Sustainability of generalized exchange in the sharing economy: the case of the "freecycling" Facebook groups

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Abstract: The growth of the sharing economy has attracted a lot of attention in recent years. These online platforms bring together individuals willing to share and those who are in need. While sharing in some of these platforms is reciprocated by money or reputation, some platforms rely heavily on individuals' good will to give their things away with no personal benefit. Why do individuals cooperate in environments where there is every incentive to free-ride instead? In this article, we examine several explanations for such peculiar behavior – namely, the hypothesis that prosocial or sharing behavior spreads from person to person, and social learning hypothesis, which tells that such behavior could be based on mimicking others. We test these hypotheses using longitudinal data from a freecycling group on Facebook with 4818 members. The group is made for people to give things away for free, thus making the group vulnerable to free-riding behavior. We find that individuals who are more active receivers are also more likely to share something with group members in the future. We also find some evidence of a positive effect of social learning on sharing behavior.

Keywords: Cooperation, economy, exchange, Facebook, freecycling, generalized, online, sharing

1. Introduction

In recent years a new phenomenon called the "sharing economy" has attracted increasing attention. As an umbrella concept, the sharing economy refers to diverse online developments aimed at enabling shared consumption of goods and services. This technological development brings people with various resources, like extra living space, redundant housing items or specific knowledge, to those who need it via online platforms. The increasing number of such initiatives has been mostly related to technological innovation, especially the emergence of Web 2.0 (Hamari et al. 2013). A more social driver argued to push sharing economy forward is a presumed shift of societal values related to reconsidering the meaning of ownership and sharing, along with the balance between economic growth and environmental issues (Botsman and Rogers 2010).

By providing easy access to various resources directly from their owners' hands, the sharing economy has been argued to shift the power away from large centralized institutions (public service providers and private corporations) to networked distribution, where goods and services move between people. This shift in the structure of distribution of resources is seen by some as a possible solution for various economic problems, since it could potentially reduce transaction costs related to administration of many present economic activities (Hamari et al. 2013). The sharing economy is also expected to alleviate problems like hyper-consumption, poverty and pollution, and to make economic development more sustainable. Sharing economy startups have been successful in attracting hundreds of millions of dollars from investors (Alsever 2012). It has also attracted media attention, being discussed as "one of the ideas that will change the world."[1]

The phenomenon has also posed many questions and attracted scholarly attention. One of the questions that naturally occurs is: what motivates individuals to share or give away their personal belongings? Why would a person be willing to participate in such transactions? These questions are important to assess the longevity and sustainability of economic projects based solely on individuals' willingness to share their private belongings. Similar questions have been widely analyzed in research on motivation of software developers that contribute to open source projects and that of contributors in knowledge sharing communities, such as Wikipedia (Yang and Lai 2010; Von Krogh et al. 2012). In cases where sharing behavior is directly reciprocated, that is, where givers receive something in exchange (e.g. money, goods or services from others), extrinsic motivation is identical to that of regular market transactions – givers receive some form of value for idle resources, while users get access to a wider set of resources that they could not afford to own (Böckmann 2013; Hamari et al. 2013). This would apply to platforms where providers receive monetary compensation such as the hospitality platform Airbnb, but to some extent also to platforms where providers are not compensated with money but instead build up a good reputation, as we

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[1] See: http://content.time.com/time/specials/packages/article/0,28804,2059521_2059717,00.html.

will argue later. Airbnb's not-for-money equivalent Couchsurfing would be an example of such a case.

The problem becomes more complicated in cases where sharing is not reciprocated directly. If the provider receives a benefit from the receiver that is lower than the cost of sharing or receives no benefit at all, why would anyone share in the first place? In other words, in such cases a social dilemma (e.g. Raub et al. 2015) may arise, in the sense that on these platforms participants face incentives to behave opportunistically and only receive from the system, while at the collective level this would endanger the sustainability of the platform. Depending on the structure of exchanges on the platform, this social dilemma may take the form of a public goods – or, as in our case study, common goods – problem. As is well-known, from a theoretical point of view, the production of such goods is vulnerable to free-riding: actors are tempted to only take from the common pool without contributing themselves (Ostrom 1990).[2] In this paper, we are concerned with such cases. We will argue that such platforms can be fruitfully understood as *generalized exchange* systems (Ekeh 1974).

Empirical research on public good games suggests that individuals are often much more cooperative than predicted by theory that relies on standard assumptions of rationality and selfishness (Ledyard 1997). There are many alternative theoretical explanations that aim to explain why individuals give away or share their personal belongings with strangers in such situations, including purely or impurely altruistic preferences of some actors or ideological concerns, that result in voluntary contributions to the public good or altruistic punishment of free-riders in repeated interactions (Becker 1976; Andreoni 1989; Fehr and Gächter 2002; Von Krogh et al. 2012).

While theories on other-regarding preferences or intrinsic motivation provide a plausible explanation for why a certain fraction of individuals behave cooperatively, it is not clear whether the high level of contribution to public goods of such actors could be sufficient to sustain cooperation online, where free-riding is prevalent and sanctioning is not always possible. Studies on motivation of software developers in open source communities show that both extrinsic and intrinsic motivation plays a role in driving individual contributions (Yang and Lai 2010; Von Krogh et al. 2012). It is unclear, however, whether cooperation in such environments could be sustainable if extrinsic rewards were completely absent.

