analysis must be taken with caution because of the change in participation likelihood across conditions. In this regard, it is remarkable that even though all treatments increased participation, they also increased the level of contribution—one may expect that these new users would report less frequently compared with users in the control group. Nevertheless, as explained in Section 2.4, we use a zero-inflated negative binomial model to account for the decision to participate and how many reports to share. Table 3 shows the results. The bottom section of the table shows the log-odds of not reporting under each treatment, using the control group as the baseline. Consistent with the previous analysis, users are more likely to report under all treatments. Overall, being in the economic incentive treatment (vs. in the control group) decreases the odds of not participating by a factor of 0.27 ($e^{-1.297}$), $p < 0.001$. In other words, the economic incentive increases the participation rate. The top section of the table shows the effect on the number of reports for those who share at least one report. Here, the economic incentive and the both treatments increase the number of reports compared to the control group. For example, for someone in the economic incentive condition, the number of reports increases by a factor of 1.34 ($e^{0.293}$), $p = 0.04$. Table 3 shows the same analysis for Previous Contributors and Previous Lurkers, with results consistent with the previous analysis. For robustness, in “Appendix 4” we show the analysis with alternative specifications (e.g., using a Poisson model or using bus reports as the outcome variable, which were not part of the campaign and were not expected to affect participation). The robustness of these analyses is consistent with the previous results.¹¹

¹¹ Compared to the negative binomial model, the Poisson distribution does not assume overdispersion of the count data. In our case, there is overdispersion as the unconditional mean number of reports is much lower than its variance for each experimental condition.

Table 3 Estimation of the effect of each experimental condition on the level of user contribution using a zero-inflated negative binomial model

Negative binomial			
	All	Previous contributors	Previous lurkers
Economic incentive	0.293* (0.139) <i>0.035</i>	0.461* (0.182) <i>0.011</i>	0.158 (0.204) <i>0.439</i>
Cooperation message	0.110 (0.172) <i>0.523</i>	0.286 (0.210) <i>0.173</i>	- 0.282 (0.295) <i>0.338</i>
Both	0.292* (0.147) <i>0.047</i>	0.458* (0.192) <i>0.017</i>	0.110 (0.216) <i>0.611</i>
Constant	0.281+ (0.145) <i>0.053</i>	0.507** (0.179) <i>0.005</i>	0.023 (0.238) <i>0.924</i>
Zero-inflated logit			
Economic incentive	- 1.297*** (0.130) < 0.001	- 0.953*** (0.176) < 0.001	- 1.668*** (0.196) < 0.001
Cooperation message	- 0.491** (0.158) <i>0.002</i>	- 0.491* (0.208) <i>0.018</i>	- 0.634* (0.259) <i>0.014</i>
Both	- 1.015*** (0.137) < 0.001	- 0.785*** (0.186) < 0.001	- 1.316*** (0.206) < 0.001
Constant	3.715*** (0.135) < 0.001	2.707*** (0.172) < 0.001	4.130*** (0.226) < 0.001
$Ln\alpha$	0.170 (0.123) <i>0.169</i>	- 0.426** (0.147) <i>0.004</i>	0.629** (0.225) <i>0.005</i>
Log-likelihood	- 10690.824	- 4059.634	- 6243.081
Observations	46,438	8082	38,356

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All columns show standard errors between parentheses and p values in italics

Effect over time

The experiment was conducted during the second week of October 2019. One day after the campaign ended, a series of massive demonstrations and severe riots known as the “Social Outburst” (*Estallido Social*) occurred throughout Chile.¹² These events paralyzed the public transport system due to the burning of buses and Metro stations. The system started

¹² <https://www.ciperchile.cl/2019/10/27/el-reventon-social-en-chile-una-mirada-historica/>.

