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Working Paper

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cege Discussion Papers, No. 269

Provided in Cooperation with:
Georg August University of Göttingen, Department of Economics

Suggested Citation: Gaudeul, Alexia; Giannetti, Caterina (2015) : Privacy, trust and social network formation, cege Discussion Papers, No. 269, University of Göttingen, Center for European, Governance and Economic Development Research (cege), Göttingen

This Version is available at:
https://hdl.handle.net/10419/123509

Center for European, Governance and Economic Development Research
cege

Discussion Papers

Number 269 – December 2015

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ISSN: 1439-2305

Privacy, Trust and Social Network Formation

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30th November 2015

Abstract

We study in the laboratory the impact of private information revelation on the selection of partners when forming individual networks. Our experiment combines a "network game" and a "public-good game". In the network game, individuals decide with whom to form a link with, while in the public-good game they decide whether or not to contribute. The variations in our treatments allow us to identify the effect of revealing one's name on the probability of link formation. Our main result suggests that privacy mechanisms affect partner selection and the consequent structure of the network: when individuals reveal their real name, their individual networks are smaller but their profits are higher. This indicates that the privacy costs of revealing personal information are compensated by more productive links.

Keywords: privacy, social networks, public goods, trust

JEL Classification: D12, D85

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The authors thank Michael Kammer, Oliver Kirchkamp, Alessio Moneta and participants at the ZEW Conference on Information and Communication Technologies in Mannheim for useful comments and suggestions. The experiment was funded by the Max Planck Institute of Economics in Jena. The authors thank Ria Stangneth for her excellent work in programming the experiment and Clara Dubois for her help in running sessions in the lab.

Having given both to the just and the unjust power to do what they will, let us watch and see whither desire will lead them. (The Ring of Gyges, Plato)

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1 Introduction

A massive amount of information about individuals is disclosed through social networks, such as hobbies or tastes in music and books, but also personally identifiable information such as names, birth-day and place. Surprisingly, this is done with the consent and participation of those individuals. Indeed, they fill in and update this information over years. Apparently, the perceived benefits of such a disclosure outweigh the possible costs that could arise from a misuse of this information – the privacy risk. Much of the research on privacy risk has focused on how firms gain personal information from individuals, by offering them discounts, better targeted ads and personalized services in exchange (see, for example, Acquisti and Grossklags (2005, 2007), Goldfarb and Tucker (2011)). The main objective of these studies was to study the economic consequences of consumers' decisions about protecting and sharing their data (see for a review Acquisti et al. (2015)). From this strand of literature, it emerges that social media networks have facilitated a culture of disclosure, with privacy choices being in the hands of consumers, and that many consumers lack the awareness and technical abilities to protect their personal information. We argue in this paper that disclosure of private information on social networks also serves an instrumental purpose, as people who reveal personnally identifiable private information in social networks are better able to connect with others and develop fruitful relations. Even those who dislike revealing personal information and know how to protect it may thus want to reveal it.

Our experiment is inspired by the debate about the conflict between protecting privacy online and protecting Internet users from anonymous attacks. Many social networks allow members to be active anonymously. However, while this (online) anonymity and invisibility gives individuals the freedom to disclose more about themselves, it can also lead them to "toxic disinhibition" (*e.g.* posting inflammatory messages in public forums, see Suler (2004), Belk (2013)). For this reason, content providers, social networking platforms and community sites are moving

towards lifting the veil of anonymity online. At the same time however, governments around the world are considering new privacy regulations which would restrict the processing and disclosing of such personal data (see *e.g.* the European Privacy Directive). For example, in Germany, Facebook is not allowed to require its users to use their real name, a policy that it applies in other countries. Despite this debate on the desirability of being able to identify or not people online, there has been no systematic study to evaluate the effect of revealing personally identifiable private information as an endogenous force in the process of network formation. Our contribution aims to fill this gap; we intend to show that being able to (but not forced) to reveal one's identity can enable people to develop relations in a context that is otherwise anonymous and disincarnate.

We report the results from an experiment that we conducted on a pool of subjects, mainly students at a German University. This experiment was designed to model the privacy concerns that arise in social networks. In all treatments, participants played a game with two phases, the "public good phase" and the "network formation phase". In the public good game, individuals needed to decide whether or not to contribute. If they contributed, they incurred a cost for each link formed but members of their network of bi-directional links received benefits in excess of the cost of the contribution. In the network formation phase, which happens after the choice of contribution in the public good phase, individuals, who were randomly matched in groups of five, decided individually whether to form a link with other individual members of the group. A link between two members (a dyad) was formed only when both individuals expressed the desire to form the link (*i.e.* the link had to be bi-directional). The purpose of the game was therefore, for a contributing members, to try to form profitable links with as many other contributing members as possible, and avoid costly and fruitless links with non-contributing members. Non-contributing members simply had to attempt to link with as many other members as possible.

Across all treatments, the monetary costs was kept constant. If a participant decided to link to someone else *and* to contribute, (s)he always incurred the same fixed monetary cost. If the participant decided to link *without* contributing, (s)he did not incur any monetary cost.

The non-monetary costs of each link, however, varied across our five treatments, which only differed in the type of information participants could decide to disclose about themselves during the network formation phase, and decide to be re-

vealed at the end of the experiment. In one treatment (*Names+Info*), the information consisted of the real name of participants, along with whether the individual contributed or not. In this case a non-monetary cost (*i.e.* a privacy cost) could arise if a participant, who decided to form links, was then identified as a non-contributor by other members of the group at the end of the experiment. This privacy cost was different among participants, as it depended on their sensitivity to the information produced in the lab: individuals may really dislike (or not care at all) about their name being associated to non-contributing behaviour. In another treatment (*Names*), the real name of participants could also be revealed, but subjects could not learn afterward which individuals had contributed or not. Other treatments included a baseline, with no information attached to any participants, and two treatments to control for the possible impact of the simple revelation of "a name" (*Fake Name*), or of incurring a cost (in this case, monetary) in giving a name (*Fee*).

Our goal in this experiment is to identify individuals' willingness to reveal information about themselves when there are no-direct monetary benefits associated with self-disclosure except promoting the development of one's individual network. In particular, we are interested in the effect of revealing one's name on the probability of forming productive links with other members of the network. The choice of a "public good game" is motivated by its similarity with provision of information on social networks. Indeed, information provision in social networks can be viewed as a non-excludable good that can be accessed and used even by people who did not make the effort of contributing information about themselves. The more people reveal about themselves in a network – which requires effort – the more valuable is the network. However, some individuals can free ride on the information provided by others without revealing anything of interest about themselves and their activity (see Goyal et al. (2014)).

Our work is the first economic experiment to consider privacy issues in network formation. Previous experiments mainly considered the impact of identification in standard games (e.g. prisoner dilemma). For example, Frey and Bohnet (1997) and Bohnet and Frey (1999) show that interaction in prisoner dilemma leads to higher cooperation rate than anonymity, and to larger amount offered in dictator game. Similarly, Charness and Gneezy (2008) consider the effect of revealing the family name of a participant's counterpart in dictator and ultimatum games. They find that in dictator games, revealing the name of the recipient results in more generous allocations, while in the ultimatum game it has no significant effect. A number of

studies on public good experiments have also investigated the role of anonymity in giving: Rege and Telle (2004), for example, show that the introduction of each person's identity significantly increase contributions in a repeated public good game as identification allows for social approval. For our research, these experiments are important as they highlight how identification of the participants impact on the interactions with other individuals.

Inspired by these experiments, we allowed participants to identify themselves in two treatments (*Names* and *Names+Info*), with participants' real names being our sensitive information. In these treatments, our participants could choose to remain anonymous rather than publicly disclosing their personal name to the other member of the group – we did not want to force participants to reveal their name, and we did not want either to invite only participants who stated in advance they would be ready to reveal their name. We always securely identified our participants by checking their identity based upon a legal document. This identity check was made in addition to checking the identity of the participants when they arrived in the lab. Our aim was to guarantee that participants, when they revealed their name, did so truthfully, so that other participants would be guaranteed that the names they saw on their screen were the real names or real participants (see also Feri et al. (2013) for more discussion of this requirement in our experiment). Our participants could therefore not lie when revealing their name, an issue that may be present in other experiments on the topic.

Beyond this experimental literature, our experiment is also related to the literature on network formation. The theoretical literature is vast and we do not attempt to summarize it here. It can be split into those that: (i) take the network as given and study equilibrium selection in a coordination game and those that (ii) allow the network to be chosen endogenously. Papers that follow the first approach are Ellison (1993), Kandori et al. (1993), and Morris (2000). Papers that follow the second approach are for example Bala and Goyal (2000), Jackson and Watts (2002) and Jackson and Wolinsky (1996). See Jackson (2005) for a review. Observational research on network formation is very limited compared to its theoretical advances (see Graham (2014) for a review). The main reason for this is that it is difficult (if not impossible) to use field data, since there are many confounding features in this environment (such as simultaneous influence, measurement errors). Moreover, it is difficult to formulate an empirical model in which agents' choices are interdependent, and knowledge of the structure of the network, as well as of the group

size and the linking opportunities, is imperfect. In this respect, controlled laboratory experiments provide a valuable tool to analyze network formation while controlling for all these factors. For these reasons, the number of experimental studies examining endogenous partner selection or network formation is rapidly increasing (see Falk and Kosfeld (2012), Caldara and McBride (2014)). The majority of these papers, however, mainly focus on the network architectures and their stability properties. A rare exception is Bravo et al. (2012) who highlight how endogenous selection of partners may have more important consequences (*e.g.* on cooperation and trust) than the structure of the network. They present an experimentally grounded agent-based model to investigate trust diffusion and cooperation, and show that when agents can choose their links, cooperation increase and free-riders are isolated. To the difference of Bravo et al. (2012), however, we did not rely on information about the past behavior of each individual subjects as a tool for partner selection, but rather on individual disclosing behaviour. Our main hypothesis is that – in the absence of past interaction experience – an individual's decision to reveal the name will be used by other participants as a predictor of that individual's contribution, and thus affect the choice to establish a link with him, and thus the structure of the network.

To summarize, none of the previous research has ever considered the effects of privacy issues on the choice of partner selection in the formation of a network. The contribution of this paper is thus to provide a simple experimental analysis of the effects of privacy concerns as an endogenous force in the formation of individual networks. To clearly identify these effects, we kept the structure of network as simple as possible, by allowing for directed links only within small clearly defined groups, and by giving our subjects the possibility to have their real name (and other similar actions) revealed to the other members of the group, along with information on contribution, at the end of the experiment.

We are interested foremost in whether individuals tend to reveal more of their personal information in order to get larger network. Is giving one's names an indicator of a more trustworthy person or does giving a fake name work similarly? Does giving a name, whatever that name is, make people more likely to contribute – the way pseudonyms work in some social networks? And finally, do we really need to reveal contributions at the end, along with, if so chosen, the name of the participant? Or does simply associating one's real name with one's contribution work as well – maybe by getting people to associate their behavior in the experiment with their

overall persona, so that their behavior in the experiment must be made to fit their own perception of themselves as an honest (or dishonest) person?