An alternative theoretical framing of the sharing problem could be made by interpreting the costly individual contribution as a form of behavior that spreads from person to person, or a network phenomenon. A fruitful approach to this interpretation is generalized reciprocity theory, which argues that altruistic behavior might be contagious (Ekeh 1974; Yamagishi and Cook 1993; Tsvetkova and Macy 2014). In brief, if an individual receives something from a stranger without

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[2] This however is not meant to imply that there are no social dilemmas involved in platforms with direct reciprocity (e.g. Airbnb). In such cases, a *trust problem* between the provider and receiver often arises which is typically addressed by rating systems (Bolton et al. 2004).

being asked to give something back, it might build generalized group trust or inspire feelings of gratitude and make that individual likely to pass the favor on. This concept has received attention in game theoretic models under the name of upstream reciprocity. Interestingly, although upstream reciprocity by itself does not lead to evolution of cooperation (Nowak and Roch 2007), and therefore leads to predictions that no such behavior should occur, experimental studies generally agree that cooperative actions spread from person A to B to C (Dufwenberg et al. 2001; Güth et al. 2001; Bartlett and DeSteno 2006; Stanca 2009; Christakis and Fowler 2010; Gray et al. 2014; however, also see: Capraro and Marcelletti 2014).

With a few exceptions (e.g. Ert et al. 2015; Thierer et al. 2015), the literature on cooperation in the sharing economy has rarely been embedded in sociological theory on social dilemmas, which offers a variety of useful insights into problems that could face these websites, like prevalence of free-riding and social mechanisms that might alleviate its negative effects. Conversely, the sharing economy could provide a fruitful environment to test predictions of generalized reciprocity theory in non-laboratory settings.

In this study, we aim to contribute to filling these gaps by analyzing a particular form of sharing behavior in an online freecycling group on Facebook. The group is made for people willing to give their personal belongings away for free in a major Dutch city. We analyze whether recipients or observers of generous behavior from other group members are more likely to pay the favor forward and thus create chains of altruistic behavior.

In the freecycling group, users post pictures or messages about the items they offer and other group members can collect these items by responding to the posts. Offered items are diverse in value, ranging from sofa beds and TV-sets to books and CDs. In the rules of the group users are asked not to post item requests or ask anything in return, and contributions are thus not directly reciprocated. Users typically give away their things to a randomly chosen individual from the list of commenters, who are mostly complete strangers. Apart from these rules, the group is entirely self-organized and offers a good real-life example of a generalized exchange system – an environment, which depends entirely on individual contributions, which are not reciprocated directly.

During the period under study, dozens of such Facebook groups emerged in the Netherlands, ranging in size from only a few members to, in some cases, tens of thousands. The groups typically focused on a specific city or region, although a few national groups emerged as well. While many of the groups used similar names and similar rules, and sometimes also linked to each other on Facebook, each group was self-organized. Although the movement shared many objectives with the global Freecycle movement, it is not affiliated with this movement.

2. Theory

In scholarly research, the concept of a sharing economy has been widely used to describe diverse services, making a precise definition of the phenomenon

problematic (Botsman and Rogers 2010). The websites differ in the types of exchanges that take place and underlying incentives for users to actively participate.

One concept that could provide a basis to categorize differences between sharing economy websites is reciprocity in the exchanges of their users (Belk 2010, 2014). Many of the services identified as part of the sharing economy resemble simple market exchanges in their structure of incentives. For example, exchanges in car or home sharing platforms like Uber or Airbnb typically involve monetary rewards in exchange for a service. Service providers are reciprocated directly and also maintain ownership of the car or the house. In some cases, incentives to contribute are not provided by money but by reputation, which can in turn be used as a resource for getting services. A typical example of such websites is Couchsurfing, where spare rooms or beds are shared between individuals for free, but reputation is awarded for hosting. Reputation, in turn, facilitates chances that hosts get accommodated in the future. There are therefore clear incentives for users in such websites to cooperate, since the benefit they receive, either monetary or indirect, covers or exceeds the cost of sharing or cooperation.[3] Such websites often include rating systems that enable dissemination of information about users' reputation and accordingly, sanctioning of individuals who fail to reciprocate (e.g. Lauterbach et al. 2009). Therefore, there are also high costs of free-riding, which leads to high levels of cooperation in the long run.[4]

There are some cases, however, where individuals engage in exchanges that are not reciprocated directly, nor indirectly via reputation. One such example is the freecycling movement and its groups on Facebook. In these groups individuals give away their items for free. Item offerings are posted online and any individual willing to receive that item makes a comment on the item listing post. The actual receiver is then typically selected randomly, which implies that reputation from giving something away cannot help with receiving something in return in the future, thus preventing the emergence of reputation effects. Additionally, the low level of organization in these groups makes the implementation of centralized punishment systems unlikely. Items given away on such websites range highly in their potential market value (Eden 2015), which means that individuals experience opportunity costs from not selling these items in online marketplaces like eBay. Finally, items are transferred to the new owner in person offline, which poses an additional risk. As a result, cooperative behavior (i.e. giving items away) is costly, cooperative behavior is not reciprocated and there are no means to punish non-cooperative individuals. An incentive structure, where the costs of cooperation are higher than the rewards of doing nothing poses a threat of freeriding behavior and may be potentially harmful to sustainability of such projects (Olson 1965).

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[3] Note that this requires that roles on the platform are "mixed," that is, that providers also play the role of receiver, as is common on Couchsurfing. Furthermore, it requires that a reputation earned as provider is also observable by other providers.