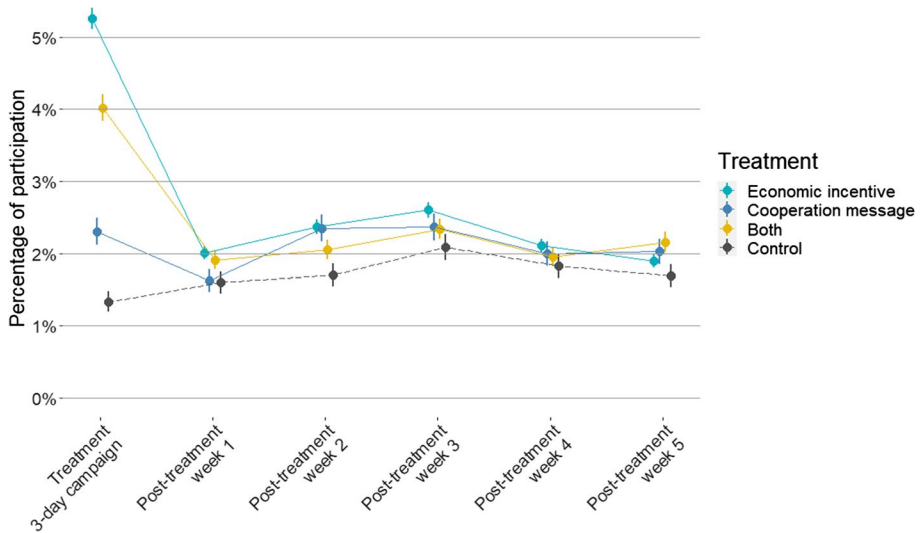


Fig. 3 Participation rates over time. Error bars represent ± 1.96 standard error

working again at partial capacity 1 week later.¹³ Because of this force majeure event, we were doubtful about the lasting impacts of the campaign, given this vast disruption to any habit-forming behavior. Nevertheless, we examined how participation rates varied over time for several weeks after the campaign ended. Figure 3 presents the percentage of users that reported (participation rates) in each treatment group over time.

The period analyzed was the three-day campaign-treatment period and the 5 weeks after the campaign ended. During the first post-treatment week, many people stayed at home due to disruptions in the public transportation system associated with the demonstrations and the declaration of a curfew and state of emergency. In the second post-treatment week, even though participation rates and levels of user contribution started to decrease after the campaign, and a major disruption, the participation rate of users in the economic incentive condition was 39% greater than those in the control condition (a 0.7 percentage points increase from 1.7%; $OR = 1.40$; $p = 0.001$). Afterward, participation rates further decreased, reaching a level of 1.9% in the fifth week after treatment, which was very similar to the participation rate of the control group at the same point (1.7%). A similar pattern was observed for the other experimental condition groups. To examine these differences, we conducted a statistical analysis using the same model from Section 2.4 for each period described below.

Table 5 in “Appendix 5” shows the results obtained from the zero-inflated negative binomial model for each period: a 2-week pre-treatment period (for which we expected there to be no effect), the three-day campaign-treatment period, and each of the 5 weeks following the campaign. The bottom panel shows the estimation for the zero-inflation portion of the model, where negative coefficients indicate a decrease in the probability of obtaining zero reports. This portion of the model indicates that, except for the first *particular* post-treatment week, the economic-incentive group’s participation rate was still higher than that of the control group for 3 weeks after the campaign ended, with the effect decreasing until it was not sizably different from zero

¹³ <https://www.interior.gob.cl/noticias/2019/10/28/informacion-oficial-del-gobierno-de-chile-con-las-medidas-para-enfrentar-la-situacion-de-emergencia/>.

during the fourth post-treatment week. The other treatment conditions showed a similar pattern, but their trends were slightly more erratic. Therefore, despite the disruption during the third week of October, the campaign was able to change users' participation behavior for several weeks. The top panel shows the estimation for the negative binomial portion of the model, where positive coefficients indicate an increase in the number of reports generated. This non-zero portion of the analysis shows that it was not possible to observe significant differences in the number of reports shared compared with users in the control group (conditional on reporting). This result is to be expected, since people who began to report after receiving the push notification would not be expected to report frequently, as they did not show an intrinsic motivation to participate prior to the campaign. In "Appendix 5", we also conduct this analysis for Previous Contributor and Previous Lurkers. It shows that the positive impact of participation in the post-treatment periods was more attributable to Previous Lurkers and an increased number of reports for 2 weeks after the treatment was driven by Previous Contributors.