Our results suggest that our participants regarded the information generated in the public good-game as sensitive. The number of individuals who did not contribute and initiate links with others (*i.e.* those who attempted to "cheat") was significantly lower in the treatment where real names could be associated to the individual contribution at the end of the experiment. Our results also suggest that the share of individuals who contribute in the public good game was higher in treatments where real names were used – whether those names could be associated with contributions at the end of the experiment or not. Finally, we observe that the size of the network was substantially lower, but profits higher, when real names were used and disclosed in the lab. However, while contributors benefited by being better able to establish a mutual link by both revealing their name, a number of non-contributors also revealed their real name to attract links from contributors so as to exploit them. We conclude that privacy mechanisms (such as giving real names) can significantly affect the selection of a partner and the consequent structure and profitability of the network.

The structure of the paper is as follows: the next section describes the design of the experiment, along with the matching technology and the payoff structure. Section 3 introduces the dataset and the statistics used in the univariate analysis. Section 4 discusses the econometric issues and the models used in the multivariate analyses, while Section 5 presents the related results. Section 6 summarizes and concludes our argument.

2 Design of the experiment

There were five treatments in our experiment, each one holding different pools of 25 subjects. Table (1) gives an overview of the structure of experiment, while an English translation of the German instructions is provided in Appendix A. In the *Baseline* treatment, we randomly match participants in groups of five, and participants choose whether to contribute zero or five ECU (the contribution stage). Right after, at the link-formation stage, participants view a screen with the identifiers (namely 1, 2, 3, 4, and 5) of the other participants in their group, and can choose with whom to initiate a link with by ticking the relevant boxes on the screen. They repeated these steps over 6 periods, in each of which they never met again with the

same person (i.e. perfect strangers matching). For each treatment, this resulted in 150 individual observations, and $^{150}/_{5} = 30$ observations at a group level. At the end of the experiment, in the revelation and pay-off stage, one random period was selected for payment and payoff were realized. A participant receives nine ECU for each reciprocated link with someone who contributed, while (s)he pays five for each reciprocated links if (s)he contributed (see below for the complete payoff structure). In the *Names* treatment there are two additional stages: the decision-stage and the information stage. In the decision stage, just before the link formation stage, individuals are asked whether they want to reveal their decision to disclose their name to their peers right after the link-formation stage. At the link-formation stage, participants view a screen with the identifiers of the other participants (1, 2, ...,5) and their decision (Yes/No) to disclose their name in the following information stage (Figure (7) reproduces the computer screen at this stage). To ensure that real names are given, the experimenter checked the document of each participant with the name that was entered on the screen. This procedure is necessary to increase the sensitivity of the information generated in the laboratory (see also Feri et al. (2013)). However, to avoid that disclosing participants be indirectly identified by other participants because of the noise they make when typing the keyboard, we also asked non-disclosing participants to type in a random string of characters. Then, in the information stage, only the real names were revealed to the other participants (Figure 8 reproduces the computer screen at this stage). It is important to remark that only at this stage – that is after the linking decision – participants will see individuals' names. In so doing we can therefore isolate the pure effect of names (i.e. and thus of privacy concern) from those of other observable characteristics that could affect the linking choice when the name is revealed (e.g. gender, religion, see Charness and Gneezy (2008)). The *Names+Info* treatment was similar to the *Names* except that each participant is now additionally informed at the end of the experiment (i.e. in the revelation and pay-off stage) about the real names of the other participants (if disclosed) along with their contribution behaviour (see again Table 1).

To check whether real names have an additional effect to the use of nicknames, we ran the *Fake* treatment which is similar to the *Names+Info* except that each participant can now choose at the decision stage whether to reveal – in the information-stage – one of the two nick names (one male and one female) the experimenter provided close to their keyboard. Even in this case the experimenter controlled that

the chosen name is typed in correctly by each participant. Finally, to control for other social mechanisms, in the last *Fee* treatment, instead of revealing their name, participants can decide to pay a fee in the decision stage and to release this information.[1] At the link formation stage, therefore, participants view a screen with the identifiers of the other participants and (possibly) their decision to pay the fee next it.

By comparing the behaviour of our participants across the different treatments, we can thus isolate the pure effect of the individual identity on the selection of partner and the formation of a social link, distinguishing it from the effects of any other signaling device, such as paying a fee. More precisely, we can identify the effect of name-revelation on the probability of link formation.

2.1 Matching technology and payoff structure

In the link formation stage, each participant i simultaneously chooses whether or not to link with each other participants in the economy. In particular, letting I denote the set of five agents in the economy, participant i takes a *link proposal action* which is a 4-tuple $p_t^i = (p_{\{I\}}^i) \epsilon\, P_t^i = \{0,1\}^4$ in round $t = 1, 2..., 6$. The action $p_{j,t}^i = 1$ denotes a decision by agent i to link to agent j, while $p_{j,t}^i = 0$ denotes i's choice not to link to j at round t. A link at round t is established only if mutually agreed, that is iff $p_{j,t}^i \cdot p_{i,t}^j = 1$. A network is the set of all agreed upon links, $g_t = \left\{(i,j) \epsilon\, I :\ p_{j,t}^i \cdot p_{i,t}^j = 1\right\} \epsilon\, \Gamma$ where Γ is the set of all possible networks. We define a neighborhood of agent i in the network g_t the set of all agents to whom (s)he is bilaterally linked and denote it $N^i(g_t) = \left\{j :\ p_{j,t}^i \cdot p_{i,t}^j = 1,\ j \neq i\right\}$. The numbers of neighbours of agent i is the cardinality of $N^i(g_t)$ and is denoted $n^i(g_t)$. The set of feasible graphs varies from the complete graph - uniform matching (Kandori et al. (1993)) where each agent has n=4 direct links - to the marriage model where each agent has n=1 direct links.

In each round t at the contribution stage, each participant decides whether or not to contribute in this round, that is $C_t^i = \{No,\ Yes\}$, and then in the decision stage, (s)he can undertake a different action $A_t^i = \{No,\ Yes\}$ depending on the treatment. For example, in *Names* the action A corresponds to the name revelation, while in

[1] In this regard, the payment of the fee can be regarded as a kind of tag. In sociological term, *tags* are socially shared communication devices that connote certain groups. These are attributes or actions (such as dressing code) that might be used to predict others' behaviours (see for example Bravo et al. (2012), Axelrod et al. (2004)).

Table 1: EXPERIMENTAL TREATMENTS

	↑	⟶⟶⟶ *repeated over 6 periods* ⟶⟶⟶		↓	
TREATMENT	CONTRIBUTION STAGE	DECISION STAGE	LINK FORMATION STAGE	INFORMATION STAGE	REVELATION AND PAYOFF STAGE
Baseline	Individuals decide to contribute 0 or 5		Participants decide with whom form a link. For each participant only a generic identifiers is available.		One period out of six is selected for payment. Payoff are realized.
Names	Individuals decide to contribute 0 or 5	Participants can decide to disclose their real name.	Participants decide with whom form a link. In addition to the generic identifier, for each participant the decision (Yes/No) to disclose their real name in the next stage is provided.	Participants real names are revealed.	One period out of six is selected for payment. Payoff are realized.
Names+Info	Individuals decide to contribute 0 or 5	Participants can decide to disclose their real name.	Participants decide with whom form a link. In addition to the generic identifier,for each participant the decision (Yes/No) to disclose their real name in the next stage is provided.	Participants real names are revealed.	One period out of six is selected for payment. Payoff are realized. Participants real names (if disclosed) are revealed to the other participants along with their contributions.
Fake	Individuals decide to contribute 0 or 5	Participants can decide to disclose their (fake) name.	Participants decide with whom form a link. In addition to the generic identifier, for each participant the decision (Yes/No) to disclose their fake name in the next stage is provided.	Participants fake names are revealed.	One period out of six is selected for payment. Payoff are realized. Participants (fake) names are revealed to the other participants along with their contributions.
Fee	Individuals decide to contribute 0 or 5	Participants can decide to pay a fee.	Participants decide with whom form a link. for each participant the decision (Yes/No) to reveal pay the fee is provided.		One period out of six is selected for payment. Payoff are realized. .

Fee corresponds to the payment of the fee. We thus denote with $a_t^i = \{C_t^i, A_t^i\}$ each participant's action in round t.
The utility of agent i in any round t depends therefore on his actions and on the actions taken by his neighbors, that is

$$u_i(g) = \sum_{j \in N^i(g_t)} u^i(a^i, a^j) = \sum p_{j,t}^i \cdot p_{i,t}^j \cdot 9 \cdot C_t^j - 5 \cdot C_t^i \cdot \sum p_{j,t}^i \cdot p_{i,t}^j - C_{Treat}(A_t^i, C_t^i) \quad (1)$$

where $p_{j,t}^i \cdot p_{i,t}^j \cdot 9 \cdot C_t^j - 5 \cdot C_t^i \cdot p_{j,t}^i \cdot p_{i,t}^j$ are the monetary benefits and costs related to the i and j' contribution in the "public good game". The public good is therefore partially excludable as individuals can always protect it by choosing not linking with another participant (i.e $p_{j,t}^i \cdot p_{i,t}^j = 0$).
$C_{Treat}(A_t^i, C_t^i)$ represents the costs (either monetary or non-monetary) related to i's actions, which depends on the treatment *Treat=Baseline,.., Fee* (see again Table 1 for an overview of the treatments). For example, if i and j established a link in round t, and both i and j decided to contribute, the monetary benefits are 9, while the monetary costs are 5, for a net monetary payoff for i of $9 - 5 = 4$. In this case $C_{Names}(A_t^i, C_t^i)$ represents the non-monetary (i.e. privacy) costs in *Names*, which depend on i's name revelation and i's choice contribution. We assume that $C_{Names}(A_t^i, C_t^i) > 0$ if $A_t^i = Yes$ and $C_t^i = No$, that is the privacy costs are positive if a participant decides to reveal the name and has contributed zero, while $C_{Names}(A_t^i, C_t^i) = 0$ if $A_t^i = Yes$ and $C_t^i = Yes$, that is there are no costs when revealing the name if a participant has contributed 5.

2.2 Hypotheses

The standard procedure in experimental economics maintains anonymity among laboratory participants (see Hoffman et al. (1994)). The introduction of the individual identity in the setting of our experiment, lead us to formulate the following hypotheses about the contribution, the selection of partner and the formation of a social link.
Hypothesis 1. As long as individuals have preferences for social approval (Akerlof (1980), Rege and Telle (2004), Charness and Gneezy (2008)), the information on contribution behaviour is regarded as sensitive by our subjects and privacy concerns may arise. Therefore, individuals who reveal their name are more likely to be con-

tributors (for the fear of being found out as not contributing in *Name+Info*, for the possible association of own persona and beliefs about oneself with action of non-contributing in *Names*). However, if individuals do not care about their name being associated to non-contributing behaviour, or if the monetary rewards for exploiting a contributor are sufficiently high, privacy concerns are of a minor order.
We hypothesize that privacy concerns arise for the majority of our participants, and thus the number of disclosing individuals who did not contribute will be lower in *Names + Info* than in all other treatments.
Hypothesis 2. Since we expect that introduction of real names will serve as a disclipling device and make it less likely that revealing individuals make no contributions (Hypothesis 1), we expect that the possibility to reveal one's real name in treatments *Name+Info* and *Names* will increase the general level of trust towards disclosing individuals, thereby increasing the probability of establishing a reciprocal link between disclosing individuals (McPherson et al. (2001), Charness and Gneezy (2008)).
Hypothesis 3. Conversely, we expect that disclosing a fake name / paying a fee will not have any positive impact on contribution behaviour and on the probability of establishing a reciprocal link in treatments where social disciplining mechanisms are not available (i.e. in treatments *Fake* and *Fee*)
Hypothesis 4. The possibility to give names as a "truthful" signal of contribution, and to identify contributors by their readiness to disclose their name, will increase the probability of establishing a link between two contributors. Since there will be more contributors and more reciprocal links between contributors when real names are used, we expect that the overall profits will be higher in *Names+Info* than in other treatments.