[4] The effort by users required to make reputation systems effective, however, poses a theoretical challenge of its own (Diekmann et al. 2014).

Online freecycling groups are especially interesting compared to their more geo-graphically based offline counterparts, since users in online groups are less likely to know other participants personally, which decreases the potential benefits of individual contributions even further. The question that arises then, is what kind of theoretical mechanisms could explain what contributes to sustainability of cooperation in freecycling groups when it is more beneficial to free-ride?

2.1. Generalized reciprocity

One of the mechanisms that could sustain cooperation in such an environment is that prosocial or altruistic behavior spreads between individuals (Ekeh 1974; Christakis and Fowler 2010; Tsvetkova and Macy 2014). It is argued that indi-viduals who receive non-reciprocated help from other individuals are more likely to pay the generosity forward to someone else. Such generalized reciprocity, or upstream reciprocity, is distinguished from indirect reciprocity discussed in the example of Couchsurfing in that in the latter case, individuals act generously anticipating that this will positively affect their chance to receive generosity in the future, while in the former case, individuals act generously because someone made them a favor beforehand (Nowak and Roch 2007).

As a result, it is not the established reputation that provides an incentive for individuals to act cooperatively, but psychological outcomes following another actor's generosity. The exact psychological mechanisms that cause such "paying it forward" behavior, however, are not clearly identified in theoretical and empirical literature (Simpson and Willer 2015). In most accounts, it is argued that a positive emotion of gratitude increases the willingness to reciprocate, and if it is impos-sible to reciprocate a favor to the same person, individuals are more likely to act favorably with someone else (Ekeh 1974; McCullough et al. 2008). As such, gen-eralized reciprocity could also be a by-product of direct reciprocity (Nowak and Roch 2007). In a series of experiments, Bartlett and DeSteno (2006) found that gratitude positively affects the occurrence of costly helping behavior, including third parties. This mechanism has been further supported by a study in neurosci-ences, which found that generalized reciprocity triggers regions of the human brain that are responsible for affective empathy, such as gratitude (Watanabe et al. 2014).

An additional mechanism that could underlie generalized reciprocity is *increased group solidarity* (Molm et al. 2007; Willer et al. 2012). It is argued that generosity from people who know that it will not be directly reciprocated, carries more expressive value and strengthens relationships and identification with other group members. This effect is also strengthened by the fact that gen-eralized reciprocity systems are particularly susceptible to free-riding, since a single free-rider could disturb the chain of paying-it-forward behavior. Since this exchange structure is more risky than direct exchange, generous acts fur-ther consolidate bonds between group members and lead to solidarity and group identification. Group solidarity and identification, in turn, are argued to increase individual's motivation to share (Molm et al. 2007; Willer et al. 2012). It is

unclear, what role group solidarity or identification could have in an online environment composed of many users, who do not know each other personally. Online ties have been described as too "thin" for group norms to emerge the same way as in offline settings (Hardin 2004). On the other hand, online freecycling groups are also often geographically located and the actual sharing of an item requires an offline meeting. The geographical aspect of freecycling groups might strengthen group solidarity.

While mechanisms underlying the spread of generosity are not evident, empirically it is a well-established phenomenon in both laboratory settings (Dufwenberg et al. 2001; Güth et al. 2001; Bartlett and DeSteno 2006; Stanca 2009; Christakis and Fowler 2010; Suri and Watts 2011; Gray et al. 2014; Tsvetkova and Macy 2014, however also see: Capraro and Marcelletti 2014) and real-world occurrences, for example paying for the next customer's coffee.[5] To sum up, we expect that in the case of freecycling groups, those individuals that received help will be more likely to provide help themselves.

> H1: Individuals who have received a non-reciprocated benefit from a stranger will be more likely to help strangers themselves

2.2. Social learning and social influence

Another explanation for why individuals collaborate without direct reciprocity is that they mimic the behavior of others (Tsvetkova and Macy 2014). In an unfamiliar environment, individuals might tend to repeat the behavior of others in order to fit in or get by. Two forms of such third-party influence may be distinguished (Deutsch and Gerrard 1955): normative and informational. The first refers to peer pressure, when individuals of a certain group push a newcomer to adapt. In contrast, *informational norms* are cues that might also be received from strangers in groups that are not necessarily important for the actor. They guide an individual towards acceptable behavior, but they are not related to any form of pressure. As such, informational norms are important in the analysis of behavior mimicry or contagion among strangers (Tsvetkova and Macy 2014). These norms might be important in sharing websites, like freecycling, since newcomers might not be familiar with usual kinds of interactions – what kind of items are shared, who gets the item – or relevant information, like whether the interaction necessarily requires face-to-face contact. The possible effect of third parties via informational norms can be related to "lurking" behavior in online groups (Preece et al. 2004; Suhonen et al. 2010). A fraction of individuals might not be free-riders but passive bystanders, who observe group norms before acting. For a local gift-giving

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[5] Pay-it-forward coffee has become a widespread phenomenon with cafes around the world encouraging clients to buy more than one cup and using the money for charitable causes (e.g. see: https://suspendedcoffees.com) or simply paying for the next customer (e.g.: http://abcnews.go.com/blogs/headlines/2013/12/starbucks-customers-break-1000-in-pay-it-forward-record).

system, Suhonen et al. (2010) found that the main reasons for not participating that users identified was difficulties in making decisions about what users could offer and appropriate norms of the service.