Discussion and conclusions

Crowdsourcing public transport applications allow commuters to report public transport system conditions along with their level of satisfaction regarding the service provided. These data collection systems face three principal challenges: (i) motivate as many users as possible to contribute information, (ii) motivate users to deliver as much information as possible, and (iii) obtain information that covers most of the transport network both spatially and temporally. In this context, we evaluated the effectiveness of economic incentives and cooperation messages to motivate users to report key information about bus stop conditions.

Our results show that economic incentives and cooperation messaging increased participation rates and the number of reports shared by users. The relative increases compared to the control group were 294% for users who received an economic incentive, 72% for those who received a cooperation message, and 201% for users who received a combination of both. The economic incentive condition increased the participation rate most effectively, especially for users who had not reported prior to the campaign, and also increased the number of reports conditional on participation.¹⁴ Furthermore, we found that offering an economic incentive helped to encourage lurkers - those users who had not made prior contributions—to participate, thereby increasing the contributor base, which is one of the most important goals of crowdsourcing applications in transportation.

The cooperation message had a positive impact on the participation rate compared to not sending any message (i.e., control group), but its impact was significantly less than offering an economic incentive. As the crowdsourcing app is inherently a platform based on providing and receiving contributions, with no economic recompense, the cooperation message most likely did not change the status quo. In other words, for most people, the cooperation message probably acted simply as a reminder with a short-lasting effect. Previous research has shown that when people are reminded of something they are already aware of, behavioral effects are short-lived (Schwartz et al. 2013). Interestingly, combining the cooperation message with an economic incentive reduced the participation rate compared to offering only an economic incentive. This result suggests that some of these users paid more attention to the first section of the notification ("Help and participate for bip! reloads of \$13.95"), reducing their chance to share a report, or

¹⁴ Regarding report quality, only a small percentage of reports may be considered dubious (i.e., more users rejected the report instead of confirming it) out of all the reports made during the campaign: economic incentive (5.5%), cooperation message (8.4%), both (6.9%), and control (11.8%).

they resisted mixing an emphasized cooperation activity with an economic (more self-centered) motivation (Heyman and Ariely 2004). In line with our results, recent research has found that monetary incentives work better to encourage behavior when offered without combining them with an emphasis on cooperation (Lacetera et al. 2012; Niessen-Ruenzi et al. 2014; Lacetera et al. 2014; Schwartz et al. 2021, 2020).

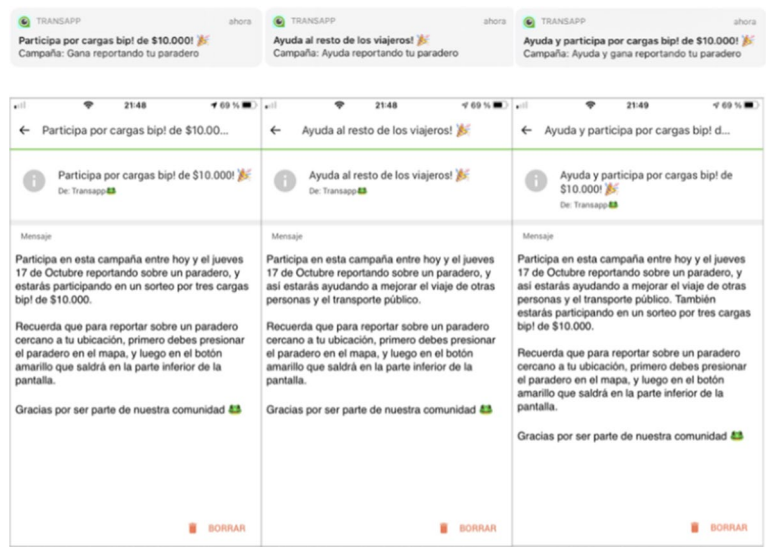
We found that providing an economic incentive can have positive impacts on participation and contribution for several weeks after a campaign ends. However, the positive effects rapidly decrease compared to the initial impact. Future research may consider whether a long-lasting effect is possible in the majority of cases, given that in the case of this experiment, a major disruption to the public transport network occurred 1 week after the campaign, which may have dampened the campaign's lasting impact, or whether using multiple messages for several weeks can strengthen collaborative habits on crowdsourcing platforms. In addition, even though a cooperation message had less of an impact than a standalone economic incentive, future research may examine whether framing the cooperation message as a personal characteristic (e.g., "those who report help improve the system") or normalizing the behavior (e.g., "many people collaborate by sending reports") can encourage cooperation behavior. The interplay of economic incentives and altruistic behavior has puzzled researchers in recent decades. Our research should help deepen the understanding of the role that economic incentives can play by providing evidence for transport planners, crowdsourcing information managers, and government authorities to more effectively increase the use of crowdsourcing systems that benefit the wider community.