3 Experimental data

The experiment was run between June and July 2013 at the Laboratory of the Max Planck Institute of Jena using z-Tree software (Fischbacher (2007)), and involved 125 students for a total of 5 sessions (i.e. 25 students per treatment). The average payoff was about 8.90 Euro. Each session lasted for about one hour and half, but did not start until all participants were familiar with the procedure. To ensure that subjects understood the game, a series of examples (non-payoff relevant) where provided both in the instructions and on the computer screen.

3.1 Descriptive statistics

One of the most important choice of our experiment is the individual decision to contribute or not in the game. We thus define a *contributor* an individual who decide to contribute five – regardless of the choice of revealing or not one's name (or paying the fee). Conditional on contribution, we can then distinguish different types of subject behaviour among participants. There are two types of extreme behaviour:

- **heavy cheaters:** subjects who contribute 0 and add all;
- **trusters:** subjects who contribute 5 and add all;

as well as intermediate types of behaviour

- **light cheaters:** subjects who contribute 0 and add some participant (but not all);
- **moderate trusters**: subjects who contribute 5 and add some participant (but not all);

In turn, these behaviours lead to different size and structure of the (individual) network. To study this issue, we construct an **indicator of network size**: the **potential of the network** is given by the *number of people added* in each round, while the *number of reciprocal links* created in each round (i.e. the degree of a node) give us a measure of the **actual size**. We can also construct a measure of the **density of the network** that gives us a ready index of the degree of dyadic connection in a population (i.e. a normalized version of the network average degree). The calculation is straightforward - known connections divided by maximum possible connections. An ideal, fully connected network would have a density of 1. For binary data, as in our case, the density is simply the proportion of all possible dyadic connections which are actually present, that is the ratio of the number of adjacencies that are present divided by the number of unique pairs (i.e. $(n * n - 1)/2$), see Graham (2014)).

Table (2) reports the summary statistics across treatments of our main variable of interests. First of all, we observe that the share of contributors is the highest in *Names+Info* (i.e 26.7%) and lowest in *Baseline* (i.e. 16.7%). We also observe that while the share of individuals who revealed the names is much larger in *Fake* (88%)

than in *Names+Info* (48%), the share of individuals who revealed the names and contributed is almost similar in the two treatments, being about 17/18%.
In all treatments – on average – the number of individuals added is quite high, being about 3.60-3.90 out of 4 individuals (i.e. about 90% of all possible links). In Figures (A.1)-(A.5) in the Appendix we further provide a detailed overview of the decomposition of people added according to each category of individuals, where we focus only on individuals who contributed (either revealing or not their name). In fact, non-contributors almost always add everyone in their group. From these figures we observe that those who revealed their name are more wary of participants who do not reveal their name in *Names+Info* (*i.e.* the share of individuals added who did not reveal their name is 23.8%=18.1+5.7), while in *Fee* contributors who did not pay a fee are particularly wary of individuals who paid a fee (i.e. the share of individuals added who paid the fee is 38.3%=13.6+22.7). In *Fake Name*, almost all participants "reveal" a fake name, so the treatment is very similar to the *Baseline*, where there are names to help select among different links.
Indeed, in *Names+Info* we observe that the share of heavy cheaters (i.e. those who contribute and add all) is (almost) the lowest, while the share of moderate trusters (i.e. those who contributed and add only some) is higher too (see again Table (2)). As a result, in *Names+Info* we observe the lowest number of reciprocal links and the lowest level of network density. In particular, even though this statistic remains extremely low, we observe that in *Names+Info* the share of reciprocal links that are established between two individuals who contributed is higher (as a proportion of all reciprocal link that were established): 6% of all reciprocal links, *vs.* 4% of all reciprocal links in the *Fake Name* treatment. In *Names+Info*, the share of reciprocal links where only one contributed is also higher, being about 36% in comparison with a share of 28% in *Fake*. The residual category (i.e. the share of reciprocal links where none contributed), which is very large in all treatments, is thus lower in *Names+Info*.
Finally, in *Names+Info*, we additionally observe the highest level of individual profits (2.8 ECU). These preliminary statistics combined suggest that in *Names+Info* participants are able to select more "productive" links.
Having finished this preliminary description of differences between treatments, we go one to assess the significance of those differences from a statistical point of view.

3.2 Univariate Analysis

We compare the previous statistics across treatments by reporting the mean of each group per period to account for the correlation of the observations at a group-level, and relying on tests for the equality of means in large sample (Table 3). At first sight, we observe that there are no significant differences between *Names* and *Names+Info*, the only exception being the share of people who revealed their names and contributed (+7% significant at 5% level). Significant differences emerge when we compare *Names+Info* with *Fake* and *Fee* treatments. These results are a first indication that our participants consider the use of real names and the information generated into the lab as sensitive, and different from other signaling devices.
More specifically, we can observe that the share of contributors is higher and statistically different when participants could use their real names. In particular, the share of contributors is 8% higher when we compare *Names+Info* vs *Fake*, and 11% when we compare *Names* vs *Baseline*. In all treatments, however, the share of contributors remains fairly low (below 30%) in all periods (see Figure 1).

Result 1 *The share of contributors is significantly higher in treatments where individuals can reveal their name (i.e. Names and Names+Info). In all treatments, however, the share of contributors is fairly low (below 30%).*

In addition, the share of individuals who reveal their fake names (+40%, significant at 1% level) or paid the fee (+10%, significant at 1% level) are substantially higher in comparison with *Name+Info*. See again Table 2. This is true in all periods, though towards the end of the experiments all treatments – with the only execption of *Fake* – tend to converge to similar share of individuals revealing the information (see Figure 2). We can further decomposed the group of disclosing individuals according to their contributing behaviour. As Table 3 and Figures 3-4 suggest, even though the difference between *Fake* and *Names+Info* are not striking when comparing the share of individuals who reveal names *and* contribute, there is a substantial difference between these two treatments when comparing the share of those who disclose their names *and* do not contribute (-40% significant at 1% level). As highlighted above, in *Names+Info* we can also observe a greater share of individuals who contribute and reveal their names in comparison with *Names* (+7% significant at 5% level) and *Fee* (+10% significant at 1% level). This result suggests that individuals do care about their real names being associated to non-contributing behaviour at the end of the experiment.

Result 2 *The share of individuals disclosing the information and contributing is significantly higher in Names+Info than in other treatments, while the share of individuals who disclose their info and do not contribute is significantly lower.*

As a result, when real names are used we do observe significant differences in terms of cheating behaviours: only a mild difference in the share of light cheaters of *Names* in comparison with *Baseline* (-3.3%), but important differences in the share of heavy cheaters of *Names+Info* in comparison with *Fake* and *Fee* (-6.7% and -10% respectively).
Trust behaviour is also different across treatments. In *Names+Info* the general level of trust is higher, though significantly only in comparison with *Fee*, where the share of trusters (i.e. those who contribute and add all) is 8% higher (significant at 1% level). We also observe that in *Names* the share of moderate trusters (i.e. those who contribute and add only some) is about 7% higher than in *Baseline* (significant at 5% level), while *Names+Info* the same share is 6% higher than in *Fake*. These latter results point to an effort of contributors to selectively choose their counterpart when real names are used. This is also confirmed if we look at the network graphs across treatments: when real names are used we rarely osberve the uniform matching (i.e. the star) that often emerge in the other treatments (see online Appendix). We thus conclude that real names can be used to selectively develop individual networks because when they are used the level of cheating is lower and trust between individuals is higher.

Result 3 *When real names are used the share of individuals who do not contribute but add all (i.e. cheaters) is significantly lower, while the share of individuals who contribute and selectively chose their partner (i.e. moderate trusters) is significantly higher.*

In terms of network size, we observe that the number of people added as well as the number of reciprocal links are substantially lower in *Names* with respect to *Baseline* (-0.24 and 0.413 individuals), and substantially lower in *Names+Info* with respect to *Fake* (-0.167 and -0.333 individuals). No differences exist between *Names* and *Names+Info*, and between *Names+Info* and *Fee*. These differences are remarkable at the beginning of the experiments, though they persist throughout the experiment. As a result, the density of the network is substantially lower than in the other treatments (-5%/-10%). In addition, the number of reciprocal links between people who contribute is substantially higher in *Names+Info* in comparison with *Fake*. Finally, we observe the profits are higher in *Names+Info* than in all other treat-

ments throughout the experiment (see Figure 5), though in mean comparisons only significantly with respect to *Fee* (see Table 3).

Result 4 *In Names+Info the size of the network (i.e. the number of reciprocal links) is substantially lower than in Fake and Fee, while profits are higher.*

All those results suggest that the combination of the revelation of the information at the end of the experiment along with real names help participants select more profitable links.

4 Multivariate analysis of Reciprocal Links: Dyadic regressions

In this section, we aim to study the probability of establishing a reciprocal link between two individuals relying on a multivariate setting. This approach allows us to jointly consider both contributing and disclosing behaviour as possible determinants of a link, as well as other individual attributes. To study network formation empirically a series of methods has been developed (see Bramoullé and Fortin (2010)). Among these, we chose to rely on dyadic regressions as in Fafchamps and Gubert (2007a,b) Mayer and Puller (2008), in which each observation expresses a relationship between pairs of individuals. Therefore, any pair of individuals i and j, either linked or not, constitutes an observation. The advantage of this method is to use information from both individuals (i.e. g_{ij} and g_{ji}) to identify the impact of individual similarity or dissimilarity (e.g. in the disclosing behaviour) on the probability of establishing a link. To apply this approach, therefore, the data must be organized in order to express for each individual the set of all possible links (expect with oneself). In our case, this consists of 4 observations for each individual (i.e. a total of 600 observations per treatment). Formally, we express with $g^*_{ij} = \alpha + \beta X_{ij} + u_{ij}$ the propensity of establishing a link, and with g_{ij}

$$g_{ij} = \begin{cases} 1 & if \quad g^*_{ij} > 0 \\ 0 & otherwise \end{cases}$$

the existence of a link between individuals i and j. g_{ij} is an $N \cdot (N-1)$ matrix, X_{ij}

is a series of $N \cdot (N-1)$ matrices.[2]

From Equation 1, we saw that a participant i derives a utility $u_i(g)$ from his network g, and this utility depends on the network structure. To tie back dyadic regressions with individual decisions, we need to assume *i)* the separability of the utility function 1 and *ii)* symmetry. That is, $u_i(g) = \sum_j u_i(g_{ij})$ and , $u_i(g_{ij} = 1) - u_i(g_{ij} = 0) = u_j(g_{ij} = 1) - u_j(g_{ij} = 0)$. The default assumption, which is consistent with our experiment ($g_{ij} = g_{ji}$ for all i and j as we have unidirectional dyadic relationships), is that every individual in the population is a potential partner.