There are many reasons, however, to also expect the opposite effect of third party influence, as becomes apparent from the literature on social dilemmas (e.g. Raub et al. 2015). Analyses on social loafing (Karau and Williams 1993), "bystander effects" (Darley and Latane 1968) and volunteer's dilemma (Diekmann 1985) all point towards a negative effect of dispersed responsibility and willingness to contribute when the overall levels of contribution are sufficiently high. Recent experimental research shows that individuals who observe altruistic behavior actually decrease one's belief that the effort is needed (Tsvetkova and Macy 2014).

There are therefore conflicting arguments of third party influence – although we can expect positive effects via social learning, there might also be negative effects of social loafing. In our case, the negative effect would mean a passive form of participation or social lurking. We therefore formulate two opposite hypotheses, expecting that individuals who observe more social interactions and spend more time in the freecycling groups will share either more or less:

> *H2a: Individuals who observe more interactions or spend more time in the group will share more (social learning effect)*

> *H2b: Individuals who observe more interactions or spend more time in the group will share less (social loafing effect)*

3. Methods

We test these hypotheses using longitudinal data from a freecycling group in Facebook. Group members post pictures or text information about the items they are willing to give away in the group and all the users who are interested make a comment below the post, expressing their willingness to receive the item. In the end, the original poster picks a person out of the list of commenters, typically at random. The users then privately agree on how the item will be given away – usually in person. After the new owner of an item is found, the post is (usually) deleted. The rules of the group forbid any kind of reciprocity: users who are sharing, cannot explicitly ask for any kind of remuneration. The group we analyze is intended for people from Utrecht area, the Netherlands (see Figure 1).

We collected data from the freecycling group for 19 days at the beginning of 2014. We used Facebook application *Netvizz* (Rieder 2013) for data collection. This app could have been used to retrieve anonymized Facebook friendship connection data, posting and "*liking*" behavior of members in any Facebook group at the time of data collection. The application collects content and interaction data (comments, likes, textual information) from the last 200 posts in the group and network data for a maximum of 5000 individuals. If the number of users exceeds 5000, the application provides network information for a random subset of individuals. In our case, the number of individuals in the group ranged from
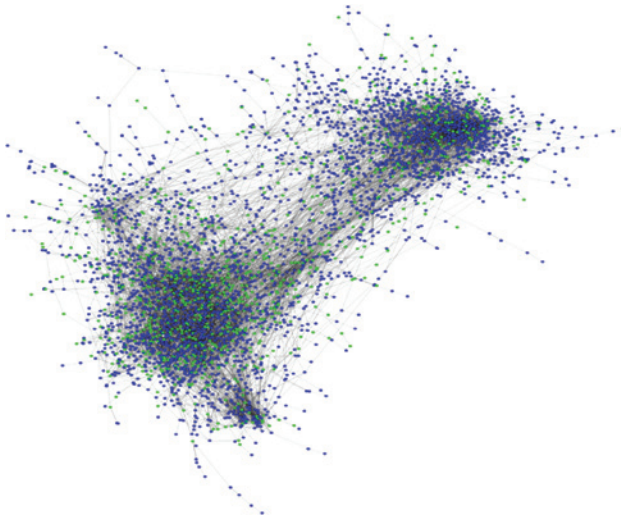
Figure 1: Friendship network of the freecycling group in Facebook (blue points – females; green points – males).

4399 to 4818, thus we can be sure that the same individuals were followed in the dataset (see Figure 2).

In this study, we will use a subset of the data, which contains information on whether a user has posted on a certain day, commenting behavior, his or her membership data (e.g. length of stay in the group) and individual friendship network properties (see Table 1 for descriptive statistics). Since data were not
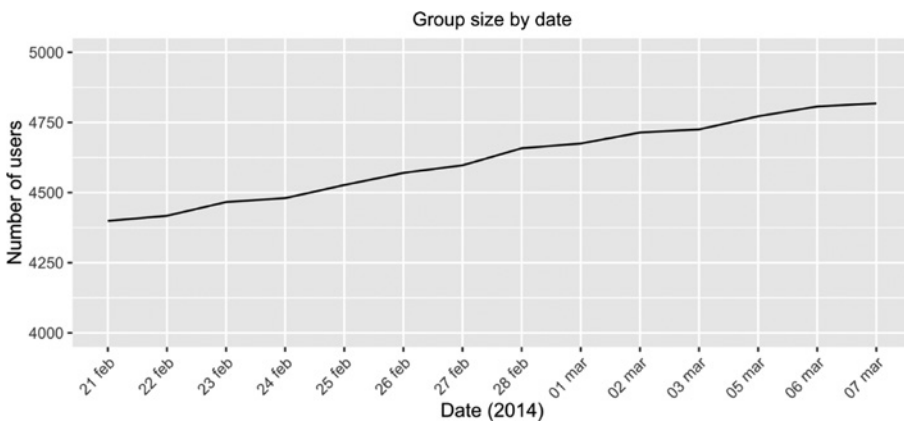

Figure 2: Number of members in the freecycling Facebook group by date.

Table 1: Descriptive statistics.