Finally, the results of this study suggest that it is possible to enrich current public transport databases, used for the understanding of public transport passenger behavior and the evaluation of public transport service, using crowdsourcing applications to provide detailed information about the system. Currently, passive data, such as Automatic Fare Collection (AFC) data, Automatic Vehicle Location (AVL) data, and Automatic Passenger Counter (APC) data, are widely used by public transport authorities and researchers to understand the demand and the operation of public transport systems (Bagchi and White 2005; Munizaga and Palma 2012; Gschwender et al. 2016; Devillaine et al. 2012). Unlike traditional data obtained from surveys, passive data allows the collection of large volumes of travel data over long periods of time. However, it lacks relevant user information, such as information related to infrastructure maintenance, which is essential for improving the public transport system. This study shows that it is possible to encourage transport-oriented crowdsourcing applications users to share the currently missing information from passive databases using cost-effective monetary incentives.

Appendix 1: Notifications received by users on their phones

Messages sent to users. From left to right: Economic incentive, Cooperation message and Both conditions. Users had to press the notification (at the top of the figure) in order to read the full message.¹⁵

¹⁵ The economic incentive condition had two possible specific messages, which could be seen only if people *opened the economic incentive notification*—one with the economic incentive specific message and another with the both specific message. Because few people likely read the messages in the app, we found no sizable differences between messages for people who received the economic incentive notification, so we decided to present the results based on the notifications only.



Details of the notifications and messages sent to users, translated to English:

	Economic incentive	Cooperation message	Both
Notification	Participate for CLP\$10,000 in bip! credits!	Help other commuters!	Help and participate for CLP\$10,000 in bip! credits!
	Campaign: Win by reporting your bus stop	Campaign: Help by reporting your bus stop	Campaign: Help and win by reporting your bus stop
Condition-specific message	Participate in this campaign between [dates] by sending reports about a bus stop, and you will be participating in a draw for three bip! credits of CLP\$10,000	By participating in this campaign between [dates] by sending reports about a bus stop, you will be helping to improve other peoples' trips, as well as the public transport system	Participate in this campaign between [dates] by sending reports about a bus stop, and you will be helping to improve other peoples' trips and the public transport system. You will also be participating in a draw for three bip! charges of CLP\$10,000
Common message	Remember that to report a bus stop near your location, you must first click on the bus stop on the map, and then on the yellow button that will appear at the bottom of the screen. Thanks for being part of our community		

Table 4 Estimation of the effect of each experimental condition on participation rate using a logit model

	All	Previous contributors	Previous lurkers
Economic incentive	1.446*** (0.116) < 0.001	1.134*** (0.160) < 0.001	1.778*** (0.173) < 0.001
Economic incentive (adding cooperation text in the app)	1.374*** (0.116) < 0.001	1.096*** (0.160) < 0.001	1.682*** (0.174) < 0.001
Cooperation message	0.555*** (0.136) < 0.001	0.624*** (0.182) < 0.001	0.488* (0.210) <i>0.02</i>
Both	1.130*** (0.118) < 0.001	0.948*** (0.162) < 0.001	1.359*** (0.177) < 0.001
Constant	− 4.302*** (0.108) < 0.001	− 3.080*** (0.145) < 0.001	− 4.972*** (0.165) < 0.001
<i>p values for pairwise comparisons</i>			
Economic incentive (adding cooperation text in the app)	<i>0.231</i>	<i>0.697</i>	<i>0.216</i>
Log-likelihood	− 7658.204	− 2635.577	− 4625.409
Observations	46,516	8136	38,380

⁺ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All columns show standard errors between parentheses and p values in italics