The main idea behind this approach is that individuals choose which links to form with each other by performing a cost-benefit analysis of each link with the following form:

$$g_{ij} = \begin{cases} 1 & if \quad B(C^j) - C(C^i, d_{ij}) + e_{ij} > 0 \\ 0 & otherwise \end{cases}$$

where g_{ij} denotes the existence of a reciprocal link between individuals i and j, d_{ij} is a set of characteristics of individual i and j, and e_{ij} is the residual effect. In the experiment, the benefits of *reciprocal* links $B(C^j)$ are supposed to be constant: equal to 9 if subject j contribute (i.e. $B(C^j_t = 1) = 9$), and equal to 0 if (s)he does not contribute ($B(C^j = 0) = 0$) . The cost of establishing a link $C(C_i, d_{ij})$ can be decomposed into various components:

$C(C_i, d_{ij}) = C_{monetary}(C_i) + C_{privacy}(C_i, d_{ij}) + C_{typing} + C_{fee}$

In the experiment, the monetary cost of a reciprocal link is always constant across treatments, equal to 5 if the subject contributes (i.e. $C_{monetary}(C_i = 1) = 5$) and 0 if the subject does not contribute (i.e. $C_{monetary}(C_i = 0)$). In *Fee*, we also consider the possibility for subjects of paying an additional a fee to signal their commitment, thus incurring in an additional cost of 1 (C_{fee}). In *Names* and *Names+Info*, individuals may incur a privacy cost, depending both on the type of action associated with the links (e.g. contribution $C(C_i = 1, \cdot)$), and on the sensitivity of the subject to the privacy concern associated with this information ($C(\cdot, d_{ij})$). This cost will thus vary across subjects. The typing cost (C_{typing}) are constant across all treatments (but *Baseline*) as we asked each and every participants (even those not disclosing) to type their name or a random string of characters. In *Fake* we assume that this is the only cost our participants have to bear during the experiment. This procedure

[2]The total number of possible pairs is N^2 but we drop the N_{ii} pairs on the diagonal. This resulted in 600 (=25*24) observations for each treatment.

also avoids indirect identification of disclosing participants (see above Section 2). As Fafchamps and Gubert (2007a) highlight, it exists a problem of identification, which is related to the form regressors X_{ij} enter the regressions. When using dyadic data, we can distinguish two type of regressors: attribute w_{ij} of the link (such as geographical distance), and attributes x_i and x_j of the nodes i and j. Regressors must enter the dyadic regression in a symmetric fashion so that the effect of (x_i, x_j) on g_{ij} is the same of (x_j, x_i) on g_{ji} , and thus $\beta X_{ij} = \beta X_{ji}$. In our setting, we assume

$$Prob(g_{ij} = 1) = \Lambda(\alpha + \beta_1 I(x_i = x_j = 1) + \beta_2 I(x_i \neq x_j) + w_i + u_{ij})$$

where x are dummies equal to one if *Only one reveal, Both reveal, One contribute, Both contribute*, and $\Lambda(.)$ is the logistic cumulative distrubution. β_1 measures the effect of equal choice on g_{ij} (e.g. both contribute), while β_2 the difference of x_i and x_j on g_{ij} (e.g. only one reveal the name). That is, in case of a dummy variable, the effect of the combination (1,1) is β_1, while β_2 gives the effect of combination {(1,0) (0,1)}. The base category is the effect of the combination (0,0). It is important to notice, that only the variable related to the revelation of the information are observable to the other participants. The variable w_i is the number of people added in each round by individual i and aims to control for individual propensity to establish a link. In alternative specifications, we also controlled for individual risk aversion and general trust.[3]

Finally, as it essential to correct standard errors in dyadic regressions, we assume that $E(u_{ij}, u_{i,k}) \neq 0$ and $E(u_{ij}, u_{k,j}) \neq 0$ for all k. We therefore clustered error terms to account for correlation within dyads (i.e. the error term is also dyadic).

4.0.1 Dyadic regression robustness: The quadratic assignment procedure

Quadratic assignment procedure (QAP) is another method used in network analysis to study dyadic data to account for correlation across unobservables. In this case, however, it is not the covariance matrix to be corrected. The procedure consists instead in scrambling the dependent variable in the regression (in our case the dependent variable measuring the reciprocal link), while keeping the independent variable in the original observation positions. After scrambling a number of

[3]To derive the level of individual risk aversion we used the tasks of Heinemann et al. (2009), while the level of general trust is measured in the exit questionnaire with general questions about trusting others as in Gächter et al. (2004).

times, no significant relationship is expected between the dependent and independent variable, and an empirical sampling distribution is obtained. By comparing the actual coefficients with the empirical distribution, the null of no-statistical association between the variables can be rejected if the coefficients are at extreme high or low percentile of the empirical distribution (e.g. below the 1/5 and above the 95/99 percentile).

4.0.2 Dyadic regression robustness: multilevel analysis

A multilevel analytic approach is an alternative method to study dyads. Snijders et al. (1995), Snijders and Bosker (2011) distinguish between two levels of data in personal network studies: the level of the relation (the dyad) is the first and lowest level (level 1), and include attributes of dyads and attributes of alters within these dyads; the level of individual (level 2), and include attributes of the ego (such as personal characteristics). In our case, we have an additional level (level 3) as our individuals are randomly matched into groups.
We thus specify a three-level random-intercept logit model with individual i nested in dyad j who are nested in group k:

$$g^*_{ijk} = \alpha + \beta_1 I(x_i = x_j = 1) + \beta_2 I(x_i \neq x_j) + \zeta^{(2)}_{jk} + \zeta^{(3)}_{k} + u_{ijk} \tag{2}$$

where $\zeta^{(2)}_{jk}$is a random intercept varying over dyads (level 2), $\zeta^{(3)}_{jk}$ is random intercept varying over groups (level 3), and u_{ijk} is the residual error, with a logistic distribution. We will use this specification to verify the robustness of the results of the dyadic regressions, and a similar one to study the determinants of individuals profits.

5 Multivariate analyses: results

Logit estimates of the probabilities that a link exists in a pair (i.e. the results from dyadic regressions) are presented in Table 4, where the coefficients represent marginal effects estimated for each of the five treatment.[4] Before comparing the results across treatments (which is complicated by an identification problem inherent

[4]This is equivalent to estimate a model with full interactions between each variable and dummies for treatments.

in logit regression, see Long (2009)), let's start discussing the general results across all treatments.

As expected, in all treatments, the higher the number of people added the higher is the probability of establishing a reciprocal link. However, when real names are used (i.e. in *Names* and in *Names+Info*), the probability of establishing a link for an extra individual added is higher (about 12% vs 10%) than in other treatments. If we consider that the average number of people added is lower in this treatment (see Table 2 and 3), this result – as in the univariate analysis – points to a greater care by participants in selectively choosing their links.

In all treatments, the probability of establishing a reciprocal link between two individuals who contributed (i.e. $C_i = C_j = 1$) is lower than the probability of establishing a reciprocal link between two individuals who did not contribute (i.e. the base category). For example, in *Baseline* the probability that two contributors will establish a reciprocal link is 2.5% lower than between two non-contributors. In all treatment, this probability is also lower even when only one of the two individuals has contributed (i.e. $C_i \neq C_j$). For example, in *Baseline* the probability that a reciprocal link is established between one contributor and one non-contributor is 3.5% lower than between two non-contributors. As we have seen in the univariate analysis, the share of contributors is extremely low (about 30%): in general, even when controlling for disclosing behaviour, it is more likely to establish a link with a non-contributor.

Moreover, if both individuals committed the same action, that is revealed the information or paid the fee ($A_i = A_j = 1$), the probability of establishing a link is higher although it is only significant (at 1% level) when real names are used. For example, in *Names* the probability that a reciprocal link is established between two individuals who revealed their name is about 17% higher than the probability of establishing a link between two individuals who do not disclose their name, while in *Names+Info* is about 20% higher. The effect of different actions (i.e. $A_i \neq A_j$) are various and milder, but in all cases are never significant. These results suggest that the revelation of names is crucial and determinant to establish a link in these treatments. Results (not reported but available upon request) from the QAP procedure and from multilevels analysis are consistent, and robust to the inclusion of individual measures of risk aversion and general trust.[5]

[5]We refrain from adding any interaction terms in this regression as the model is non linear and the coefficients on the interaction terms (i.e. how the effect of one variable changes when another variable

We now compare the results in *Names+Info* with those in the other treatments. However, as the traditional tests of the equality of coefficients across groups in non-linear regressions is complicated by an identification problems (i.e. the residual variation confound the magnitude of the effects, see Long (2009)), we compare predicted probabilities across groups at multiple levels of the variable *People Added*. The results from this exercise are reported in Figure 6, which depicts the difference in probability between treatments along with the confidence intervals. As these figures highlight the differences are significant (i.e. the confidence interval does not contain the zero) only if we compare the predicted probabilities of *Names* vs *Baseline*, and *Names+Info* vs *Fake*, when only few people are added (less than 3). More precisely, in *Names+Info,* and when only few individuals are added, the probability of establishing a reciprocal links are between 10-20% higher. No significant differences emerge when many individuals are added, and with respect to the other treatments. This result is in line with the univariate analysis, suggesting that in these treatments individuals who use real names tend to select few but specific links. As we hypothesize, the revelation of names increase the level of trust towards those who similarly revealed their names, and help participants to selectively choose among participants.

Result 5 *In all treatments the probability of establishing a links between two contributors is significantly lower than the probability of establishing a link between two non-contributors. When both individuals reveal their names (i.e. in Names and Names+Info) the probability of establishing a reciprocal link increase significantly.*

Finally, Table 5 reports the determinants of individual profits per period. The dependent variable is now the total amount of individual profits resulting from all the established links in each period. These results suggest that, across all treatments, contributors earn significantly less than non-contributors (i.e. the base category). This is remarkable in *Fake*, where contributors earned about 20 ECU less than non-contributors. This result is consistent with previous experimental research on public-good games. Even if we will see that the use of real names partially mitigate this problem, non-contributors still manage to exploit contributors. In particular, we observe that in *Names+Info*, individuals who disclose their names earned about 5 ECU more (significant at 5% level) than those who do not disclose their

changes) do not provide the change in the partial effect of the variables on the conditional mean function. In addition, in some cases, the results of hypothesis tests are an artefact of the functional form and do not necessarily have an economically meaningful content. See Greene (2010).

names. That means, in this treatment, an individual who committed to disclose his name at the end of the experiment was able to earn 5 ECU more than an individual who did not commit to disclose his name. However, since the interaction term between dummies for contribution and disclosure behaviour is not significant, we can also infer that an individual who contributed and revealed the name did not earn significantly more than a non-contributor who commited to disclose his name. Therefore, although two contributors managed to establish a reciprocal link by both revealing their names, there is also a number of non-contributors who managed to establish a reciprocal link with a contributor by disclosing their name. Results (not reported but available upon request) that control for the number of reciprocal link established are consistent.