N = 64,625 (multiple obs per individual)	Mean/%	SD	Range
Dependent variable			
Posting behavior	0.005	0.07	0–1
Independent variables			
Commenting behavior (past 3 days)	0.090	0.63	0/18
Length of stay	23.864	6.89	1/33
Total posts observed (past 3 days)	39.186	15.49	0/87
Controls			
Total number of comments (past 3 days)	411.377	81.41	0/529
Degree centrality	5.046	5.78	0/58
Local clustering coefficient	0.134	0.225	0/1
Day 1	0.008		0–1
Newcomer (N = 4910)	0.105		0–1
Female (N = 4910)	0.738		0–1

collected daily between the first and last day of data collection, we use a subset of the original dataset. This subset contains 14 daily observations between February 21 and March 7, with an exception of March 4, which is not included in the data.

3.1. Dependent variable

Our dependent variable is a dichotomous variable indicating whether a person made a new post (offered an item) on a particular day. Group posts contain listings of shared items and unrelated posts (e.g. discussions and requests) are removed by group administrators. This variable therefore indicates occurrences of sharing behavior for each individual on a particular day. We constructed this variable from the interaction data retrieved via *Netvizz*. The data only provides a number of posts a person had online each particular day. We coded the dependent variable as '1' if the count of posts that an individual had on a certain day exceeded the number of posts the same person had had a day before. This means that our variable could underestimate the total number of posts as some of them might have been published and deleted on the same day. We also coded the variable as '1' for those individuals that had any number of posts online at the first day of the data collection.

    We cannot be certain whether an item in the post was actually given away to some group member. Although virtually all posts received comments, we cannot know from the data whether an offline meeting took place and the item was given away. We argue, however, that posting an item listing on the group already shows the intent of a user to give an item away.

    In our analyses, we will estimate how individual's likelihood of sharing behavior (i.e. number of posts being equal to 1 on a particular day) depends on variation in several independent variables over time.

3.2. Independent variables

To test the first hypothesis, we use *commenting behavior* of individuals in the group as a proxy for receiving an item. Comments in the freecycling group are intended to express willingness of a certain user to receive the posted item. There is no way, however, to directly measure which users out of all who have commented actually received an item, since this communication moves to the private messaging system of Facebook, which is not available for data collection. Therefore, we use the rolling sum of the number of comments over three day windows as a proxy of getting an item. For each particular day, we calculate the sum of all comments that the user has posted in the previous three days. We assume that the probability that an individual has actually received an item grows with each subsequent comment he or she has made. Since the receiver of a particular item is selected randomly from only those people who make comments under an item offering (see Figure 3 for an example of item offering), and the overall commenting activity in the group is very low (see 'Results' section), the probability that a commenter received an item is likely to be associated with the total number of comments. We control for the *total number of comments* made in the group during the same 3-day window, to account for the fact that the likelihood of a commenter receiving an item also depends on the number of other group members who are willing to receive an item. We cannot link each user's comment to a particular item and therefore can only control for the total number of comments in the entire group and not on a particular item the user has commented on.

To test hypotheses 2a and 2b, we use two alternative measures: *the length of time* and *number of posts observed*. The length of time reflects how long each individual had stayed in the group until the time of observation. We can only measure the length of stay for each individual starting with the date we began collecting the data, since information about membership prior to data collection is not available. The beginning of data collection precedes the one we use in this dataset, since we are using a subset of a larger dataset. Therefore, the length of stay for each individual can range up to 33 days. Accordingly, each individual receives the duration of stay equal to "1" on the first date of data collection, but this value might be higher for the first observation of each user in the subset we use in the analyses if a user was observed before that date. Variable "number of posts observed" captures the total number of posts each individual has observed during previous 3 days. The variable is constructed by summing up the number of all unique posts made in the group up to 3 days prior to the date of observation. We assume that individuals actually observe the posts made in the group, which might not always be the case.

Additionally, we control for several network characteristics to find out whether having friends in the group or being central in the friendship network is associated with posting activity. Specifically, we look at *degree* and the *local clustering* coefficient to control for friendship network characteristics of each individual. Each of these measures reflects different aspects of an individual's network ties.

6 winterjurkjes 1witte blouse (niet gestreken) 2 rokjes 2 korte broeken 1
zomerjurkje 2 truitjes en een broek! Vanaf maat 116 tot 140. Alleen voor
mensen die het echt nodig hebben! Geen reactie = container!meerdere
reacties = loten! Geen zielige berichtjes in pb ben ik niet gevoelig voor!!!!
Op te halen in Overvecht.

Like · Comment · Share

graag
51 mins · Like

Ik loot graag mee 😊
26 mins · Like

graag zou ik het op komen halen
24 mins · Like

*Figure 3: An example of a typical item offer (children's clothing) and item requests (comments)
in the group. The highlighted text above the picture reads, translated from Dutch: "Only for
people who really need it! No response = trash! Multiple responses = lottery! No desperate
private messages please, I'm not sensitive to that! Pick up in Overvecht!". The three comments
read "yes please", "I'd like to participate in the lottery please ☺"and "I'd like to come and
pick it up," respectively.*

Degree centrality captures the number of Facebook friends each user has in the
group. Interestingly, only 16.8% (N = 825) of all individuals have no friends at
all in the group, while the average degree is equal to 5, which hints at possible
recruiting effects in the group. Degree centrality might be related to both sharing
and commenting behavior (e.g. because of peer pressure or due to reactions to
friends' posts). The local clustering coefficient captures to what extent friends of

a user also know each other. To the extent that sharing is driven by group norms, it may be expected that these norms can be more adequately enforced in networks with higher closure (Coleman 1990).