Appendix 2: Sample size

To identify the sample size required for each treatment, we perform a statistical power analysis based on the results of a pilot. This pilot showed that the cooperation message had the smallest effect compared to the control (0.8 p.p. from 1.1%). Therefore, we required approximately 6000 individuals in each of these experimental conditions to have a 95% statistical power (we added a few hundred people because some phones may have changed or not be working). The rest of the sample was evenly distributed to detect differences between the economic incentive and both conditions, and to be able to split the economic incentive condition into two additional conditions for people who *opened the economic incentive notification*. For the latter, the message section in the app either repeated the text from the notification (i.e., offering an economic incentive) or also included the text from the cooperation message. We expected the difference to be small, if detectable, because few people may use the message section in the app. Therefore, the final sample was 11,164 for each of these three groups (the Both condition and the two inside the economic incentive one). Consistently, Table 4 shows no significant difference between the texts in the message section for the economic incentive condition ($p > 0.2$ for all models).

Appendix 3: Estimation of the effect of each experimental condition on participation rate using a linear probability model

	All	Previous contributors	Previous Lurckers	All with interactions
Economic incentive	0.039*** (0.003) < 0.001	0.079*** (0.010) < 0.001	0.031*** (0.003) < 0.001	0.024*** (0.003) < 0.001
Cooperation message	0.010** (0.003) <i>0.005</i>	0.035** (0.013) <i>0.005</i>	0.004 (0.003) <i>0.169</i>	-0.002 (0.004) <i>0.538</i>
Both	0.027*** (0.003) < 0.001	0.062*** (0.011) < 0.001	0.019*** (0.003) < 0.001	0.013*** (0.003) < 0.001
Contributors-economic incentive				0.085*** (0.003) < 0.001
Contributors-cooperation message				0.068*** (0.006) < 0.001
Contributors-both				0.080*** (0.005) < 0.001
Constant	0.013*** (0.002) < 0.001	0.044*** (0.009) < 0.001	0.007** (0.002) <i>0.002</i>	0.013*** (0.002) < 0.001
<i>p values for pairwise comparisons</i>				
Economic incentive versus cooperation message	< 0.001	< 0.001	< 0.001	< 0.001
Economic incentive versus both	< 0.001	<i>0.043</i>	< 0.001	< 0.001
Cooperation message versus both	< 0.001	<i>0.016</i>	< 0.001	< 0.001
R ²	0.006	0.008	0.006	0.027
Observations	46,516	8136	38,380	46,516

⁺ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All columns show standard errors between parentheses and p values in italics

Appendix 4: Estimation of the effect of each experimental condition on the level of user contribution using different models and different analyses

Negative binomial			
	Without exclusion	With Poisson	With bus reports
Economic incentive	1.231** (0.408) <i>0.003</i>	0.235* (0.112) <i>0.036</i>	0.322 (0.430) <i>0.453</i>
Cooperation message	0.517+ (0.289) <i>0.074</i>	0.088 (0.139) <i>0.523</i>	0.685 (0.693) <i>0.323</i>
Both	1.526* (0.590) <i>0.010</i>	0.234* (0.119) <i>0.048</i>	0.226 (0.639) <i>0.724</i>
Constant	- 2.43*** (0.231) <i>< 0.001</i>	0.752*** (0.108) <i>< 0.001</i>	0.108 (1.039) <i>0.916</i>
Zero-inflated			
Economic incentive	- 18.1*** (0.348) <i>< 0.001</i>	- 1.33*** (0.118) <i>< 0.001</i>	- 0.28 (0.106) <i>0.239</i>
Cooperation message	- 0.63+ (0.371) <i>0.089</i>	- 0.50*** (0.143) <i>< 0.001</i>	0.106 (0.164) <i>0.739</i>
Both	- 1.21+ (0.656) <i>0.065</i>	- 1.05*** (0.124) <i>< 0.001</i>	0.164 (3.695) <i>0.588</i>
Constant	0.345 (0.317) <i>0.277</i>	4.196*** (0.113) <i>< 0.001</i>	3.695 (1.030) <i>< 0.001</i>
Ln alpha	3.965*** (0.125) <i>< 0.001</i>		2.454* (0.037) <i>0.037</i>
alpha	52.751 (6.637)		11.641 (13.72)
Log-likelihood	- 11865.09	- 11057.26	- 2431.907
Observations	46,516	46,438	46,516

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All columns show standard errors between parentheses and p values in italics

Appendix 5: Estimation of the effect of each experimental condition on the level of user contribution using a Zero-inflated negative binomial model

See Tables 5, 6 and 7.