Result 6 *In all treatments contributors earn significanlty less than non-contributors. In Names+Info individuals who disclose their personal names earn significantly more (if non-contributors), or lose significanlty less (if contributors), than non-disclosing individuals.*

In line with the univariate analysis above, we thus conclude that individuals are able to select "more valuable" links through the privacy mechanism of real names. However, the privacy mechanisms is not enough to isolate non-contributors with a low cost of privacy loss, which are able to exploit contributors by revealing their name. This is a very simple mechanism at work, which however suggests that by increasing the privacy costs of individuals, it is possible to isolate from the network individuals who misbehave behind the veil of the anonimity.

6 Conclusion

We studied in the laboratory the effect of being able to reveal one's name on the selection of partners when forming individual networks, and on the likelihood to contribute to a (partially excludable) public good. Our experiment consisted of both a "network game" and a "public-good game". In the public good game, individuals decided whether or not to contribute. If they decided to contribute, they had to pay a fixed cost but the members of their network received a multiple of their contribution. In the "network game", they had to decide with whom to establish links. The variation in the privacy costs generated in our experiment allowed us to identify the effect of the readiness to reveal one's name on the probability of a link formation. More precisely, the privacy costs associated with the behaviour of our participants changed across treatments, while the monetary costs

remained constant. In two treatments, participants could decide whether to reveal their real name at the end of the experiment, either without revealing their contribution (treatment *Name*), or along with information on their contribution (treatment *Names+Info*). In three other treatments, there was no such possibility (*Baseline* treatment), or participants could disclose fake-names (treatment *Fake*) or pay a fee (treatment *Fee*).

Our results suggest that the number of individuals who did not contribute but initiated links with others was significantly lower when real names could be associated to the individual action at the end of the experiment. Our participants thus considered the revelation of information about their contribution as sensitive and tended to cheat less when the possibility to be individually identified existed. Moreover, the share of individuals who contributed in the public good-game was higher in treatments where real names were used. We also observed that when real names were used, the size of individual networks was substantially lower while average profits were higher, especially for those who disclosed their names. However, there were a number of individuals who misled others by using their own readiness to give their real name to pass as a likely contributor. We conclude that privacy mechanisms (such as revealing one's name) affect the selection of a partner and the consequent structure of the network. Allowing participants to lift the veil of anonymity, thereby increasing their privacy costs, can help them mitigate the exploitative behaviour of some network members and promote the establishment of fewer but more valuable links between people.

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Table 2: SUMMARY STATISTICS

	BASELINE		NAMES		NAMES+INFO		FAKE		FEE	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
% who contribute 5 (Contributors, i.e. $C_i = 1$)	0.167	0.374	0.213	0.411	0.267	0.444	0.187	0.391	0.153	0.362
% who reveal names (or paid the fee, i.e. $A_i = 1$)			0.447	0.499	0.48	0.501	0.88	0.326	0.547	0.499
% who reveal names & contribute (i.e. $C_i = 1$,$A_i = 1$)			0.1	0.301	0.173	0.38	0.18	0.385	0.073	0.262
% who reveal names & do not contribute (i.e. $C_i = 0$,$A_i = 1$)			0.347	0.477	0.307	0.462	0.7	0.459	0.473	0.501
% who contribute 5 and add all (Trusters)	0.12	0.326	0.1	0.301	0.12	0.326	0.1	0.301	0.04	0.197
% who contribute 0 and add all (Heavy cheaters)	0.773	0.42	0.727	0.447	0.687	0.465	0.753	0.433	0.787	0.411
% who contribute 5 and add some (Moderate trusters)	0.047	0.212	0.113	0.318	0.147	0.355	0.087	0.282	0.113	0.318
% who contribute 0 and add some (Light cheaters)	0.053	0.225	0.02	0.14	0.047	0.212	0.053	0.225	0.053	0.225
Nr of people added	3.82	0.625	3.58	1.051	3.607	0.882	3.773	0.625	3.707	0.719
Nr of reciprocal links	3.64	0.762	3.227	1.069	3.213	0.938	3.547	0.747	3.427	0.838
Nr of reciprocal links if only one contribute (i.e. $C_i \neq C_j$)	0.947	1.157	1.040	1.080	1.098	1.099	0.973	1.099	0.627	0.902
Nr of reciprocal links if both contribute (i.e. $C_i = C_j = 1$)	0.093	0.496	0.067	0.250	0.160	0.465	0.120	0.400	0.080	0.496
Nr of people added if only one reveal (i.e. $A_i \neq A_j$)			1.820	1.030	1.787	1.103	0.787	1.213	1.860	1.062
Nr of people added if both reveal (i.e. $A_i = A = 1_j$)			0.713	1.019	0.853	1.120	2.953	1.328	1.127	1.297
Nr of reciprocal links if only one reveal (i.e. $A_i \neq A_j$)			1.573	1.038	1.493	1.048	0.693	1.023	1.680	0.999
Nr of reciprocal links if both reveal (i.e. $A_i = A_j = 1$)			0.707	1.014	0.827	1.073	2.827	1.320	1.093	1.266
Share of reciprocal links if only one contribute (i.e. $C_i \neq C_j$)	0.270	0.325	0.338	0.337	0.362	0.338	0.284	0.327	0.207	0.318
Share of reciprocal links if both contribute (i.e. $C_i = C_j = 1$)	0.024	0.126	0.025	0.122	0.061	0.173	0.037	0.123	0.032	0.150
Share of people added if only one reveal (i.e. $A_i \neq A_j$)			0.428	0.254	0.400	0.274	0.179	0.261	0.444	0.259
Share of people added if both reveal (i.e. $A_i = A_{j=1}$)			0.219	0.308	0.272	0.357	0.756	0.329	0.291	0.335
Share of reciprocal links if only one reveal (i.e. $A_i \neq A_j$)			0.470	0.269	0.447	0.286	0.209	0.315	0.488	0.282
Share of reciprocal links if both reveal (i.e. $A_i = A_j = 1$)			0.233	0.324	0.278	0.366	0.784	0.329	0.313	0.349
Density	0.91	0.15	0.807	0.197	0.803	0.15	0.887	0.118	0.857	0.141
Profits	2.267	9.156	2.347	9.282	2.853	9.379	2.427	9.039	1.027	6.883
N Observations	150		150		150		150		150	

Table 3: COMPARISONS ACROSS TREATMEANT OF (GROUP) MEANS

This table reports in columns the mean-difference between treatments for each one of the variable listed in rows. The means are computed by keeping for each treatment the mean of each group per period (to account for group correlations), and relying on one-sided test for the equality of means in large sample. Results from pr-test are consistent. The means for each variable (computed at individual level) are reported in Table (2).

Variable	NAMES VS BASELINE	NAMES+INFO VS NAMES	NAMES+INFO VS FAKE	NAMES+INFO VS FEE
% who contribute 5 (Contributors)	0.047	0.053	0.08**	0.113***
% who reveal names (or paid the fee)		0.033	-0.4***	0.067
% who reveal names & contribute		0.073**	0.033	0.100***
% who reveal names & do not contribute		-0.04	-0.393***	-0.167**
% who contribute 5 and add all (Trusters)	-0.02	0.02	0.02	0.08***
% who contribute 0 and add all (Heavy cheaters)	-0.047	-0.04	-0.067*	-0.10**
% who contribute 5 and add some (Moderate trusters)	0.067**	0.033	0.06**	0.033
% who contribute 0 and add some (Light cheaters)	-0.033**	0.027*	0.007	0.007
Nr of people added	-0.24***	0.027	-0.167**	0.1
Nr of reciprocal links	-0.413**	-0.013	-0.333**	-0.213
Nr of reciprocal links if only contribute	0.093	0.067	0.133	0.48***
Nr of reciprocal links if both contribute	-0.027	0.093	0.04	0.08
Nr of people added if only one reveal		0.033	1***	-0.073
Nr of people added if both reveal		0.14	-2.1***	-0.99
Nr of reciprocal links if only one reveal		-0.08	0.8***	-0.187
Nr of reciprocal links if both reveal		0.12	-2***	-0.267
Share of reciprocal links if only one contribute (i.e. $C_i \neq C_j$)	0.072*	0.022	-0.081*	0.157***
Share of reciprocal links if both contribute (i.e. $C_i = C_j = 1$)	0.004	0.033	0.023	0.029
Share of people added if only one reveal (i.e. $A_i \neq A_j$)		-0.022	0.22***	-0.043
Share of people added if both reveal (i.e. $A_i = A_j = 1$)		0.053	-0.484***	-0.020
Share of reciprocal links if only one reveal (i.e. $A_i \neq A_j$)		-0.201	0.236***	-0.042
Share of reciprocal links if both reveal (i.e. $A_i = A_j = 1$)		0.044	-0.506***	-0.036
Density	-0.103**	-0.003	-0.083**	-0.053*
Profits	0.08	0.507	0.427	1.827***
N	60	60	60	60

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

Table 4: PROBABILITY OF ESTABLISHING A RECIPROCAL LINK

The dependent variable is a dummy equal to 1 if a link between any pair of individuals *i* and *j* exists, and zero otherwise. The data are therefore organized to express for each individual the set of all possible links (expect with oneself). This consists of 4 observations for each individual per period (i.e. a total of 600=25*4*6 observations per treatment). *One contribute* is a dummy variable equal to 1 if either *i* or *j* has contributed and zero otherwise, *Both contribute* is a dummy variable equal to 1 if *both i* and *j* has contributed and zero otherwise, *One reveal* is a dummy variable is equal to 1 if either *i* or *j* has revealed the information and zero otherwise, *Both reveal* is a dummy variable equal to 1 if *both i* and *j* has contributed and zero otherwise, while *People Added* is the total number of individual added per round. Summary statistics for these variables are reported in Table (2).

	BASELINE	NAMES	NAMES+INFO	FAKE	FEE
One contribute (i.e. $C_i \neq C_j$)	-0.0346	-0.0497	-0.1785***	-0.0883***	-0.2161***
	(0.024)	(0.039)	(0.043)	(0.029)	(0.056)
Both contribute (i.e. $C_i = C_j = 1$)	-0.0266	-0.2327**	-0.2469***	-0.0634	-0.0514
	(0.060)	(0.098)	(0.076)	(0.080)	(0.064)
One reveal (i.e. $A_i \neq A_j$)		-0.0484	-0.0532	0.0796	-0.0390
		(0.037)	(0.055)	(0.075)	(0.051)
Both reveal (i.e. $A_i = A_j = 1$)		0.1726***	0.1986***	0.3043	0.0752
		(0.033)	(0.045)	(0.191)	(0.048)
People added	0.0992***	0.1234***	0.1275***	0.1067***	0.0801***
	(0.014)	(0.017)	(0.010)	(0.010)	(0.017)
Log-likelihood	-131	-185	-199	-156	-156
N	600	600	600	600	600

*p<0.10,** p<0.05, ***p<0.01

Table 5: REGRESSIONS OF INDIVIDUAL PROFITS ACROSS TREATMENTS

The dependent variable is the total amount of individual profits resulting from all the established links in each period. Contribution dummy is a dummy equal to 1 if the individual has contributed, while Reveal dummy is a dummy equal to one if the individual reveal the information.