Finally, it is possible that users might join the group only in order to give away a particular item or comment on an item they observed prior to joining the group. To account for this possibility, we control for *group entry*. We add a dummy, which has a value of 1 on the first observation of a user, if he or she joined the group during the data collection. We code users who were already on the group on the first day of data collection as zeros on this variable. We also add a dummy for *newcomers* – individuals who joined the group during data collection. We have less information about people who were already in the group before data collection. It is possible that their commenting and sharing activity differs from those who are observed from day 1. The newcomer variable differs from group entry in that it is an individual level (level 2) variable, while the latter one is an individual-time variable (level 1) and marks a particular daily observation of an individual. Finally, we control for the *gender* of each individual.

3.3. Method

We use a multilevel mixed-effects logistic regression model to test our hypotheses (Stata 'melogit'; StataCorp 2014). In our data, each individual is observed multiple times (days). In our model, all the cases are nested within individuals, making each individual a "group" consisting of date-to-date observations. There is a total of 50,228 observations across 4795 individuals, as most of the individuals in the group had joined before the beginning of data collection.

4. Results

Descriptive results show that the general activity of the group members is relatively low. Figure 4 shows that each day there were from 58 to 87 items "on the market". However, the number of new items added each day was relatively low compared to the group size (almost 5000 members) and did not exceed 22 new items per day. There are on average 20.3 new comments posted each day for each new item on the group, which shows that users try to receive items much more frequently than share themselves. Descriptive analysis of the full dataset (Feb 3rd–Mar 07, 18 time points) shows that only around 8% of all the users in the group had ever commented and 2.8% of them posted, while only 4.9% and 1.8% commented and posted during the period of our analyses. Out of all the people who have ever made at least one comment, 12.31% have also shared something, while almost 36% of all those who shared, also commented. Thus, although sharing is a much less prevalent form of behavior than trying to receive an item, sharing might also be associated to receiving.

Table 2 provides the results of the 3 step-wise multilevel logistic regression models. Model 1 includes length of stay (H2) and control variables. We start with this model as a base model, since length of stay is also a measure of time,
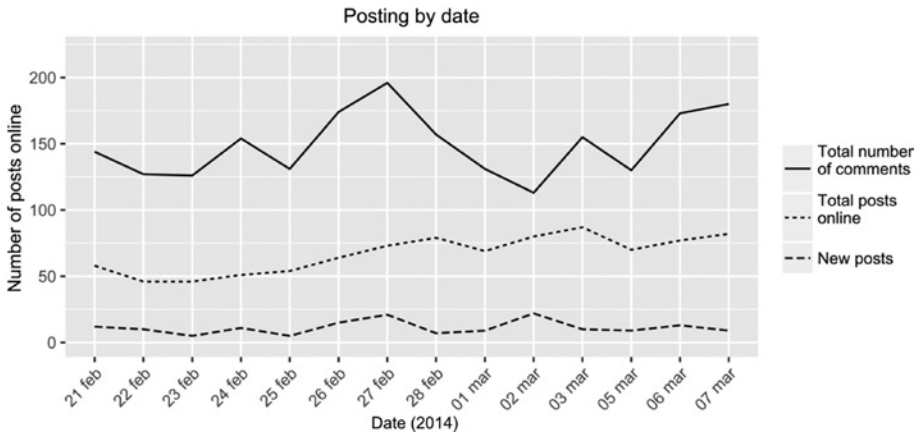
Figure 4: Number of posts in the group by date.

which is important to be included in all subsequent models. Model 2 also includes commenting behavior (H1) and a control variable for the total number of comments. Model 3 includes the number of posts observed along with the variables of Model 2, and is used as an alternative test for hypothesis 2. The intraclass correlation (ICC) of the random-intercept only model (not shown) is 86% (s.e. = 0.025), which shows that the majority of differences in posting behavior is between individuals and not across time for each individual.

The results in Model 1 show that the duration of group membership is positively associated with the likelihood of sharing. With each day spent in the group, the odds of the individual to share increases 1.05 times. This result is in line with hypothesis 2a and hints to a possible effect of social learning taking place (H2a). Additionally, we find that individuals who joined the group during the time of data collection have odds of sharing 6.9 times higher than those who were already in the group (p = 0.006). While this effect might seem inconsistent with the social learning hypothesis, it might be that a fraction of individuals only join the group to share a particular item. After the activity of these individuals is controlled for, social learning effects might take place. It does not necessarily contradict the previous finding, which shows that the odds of sharing increase with time spent in the group. We also find that female users have 2.7 times higher odds to share than males. This result, along with the high relative representation of females in the group (74.5%) shows that women might be more active in sharing behavior. Model 1 also indicates that there is no significant effect of degree centrality and local clustering. This model explains a modest 15.2% of initial variation in sharing behavior between individuals.

The results in Model 2 shows that commenting behavior during the recent 3 days has a positive significant effect on the likelihood of sharing (exp(B) = 1.351; p = 0.004). This effect is significant after controlling for the total number of com-

Table 2: Multilevel logistic regression on posting behavior in the freecycling group.