Table 5 Estimation of effects of each experimental condition on the level of all users' contributions over time

Negative binomial							
	Pre-treatment (2 weeks)	Treatment (3 days)	Post-treatment Week 1	Post-treatment Week 2	Post-treatment Week 3	Post-treatment Week 4	Post-treatment Week 5
Economic incentive	-0.095 (0.140) <i>0.499</i>	0.293* (0.139) <i>0.035</i>	0.299 (0.188) <i>0.112</i>	0.134 (0.155) <i>0.388</i>	0.004 (0.149) <i>0.981</i>	-0.041 (0.187) <i>0.826</i>	0.056 (0.144) <i>0.697</i>
Cooperation message	0.188 (0.179) <i>0.294</i>	0.110 (0.172) <i>0.523</i>	0.831** (0.253) <i>0.001</i>	0.141 (0.205) <i>0.491</i>	0.263 (0.189) <i>0.164</i>	0.193 (0.238) <i>0.418</i>	-0.010 (0.192) <i>0.959</i>
Both	-0.045 (0.155) <i>0.770</i>	0.292* (0.147) <i>0.047</i>	0.166 (0.204) <i>0.418</i>	-0.110 (0.178) <i>0.535</i>	-0.361+ (0.185) <i>0.050</i>	-0.141 (0.206) <i>0.495</i>	0.037 (0.156) <i>0.812</i>
Constant	-1.300 (0.941) <i>0.167</i>	0.281+ (0.145) <i>0.053</i>	-0.627 (0.441) <i>0.155</i>	-0.021 (0.266) <i>0.937</i>	0.250 (0.220) <i>0.256</i>	-0.197 (0.349) <i>0.572</i>	0.209 (0.221) <i>0.345</i>
<i>Zero-inflated</i>							
Economic incentive	-0.270 (0.565) <i>0.633</i>	-1.297*** (0.130) <i>< 0.001</i>	-0.107 (0.149) <i>0.472</i>	-0.279* (0.128) <i>0.030</i>	-0.221+ (0.116) <i>0.057</i>	-0.164 (0.137) <i>0.232</i>	-0.087 (0.125) <i>0.485</i>
Cooperation message	0.144 (0.367) <i>0.694</i>	-0.491** (0.158) <i>0.002</i>	0.323+ (0.184) <i>0.080</i>	-0.260+ (0.157) <i>0.098</i>	-0.012 (0.143) <i>0.934</i>	0.004 (0.170) <i>0.980</i>	-0.155 (0.156) <i>0.321</i>
Both	-0.049 (0.276) <i>0.859</i>	-1.015*** (0.137) <i>< 0.001</i>	-0.114 (0.164) <i>0.488</i>	-0.232 (0.145) <i>0.110</i>	-0.265+ (0.137) <i>0.054</i>	-0.126 (0.153) <i>0.411</i>	-0.238+ (0.135) <i>0.078</i>
Constant	-0.585 (2.627) <i>0.824</i>	3.715*** (0.135) <i>< 0.001</i>	2.479*** (0.459) <i>< 0.001</i>	2.931*** (0.260) <i>< 0.001</i>	2.896*** (0.212) <i>< 0.001</i>	2.641*** (0.354) <i>< 0.001</i>	3.143*** (0.210) <i>< 0.001</i>

Table 5 (continued)

Negative binomial							
	Pre-treatment (2 weeks)	Treatment (3 days)	Post-treatment Week 1	Post-treatment Week 2	Post-treatment Week 3	Post-treatment Week 4	Post-treatment Week 5
Ln alpha	3.389*** (1.001)	0.170 (0.123)	1.886*** (0.506)	1.326*** (0.331)	1.166*** (0.287)	1.641*** (0.414)	1.063*** (0.281)
Log-likelihood	0.001 – 10690.824	0.169 – 10690.824	< 0.001 – 10690.824	< 0.001 – 10690.824	< 0.001 – 10690.824	< 0.001 – 10690.824	< 0.001 – 10690.824
Observations	46,438	46,438	46,438	46,438	46,438	46,438	46,438

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All columns show standard errors between parentheses and p values in italics