	BASELINE	NAMES	NAMES+INFO	FAKE	FEE
Contribution dummy	-11.0303***	-13.1274***	-15.0668***	-20.0326***	-8.1129***
	(1.188)	(3.906)	(4.840)	(3.200)	(2.443)
Reveal (paid fee) dummy		1.4390	4.9413**	1.0582	-2.4126
		(1.677)	(2.272)	(3.168)	(1.679)
Reveal · Contribution		-2.3469	-0.1026	5.5787	0.2503
		(3.734)	(5.178)	(3.622)	(4.662)
Constant	4.1051***	4.7391***	4.5171***	4.2307	3.5712***
	(0.198)	(0.782)	(1.231)	(2.838)	(1.004)
	-487	-470	-480	-488	-459
Individual fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N Observations	150	150	150	150	150

*p<0.10,** p<0.05, ***p<0.01

Figure 1: EVOLUTION OVER TIME: CONTRIBUTION

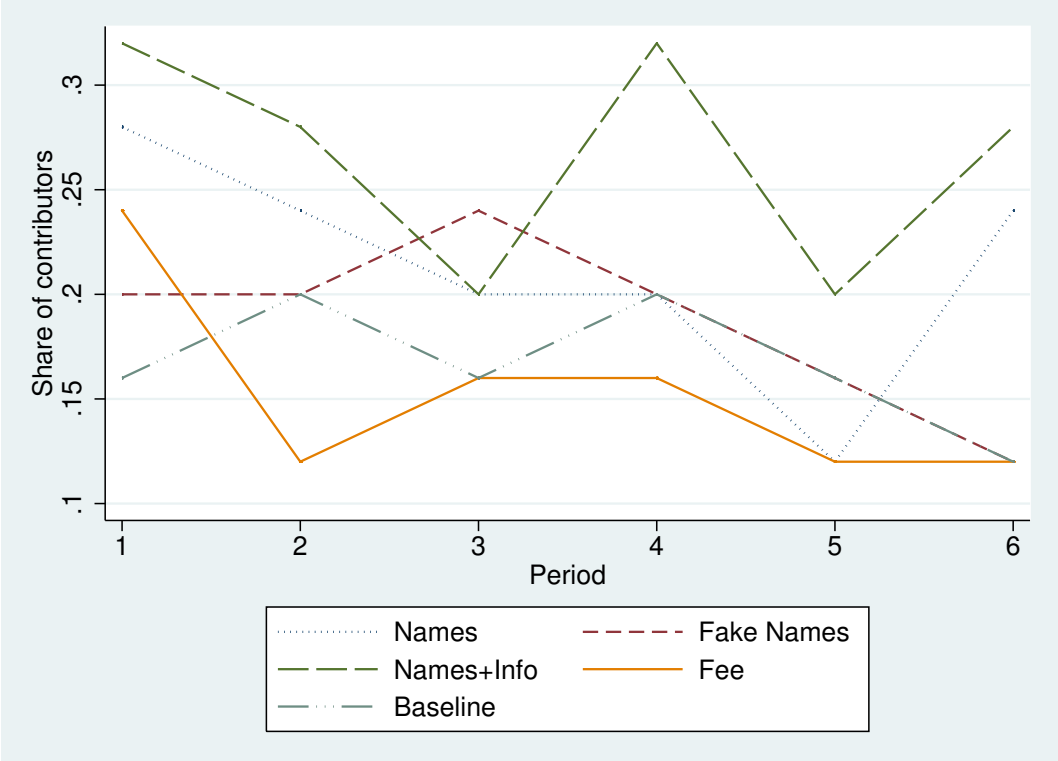


Figure 2: EVOLUTION OVER TIME: NAME REVELATION/FEE

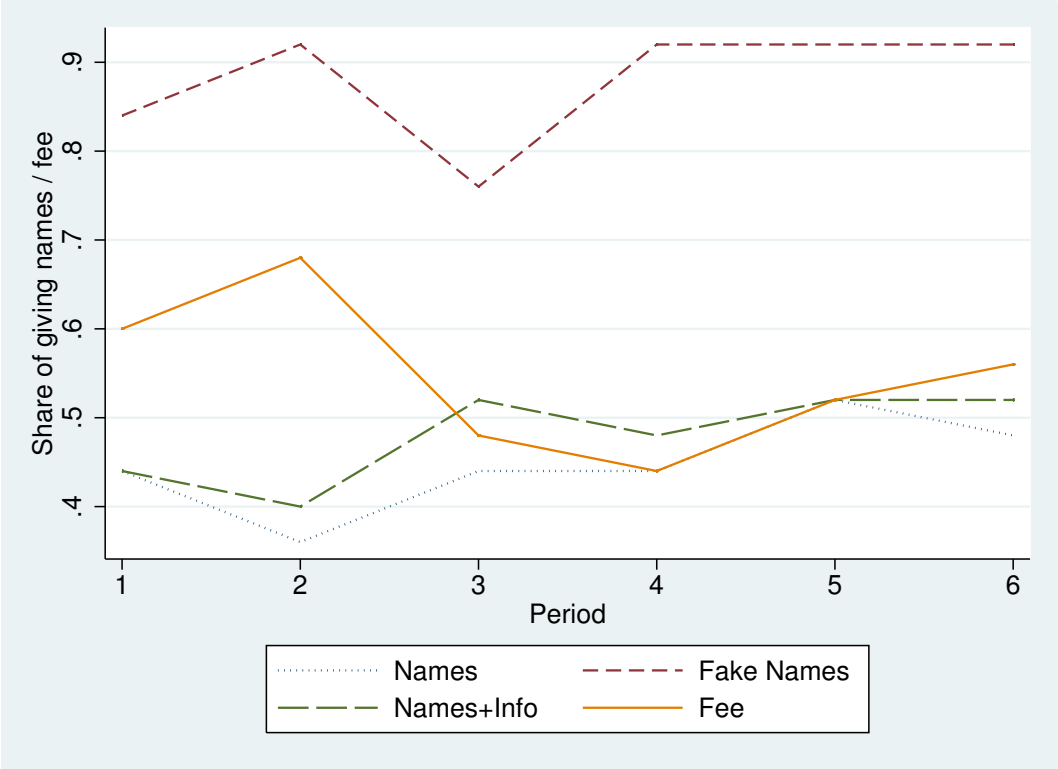


Figure 3: EVOLUTION OVER TIME: CONTRIBUTORS REVEALING NAMES

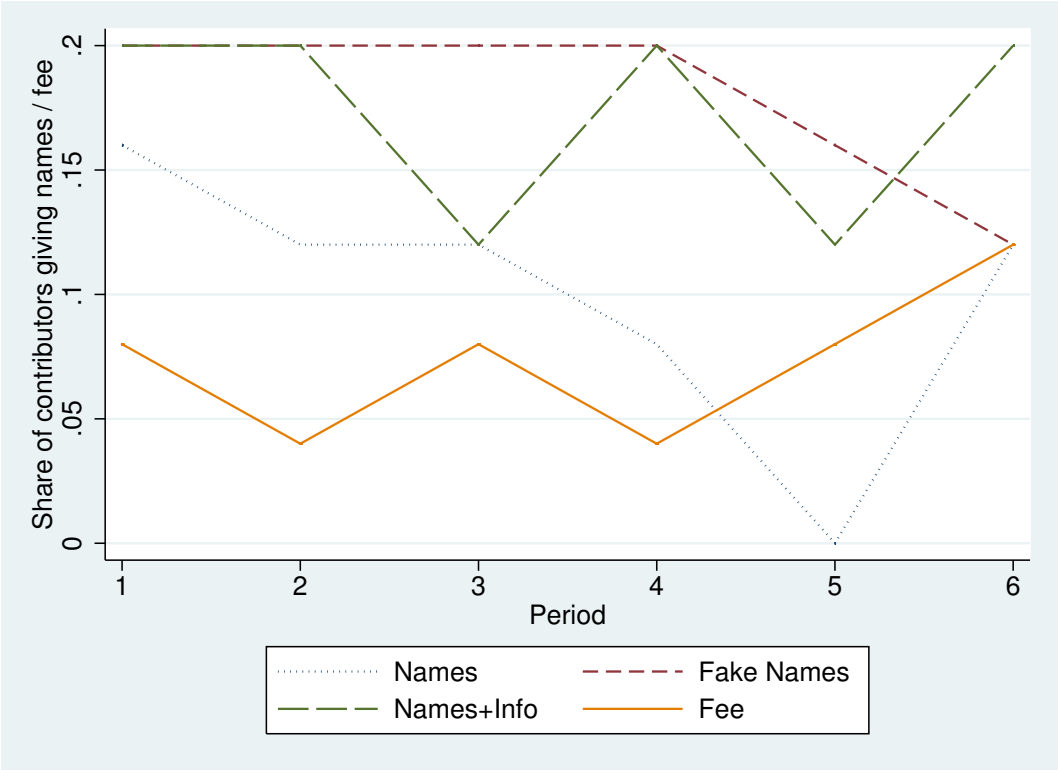