N = 64,625 N (groups) = 4910	M1		M2		M3	
	B (S.E.)	Odds ratio	B (S.E.)	Odds ratio	B (S.E.)	Odds ratio
Intercept	−15.691 (1.53)		−15.153 (1.37)		−15.837 (1.42)	
Length of stay	**0.047** (0.01)**	**1.049**	0.029 (0.01)	1.029	**0.037* (0.01)**	**1.038**
Commenting behavior (past 3 days)			**0.301** (0.10)**	**1.351**	**0.304** (0.10)**	**1.355**
Total posts observed (past 3 days)					**0.009* (0.00)**	**1.009**
Total comments (past 3 days)			0.001 (0.00)	1.001	0.002 (0.00)	1.002
Log(Degree)	−0.308 (0.20)	0.734	−0.310 (0.19)	0.732	−0.319 (0.19)	0.726
Clustering coefficient	−0.802 (0.83)	0.447	−0.777 (0.81)	0.459	−0.759 (0.81)	0.467
Day 1	0.819 (0.74)	2.269	**1.502* (0.74)**	**4.494**	**1.955* (0.79)**	**7.069**
Newcomer	**1.929*** (0.70)**	**6.886**	**1.636* (0.70)**	**5.135**	**1.873* (0.72)**	**6.510**
Female	**1.007* (0.42)**	**2.737**	**0.998* (0.41)**	**2.713**	**0.998* (0.41)**	**2.713**
Variance (intercept)	22.361 (5.07)		19.219 (4.03)		19.220 (4.03)	
Log likelihood	−1227.917		−1220.148		−1218.197	

*– significant at p < 0.05.
**– significant at p < 0.01.
Statistically significant coefficients provided in bold.

ments in the group and is in line with H1. The effect of commenting behavior also reduces the significance of the effect of length of stay in the group (p = 0.103). Similar to Model 1, we find that individuals who have joined the group during the data collection are more likely to share (exp(B) = 5.135; p = 0.021) and especially on the first day after joining the group (exp(B) = 4.494; p = 0.045).

Model 3 shows a modest in size, but statistically significant positive effect of the number of posts observed on sharing behavior (exp(B) = 1.009; p = 0.048). This finding is in line with the positive effect of user's length of stay, which is significant again in this model (exp(B) = 1.038, p = 0.042), which confirms H2a (social learning effect) and rejects H2b (social loafing effect).[6] Individuals who stay in the group for a longer time and therefore are more likely to observe sharing by other users, are more likely to share themselves. The size of this effect, however, is much smaller than that of commenting behavior, even given the unequal range of these variables. In the final model, we still observe that individuals who have recently joined the group are more likely to share (exp(B) = 6.510; p = 0.010), especially on day 1 (exp(B) = 7.069; p = 0.014). As discussed before, these findings might hint that there are some individuals who join the group specifically to give some item away.

5. Conclusion and discussion

In this paper, we analyzed social mechanisms that increase individuals' likelihood to participate in the sharing economy. In particular, we were interested in why an individual would be generous to strangers, when he or she receives nothing in return and no potential reputation benefits in the future. We examined the potential problem of free-riding in a part of the sharing economy, namely, non-reciprocated exchanges in freecycling groups. Individuals in these groups offer their personal items of diverse monetary value to individuals they usually do not know, and receive nothing in return. We would expect that free-riding behavior would emerge in such groups, since there are no incentives to share, but many incentives to claim items for free. As a result, free-riding behavior could be harmful for the sustainability of such groups in the long run.

We reviewed several theories that explain why sustainable cooperative behavior could emerge under such conditions. One possible explanation is that prosocial behavior, such as giving items away in freecycling groups, might be contagious– a member who received something is more likely to pass the favor on to another person in the group. Additionally, it has been argued that individuals might not only pass on the behavior that they themselves have received but also be more likely

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[6] We also tested Model 3 with non-linear (quadratic) effects of users' length of stay and the number of posts observed, since it has been found in previous literature that social loafing effect (H2b) might only take place after observing very high levels of sharing behavior. We found no significant effects, however, which helps to further confirm a social learning effect (H2a) and reject social loafing effect (H2b).

to share if they observe third parties get involved in sharing behavior (Tsvetkova and Macy 2014). In the case of freecycling groups or other groups, individuals might be more willing to share once they get acquainted with group norms, for example, what kind of items are shared, how the posts are made and how the actual exchanges take place. Although this theory cannot explain how sharing emerges, it can shed light on inactivity of some individuals in the group – while it may seem like free-riding behavior, these individuals might actually observe and get acquainted with group norms before acting. On the other hand, exposure to cooperation might increase social loafing. In other words, if everyone is giving away their things online anyway, one might not feel inclined to do so.

We tested the hypotheses of contagion of sharing behavior and social learning using longitudinal data from a freecycling group in Facebook. Our results confirm the social contagion hypothesis. We also find some evidence of a relatively small effect of social learning. We operationalized *receiving an item* as the cumulative sum of the number of comments an individual had made over the period of three days, assuming that with each comment the probability that an individual actually received an item increased. The results show that with each comment made within a three-day window, individuals were more likely to share an item themselves. The duration of stay within the group and observing other users' sharing behavior, which we used as proxies for social learning, showed to increase an individual's likelihood to share.

Although both effects are statistically significant, the effect size of social learning on sharing behavior is much smaller than that of commenting behavior. It is therefore possible that while some individuals are more likely to share after they observe others do the same, the most important effect that helps sustain sharing behavior in the analyzed freecycling group is generalized reciprocity or paying the favor forward. This result is only partly in line with the experimental evidence of Tsvetkova and Macy (2014), who also found a positive effect of generalized reciprocity and some results in line with both social learning and social loafing. Namely, they found that observing others' sharing behavior might help, but observing high levels makes people hesitant to share, since the overall level of sharing is high already. We cannot confirm any effect of social loafing taking place. Individuals in the freecycling group share more over time and with more generosity of others observed. This tendency does not change with time or level of sharing observed.