Table 6 Estimation of effects of each experimental condition on the level of Previous Contributors' contributions over time

Negative binomial		Pre-treatment (2 weeks)	Treatment (3 days)	Post-treatment Week 1	Post-treatment Week 2	Post-treatment Week 3	Post-treatment Week 4	Post-treatment Week 5
Economic incentive		- 0.201 (0.162)	0.461* (0.182)	0.455* (0.204)	0.308+ (0.165)	0.260 (0.195)	- 0.167 (0.211)	0.175 (0.183)
		0.214	0.011	0.026	0.063	0.182	0.430	0.339
	Cooperation message	0.169 (0.203)	0.286 (0.210)	0.859** (0.264)	0.457* (0.218)	0.412+ (0.239)	0.019 (0.286)	0.054 (0.236)
	Both	0.405 (0.174)	0.173 (0.192)	0.001 (0.226)	0.036 (0.193)	0.084 (0.235)	0.947 (0.236)	0.820 (0.192)
	Constant	- 0.153 (0.380)	0.458* (0.192)	0.327 (0.148)	0.077 (0.689)	- 0.124 (0.597)	- 0.312 (0.187)	0.168 (0.380)
Zero-inflated		0.657** (0.236)	0.507** (0.179)	0.234 (0.251)	0.505** (0.194)	0.541** (0.206)	0.679** (0.256)	0.642** (0.197)
		0.005	0.005	0.352	0.009	0.009	0.008	0.001
	Economic incentive	- 0.286+ (0.160)	- 0.953*** (0.176)	- 0.075 (0.189)	- 0.203 (0.169)	- 0.022 (0.162)	- 0.247 (0.175)	- 0.153 (0.174)
	Cooperation message	0.074 (0.187)	< 0.001 (0.208)	0.691 (0.231)	0.229 (0.207)	0.893 (0.196)	0.157 (0.218)	0.381 (0.212)
	Both	- 0.023 (0.903)	- 0.491* (0.018)	0.230 (0.318)	- 0.033 (0.874)	0.045 (0.817)	- 0.133 (0.541)	- 0.302 (0.154)
Constant		- 0.240 (0.175)	- 0.785*** (0.186)	- 0.056 (0.208)	- 0.189 (0.189)	- 0.032 (0.188)	- 0.239 (0.196)	- 0.297 (0.187)
		0.174	< 0.001	0.787	0.317	0.867	0.222	0.111
		0.559+ (0.333)	2.707*** (0.172)	2.187*** (0.250)	2.243*** (0.200)	1.910*** (0.199)	2.122*** (0.243)	2.411*** (0.193)
		0.093	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001

Table 6 (continued)

Negative binomial							
	Pre-treatment (2 weeks)	Treatment (3 days)	Post-treatment Week 1	Post-treatment Week 2	Post-treatment Week 3	Post-treatment Week 4	Post-treatment Week 5
<i>Lna</i>	1.597*** (0.287)	- 0.426** (0.147)	0.792** (0.287)	0.618* (0.247)	0.736** (0.255)	0.961** (0.295)	0.504* (0.239)
Log-likelihood	< 0.001 - 6339.622	0.004 - 4059.634	0.006 - 2641.881	0.012 - 3002.615	0.004 - 3314.733	0.001 - 2885.729	0.035 - 2835.970
Observations	8122	8082	8129	8126	8124	8129	8125

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All columns show standard errors between parentheses and p values in italics

Table 7 Estimation of effects of each experimental condition on the level of previous lurkers' contributions over time