Figure 4: EVOLUTION OVER TIME: NON-CONTRIBUTORS REVEALING NAMES

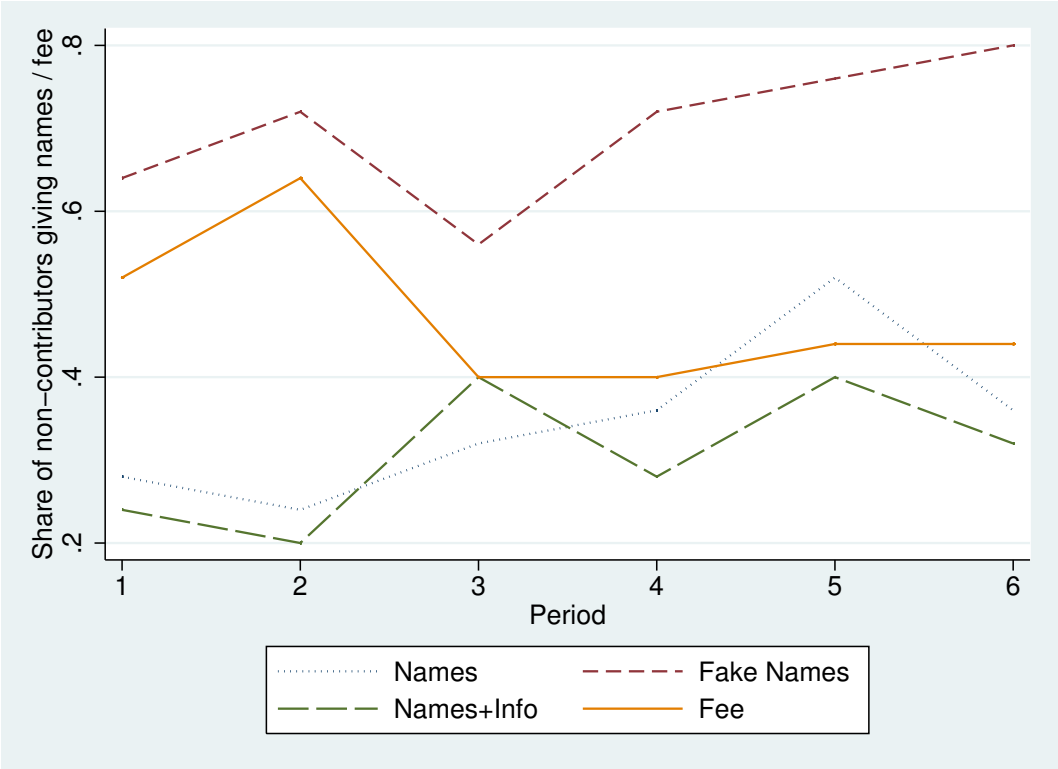


Figure 5: EVOLUTION OVER TIME: LINKS

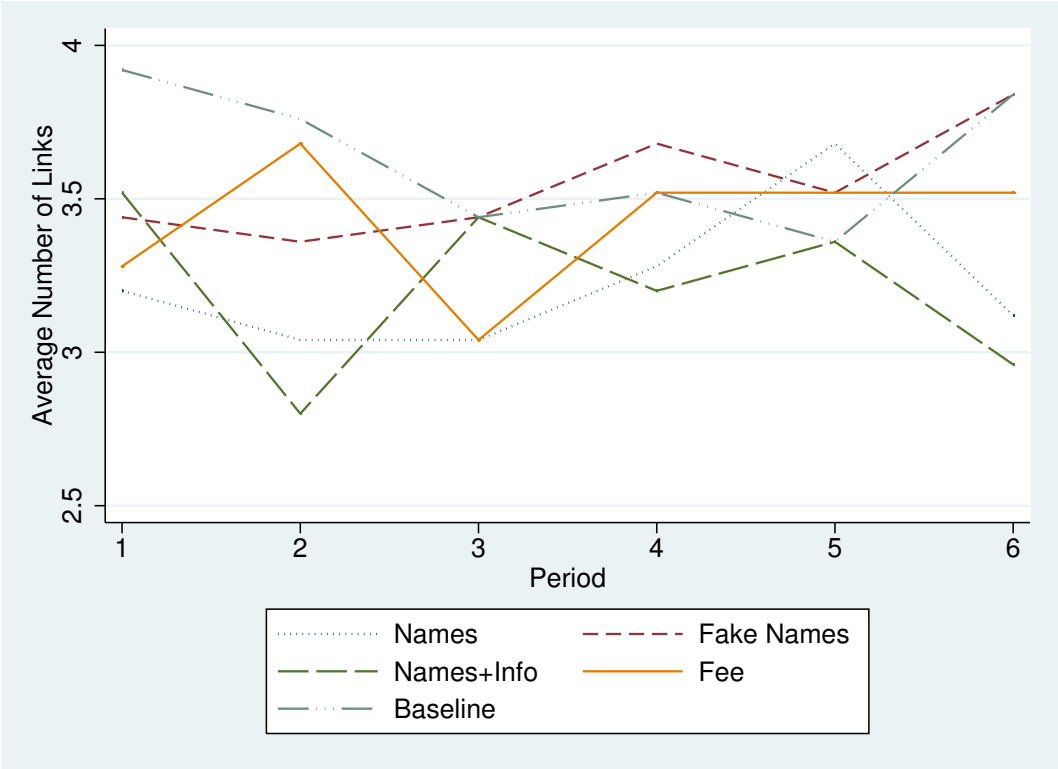


Figure 6: DIFFERENCE IN PROBABILITY OF ESTABLISHING A LINK

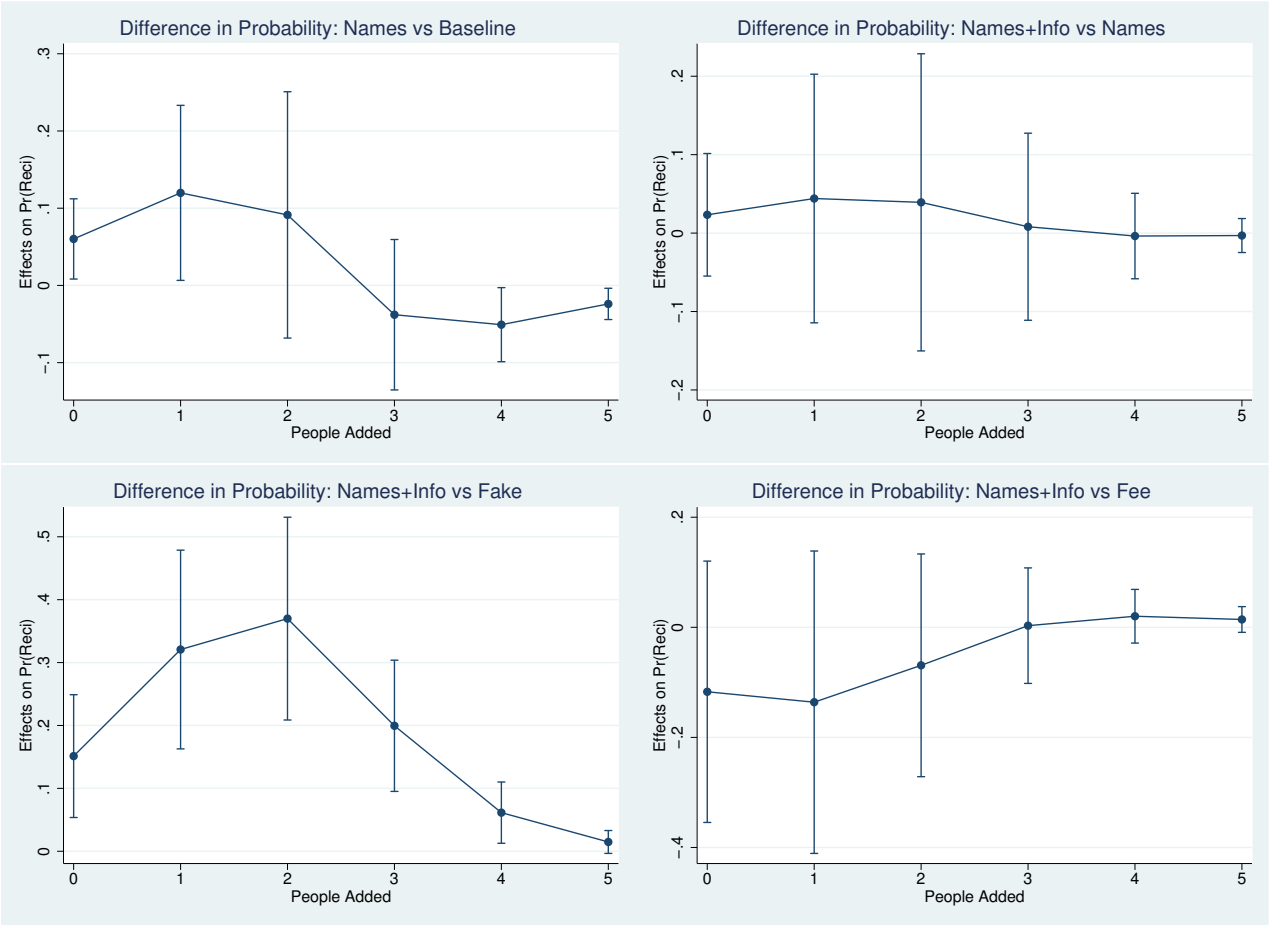
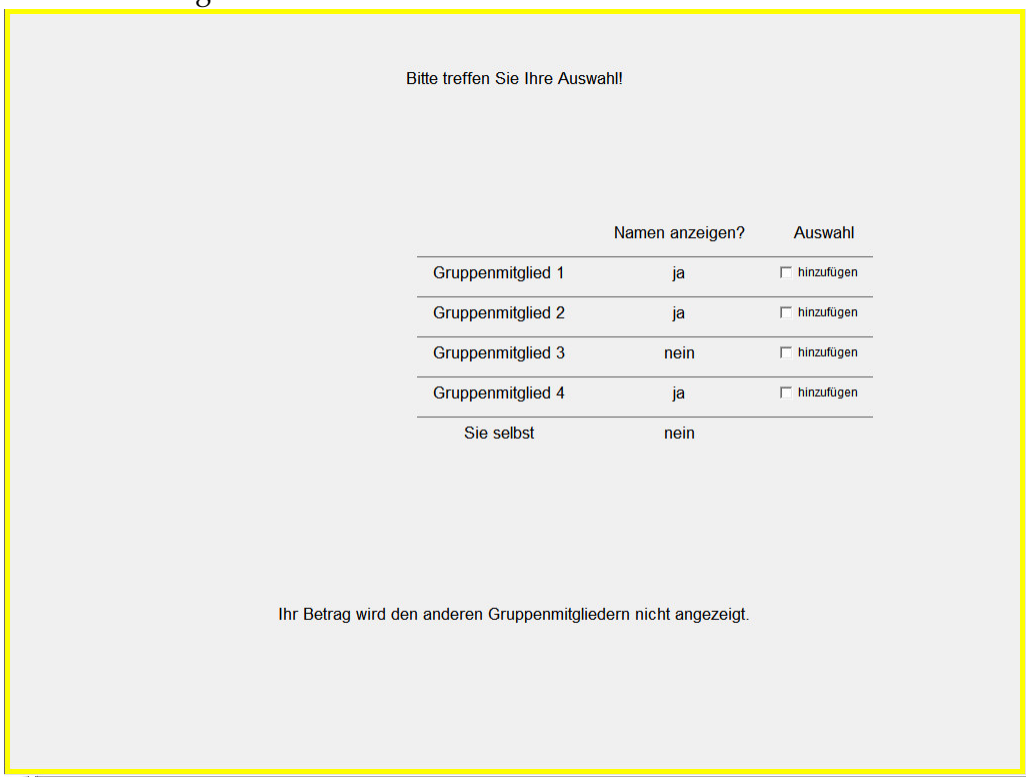


Figure 7: COMPUTER SCREEN AT THE LINKING STAGE



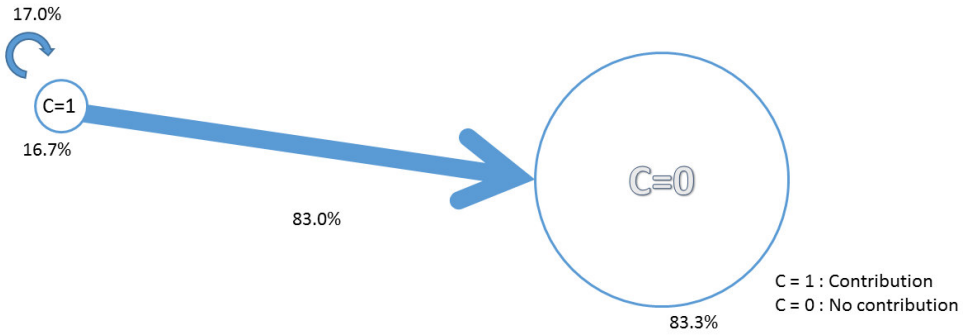
	English Translation
Name Anzegein?	Name Revelation
Hinzufügen	To add
Gruppenmitglied	Group Member
Ihr Betrag wird den anderen Gruppenmitgliedern nich anzgezeigt	Your choice will not be displayed to the other group-members

Figure 8: COMPUTER SCREEN AT THE INFORMATION STAGE

	English Translation
Hinzugefügt	Added
Nicht Hinzugefügt	Not Added
Gruppenmitglied	Group Member
Ihr Name wird den anderen Guppenmitglieder angezeigt	Your name will be displayed to the other group-members