We also found that individuals who had recently joined the group were more willing to share than older members, especially on their first day of being a member of the group. It is possible that some individuals know the purpose of the group prior to participating and join the group only in order to give some particular item away. While this finding may sound like a contradicting effect to that of social learning, it is possible that both of these effects operate in the group. Alternatively, it is also possible that observed and learned social norms have a temporary effect and an individual's likelihood to share declines again after some time if no other mechanisms sustain it.

Additional findings revealed that, interestingly, there are large gender differences in sharing behavior. Female users were much more prevalent in the freecycling group, accounting for 75% of all individuals, although there are only slightly more Dutch female users of Facebook (estimated 53%, 2016; Statista 2016). Additionally, these users were about 4 times as likely to share as the male users. Gender was largely excluded from experiments and analyses reviewed in this paper. Gender differences in sharing behavior online could be an interesting prospect for future research.

Finally, we did not find any results regarding network centrality, which shows that friendship relations might only play a marginal role in this type of sharing groups, as interactions mostly happen between strangers. Individuals who have more friends in the group or are more central, do not share more. This question was not in the center of our paper, however, and network effects could be an interesting prospect for future research. Although one of the assumptions made in this paper was that interactions take place between strangers, this is in fact an empirical question. Additionally, we took into account the number of Facebook friends within the group, but not the activity level of those friends. It might be the case that social learning has different effects when reinforced by friends. Sharing friends might exercise a stronger normative influence or even control on an individual than strangers.

It is possible that sharing behavior to some extent could also be explained by individuals' altruistic motivations and preferences. Analysis of individual preferences was unfortunately beyond the scope of this paper. On the other hand, it could be argued that the effects we found can be explained away by individual preferences to only a limited extent. If we assume that such preferences are constant over time, we should not observe co-occurrences of receiving and sharing behavior over time, nor social learning effects. Assumptions about intrinsic motivation of individuals might be important in explaining why people join freecycling groups in the first place, or who are the "early birds" in the beginning of such groups.

This paper sheds light on sharing behavior as a socially contagious phenomenon and on micro-level mechanisms that increase cooperative behavior in environments in which such behavior is not directly reciprocated and no sanctions are possible. Obviously, our findings provide only the first steps in answering broader questions on the conditions under which generalized exchange systems such as online freecycling groups are successful. Future research could focus on the diffusion dynamics of sharing given the contagion mechanisms that we identified, or aim to specify macro-level conditions that foster the operation of these mechanisms. Our findings suggest, for instance, that group-level rules that ensure that goods are shared among many *different* people (and the convention of lottery systems in place in many groups might be interpreted as such) may be more effective in promoting further sharing than activities that emphasize group norms on sharing. Such questions, however, are beyond the scope of this paper. In the remainder, we discuss the limitations of our study and the possibilities of doing further analyses.

6. Limitations and feasibility of further analyses

There are several data-related limitations that should be addressed in future analyses. First and foremost, the data used in this paper covers a period of 14 days. The comparison of activity in the overall coverage in the dataset (Feb 3rd–Mar 07; 18 observations; 8% of users commented and 2.8% posted) and data used in the subset of this paper (Feb 21nd–Mar 7th, 14 observations, 5.7% commented, 2% posted) shows that even a small increase in the number of observations and period of time could increase the fraction of active individuals significantly, which, otherwise, might lead to wrong conclusions about sharing behavior and overall activity. Additionally, a longer period of time is necessary to adequately test the effects of social learning via observation. An optional scenario could be a more "balanced" dataset, which includes only individuals who have joined the group during the data collection and follows their behavior over time.

The second limitation is that we do not directly observe who receives items. It is quite hard to overcome this obstacle, since recipients of items receive private messages that cannot be collected. The main limitation of this approach is that the quality of the proxy that is used, namely commenting behavior, cannot be assessed. It might be the case that some individuals are merely more active Facebook users, thus they comment and post more, although it is interpreted as contagion in the analyses. It is also likely that both commenting and posting are caused by a confounding variable, for example age, which is not observed. Younger users tend to be more active in social networks than older ones, which could explain the co-occurrences of commenting and sharing.

Thirdly, and related to the previous point, we have no direct insight in how sharers choose the recipients of their items. Most sharers explicitly announce that they will do so using a lottery, but we have no way to verify that they actually do this (nor do the potential recipients). It is possible that, despite their promise, sharers deal out favors to certain group members. This, in turn, opens the door to reputation effects: in this way, individuals who share more might also receive more as a reward. Although we cannot exclude such dynamics, we also do not have any evidence that this is the case.

The data of the freecycling and other related groups in Facebook, however, could help to overcome many of these limitations. Although receiving cannot be observed directly, data from smaller groups with a lower overall number of comments could be collected, which would increase the likelihood that the commenter actually received an item. This would also be less time-consuming and could provide opportunities to collect data from multiple groups for comparison or even analysis with variables on the group level (e.g. network structure or institutional arrangements). A longer period of time of data collection could also help to follow the activity of the users more precisely.

Overall, many of the research articles on sharing economy reviewed in this paper are focused on possible consequences for current patterns of consumerism on the global scale, the meaning of sharing for individuals, their norms, ritualistic aspects of

sharing and outcomes to identity (Arsel 2013). A large fraction of these articles rely on descriptive qualitative data, while only a few of them focus on social dynamics and structural, network effects. Further research on the sharing behavior in Facebook groups could provide valuable additions to the current body of literature.

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