Negative binomial							
	Pre-treatment (2 weeks)	Treatment (3 days)	Post-treatment Week 1	Post-treatment Week 2	Post-treatment Week 3	Post-treatment Week 4	Post-treatment Week 5
Economic incentive	0.121 (0.169) <i>0.491</i>	0.158 (0.204) <i>0.439</i>	0.006 (0.334) <i>0.986</i>	-0.160 (0.278) <i>0.566</i>	-0.374+ (0.212) <i>0.078</i>	0.249 (0.281) <i>0.374</i>	-0.216 (0.220) <i>0.325</i>
Cooperation message	0.093 (0.204) <i>0.649</i>	-0.282 (0.295) <i>0.338</i>	0.707 (0.484) <i>0.144</i>	-0.346 (0.365) <i>0.344</i>	0.002 (0.288) <i>0.996</i>	0.540+ (0.320) <i>0.092</i>	-0.208 (0.304) <i>0.494</i>
Both	0.084 (0.223) <i>0.707</i>	0.110 (0.216) <i>0.611</i>	-0.117 (0.353) <i>0.740</i>	-0.479 (0.307) <i>0.118</i>	-0.666* (0.279) <i>0.017</i>	0.237 (0.312) <i>0.477</i>	-0.256 (0.250) <i>0.305</i>
Constant	-1.326 (1.109) <i>0.232</i>	0.023 (0.238) <i>0.924</i>	-3.526*** (0.334) <i>< 0.001</i>	-0.378 (0.600) <i>0.529</i>	0.183 (0.408) <i>0.654</i>	-0.825 (0.568) <i>0.146</i>	-0.266 (0.618) <i>0.668</i>
<i>Zero-inflated</i>							
Economic incentive	0.099 (0.170) <i>0.562</i>	-1.668*** (0.196) <i>< 0.001</i>	-2.592 (7.648) <i>0.735</i>	-0.445* (0.206) <i>0.030</i>	-0.506** (0.171) <i>0.003</i>	0.026 (0.222) <i>0.908</i>	-0.113 (0.188) <i>0.547</i>
Cooperation message	0.105 (0.203) <i>0.605</i>	-0.634* (0.259) <i>0.014</i>	1.056 (1.118) <i>0.345</i>	-0.621* (0.264) <i>0.018</i>	-0.129 (0.215) <i>0.550</i>	0.261 (0.260) <i>0.314</i>	-0.079 (0.245) <i>0.746</i>
Both	0.209 (0.218) <i>0.338</i>	-1.316*** (0.206) <i>< 0.001</i>	-8.148*** (1.883) <i>< 0.001</i>	-0.397+ (0.235) <i>0.091</i>	-0.553** (0.207) <i>0.008</i>	0.124 (0.245) <i>0.613</i>	-0.284 (0.207) <i>0.171</i>
Constant	1.159 (1.444) <i>0.422</i>	4.130*** (0.226) <i>< 0.001</i>	-1.292 (1.144) <i>0.259</i>	3.216*** (0.608) <i>< 0.001</i>	3.517*** (0.392) <i>< 0.001</i>	2.960*** (0.579) <i>< 0.001</i>	3.249*** (0.611) <i>< 0.001</i>

Table 7 (continued)

Negative binomial		Pre-treatment (2 weeks)	Treatment (3 days)	Post-treatment Week 1	Post-treatment Week 2	Post-treatment Week 3	Post-treatment Week 4	Post-treatment Week 5
<i>Lna</i>		2.507* (1.236)	0.629** (0.225)	4.856*** (0.134)	1.625* (0.766)	1.176* (0.550)	1.449* (0.694)	1.535* (0.774)
Log-likelihood		0.042 – 6178.482	0.005 – 6243.081	< 0.001 – 3029.881	0.034 – 3439.630	0.033 – 3767.970	0.037 – 3067.687	0.047 – 2987.203
Observations		38,380	38,356	38,380	38,378	38,380	38,380	38,380

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All columns show standard errors between parentheses and p values in italics

Acknowledgements We would like to acknowledge two anonymous reviewers for their helpful and comprehensive comments and suggestions. This research was partially funded by ANID-PFCHA/Doctorado Nacional/2017 Grant 21170750, Fondecyt Grant 1191104, Fondecyt Grant 1191745, ANID-PIA/BASAL Grant AFB180003, and MIPP (ICS13_002 ANID).

Author Contributions All authors contributed to the formulation of the study goal, methodology, formal analysis, and the research and investigation process. JA and CM performed the data collection process and creation of the initial draft. CM and DS performed the experimental design and implementation of the computer code for the analysis. The revision and edition of the final draft were performed by JA, MM, and DS. Finally, the management and coordination responsibility for the submission of the paper was performed by JA.

Declarations

Conflict of interest Claudio Mena, Marcela Munizaga, and Daniel Schwartz declare that they have no conflict of interest. Jacqueline Arriagada declares that she is involved with Transapp as co-founder. Transapp has provided the data for this study.

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Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.


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