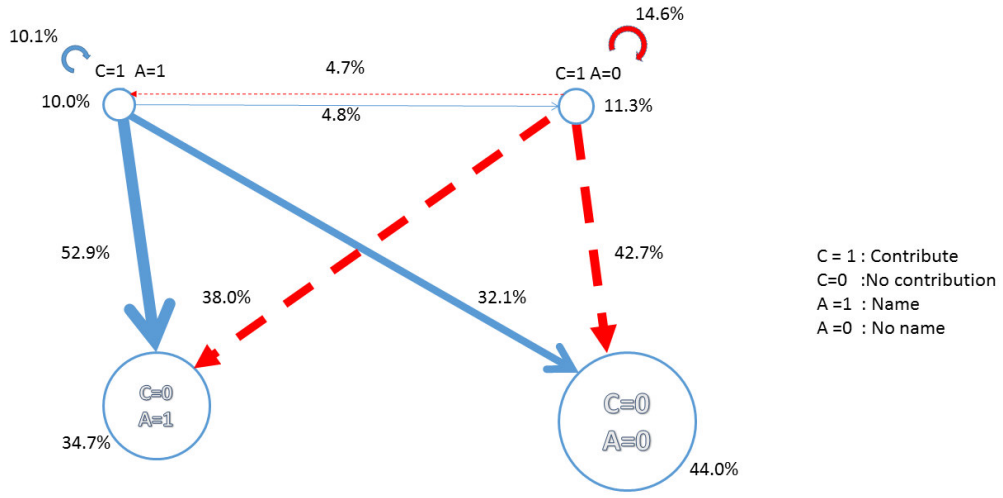
A People Added Decomposition

Figure A.1: BASELINE



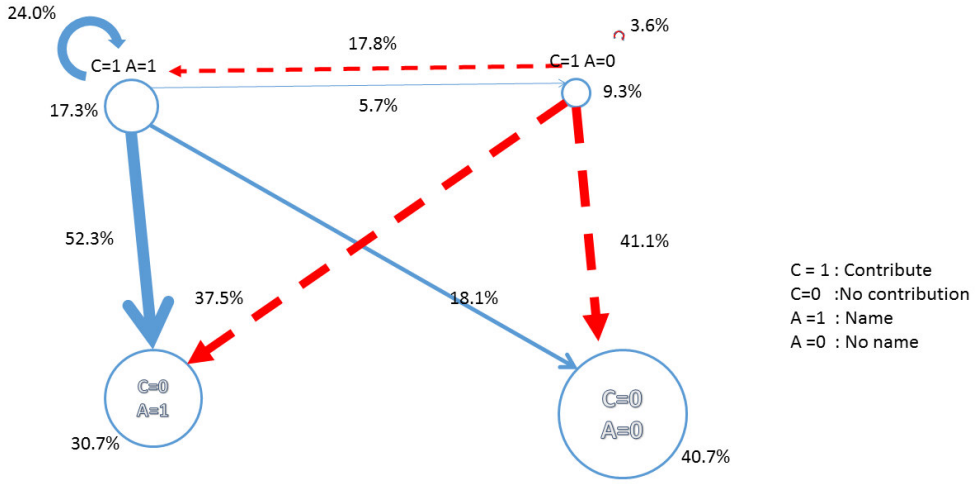
The share beside each circle represents the share of individuals in each category. For example, 16.7% of the individuals contributed (i.e. C=1) in the public good game. The share beside each blue arrow represents the share of individuals added by individuals who contributed (i.e. C=1) out of all people added. They sum up to 100%. For example, 17.0% of people added by contributors were individuals who also contributed.

Figure A.2: NAMES



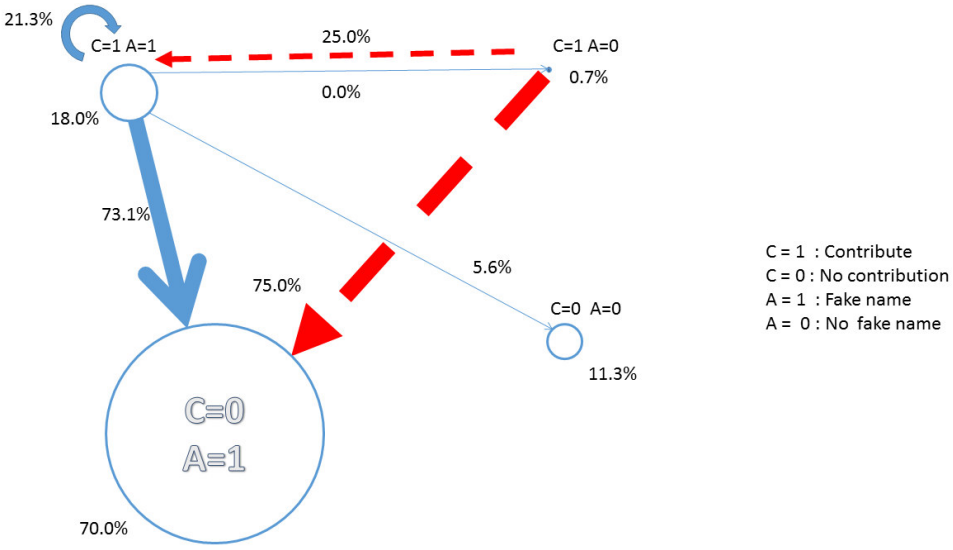
The share beside each circle represents the share of individuals in each category. For example, 10.0% of the individuals contributed in the public good game and revealed the name (i.e. C=1 and A=1). The share beside each blue arrow represents the share of individuals added by individuals who contributed and revealed the name (i.e. C=1 and A=1) out of all people added. They sum up to 100%. For example, 52.9% of people added by contributors who revealed their name were individuals who revealed their name and did not contribute. To know the total share of individuals added who revealed their name, both shares of individuals who revealed the name (disregarding contribution) must be added (i.e. 52.9% + 10.1%). Similarly, the shares beside each red-dashed arrow represents the share of individuals added by individuals who contributed and *did not* reveal their name (i.e. C=1 and A=0) out of all people added.

Figure A.3: NAMES+INFO



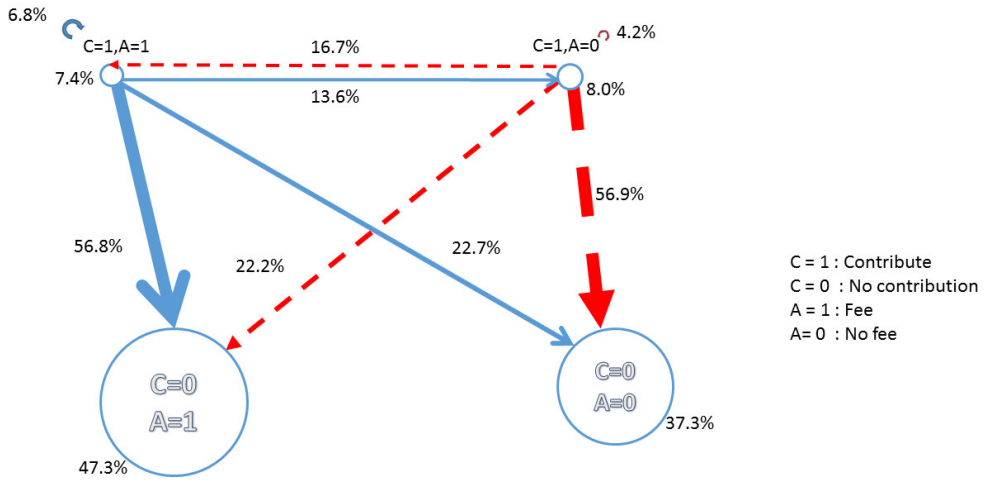
The share beside each circle represents the share of individuals in each category. For example, 9.3% of the individuals contributed in the public good game and did not reveal the name (i.e. C=1 and A=0). The share beside each blue arrow represents the share of individuals added by individuals who contributed and revealed the name (i.e. C=1 and A=1) out of all people added. They sum up to 100%. For example, 18.1% of people added by contributors who revealed their name were individuals who did not reveal their name and did not contribute. To know the total share of individuals added who revealed their name, both shares of individuals who revealed the name (disregarding contribution) must be added (i.e. 52.3+24.0%). Similarly, the shares beside each red-dashed arrow represents the share of individuals added by individuals who contributed and *did not* reveal their name (i.e. C=1 and A=0) out of all people added.

Figure A.4: FAKE NAMES



The share beside each circle represents the share of individuals in each category. For example, 70.0% of the individuals did not contribute in the public good game and revealed the name (i.e. C=0 and A=1). The share beside each blue arrow represents the share of individuals added by individuals who contributed and revealed their name (i.e. C=1 and A=1) out of all people added. They sum up to 100%. For example, 5.6% of people added by contributors who revealed their name were individuals who did not reveal their name and did not contribute. To know the total share of individuals added who revealed their name, both shares of individuals who revealed their name (disregarding contribution) must be added (i.e. 73.1+ 21.3%). Similarly, the shares beside each red-dashed arrow represents the share of individuals added by individuals who contributed and *did not* reveal their name (i.e. C=1 and A=0) out of all people added.

Figure A.5: FEE



The share beside each circle represents the share of individuals in each category. For example, 37.3% of the individuals did not contribute in the public good game and did not pay the fee (i.e. C=0 and A=0). The share beside each blue arrow represents the share of individuals added by individuals who contributed and paid the fee (i.e. C=1 and A=1) out of all people added. They sum up to 100%. For example, 13.6% of people added by contributors who paid the fee were individuals who did not pay the fee and contributed. To know the total share of individuals added who paid the fee, both shares of individuals who paid the fee (disregarding contribution) must be added (i.e. 56.8% + 6.8%). Similarly, the shares beside each red-dashed arrow represents the share of individuals added by individuals who contributed and *did not* pay the fee (i.e. C=1 and A=0) out of all people added.

Treatment Name+Info

INSTRUCTIONS

Welcome and thank you for your participation! You will earn an amount of money that depends on your decisions and the decisions of the other participants in this experiment. It is therefore very important that you thoroughly read these instructions.

If you have a question, please raise your hand. We will then come to you and answer your question. If you violate this rule, we will be forced to exclude you from the experiment.

Please turn off your mobile phone now!

You will make decisions in the course of the experiment. All results of the study will be kept strictly confidential.

Your earnings will be calculated in ECU (Experimental Currency Units). 1 ECU corresponds to €0.50. At the end of today's session, your total earnings will be calculated and converted into euros to be paid to you confidentially and in cash.

While very unlikely, you may make losses in this experiment. If so, you will be asked to fill the a's and A's of a page of text for every 2 ECU of losses, up to a maximum of three pages. An example of the text to be filled is to be found on the last page of the instructions.

After having read the instructions, you will be given the opportunity to answer a few control questions to check your understanding of the experiment. The experiment begins when all participants have answered the control questions correctly. In the course of the experiment, you will have to make several decisions that affect you and other participants. Once the experiment is complete, we will ask you to complete a questionnaire.

EXPLANATION OF THE EXPERIMENT

As a starting amount you receive 10 ECU. You will first be randomly assigned to a group with four other participants. Here you have to make three consecutive decisions.

DECISION 1:

First, you must decide how many ECU you want to invest. You can choose between investing either 0 or 5 ECU.

When you invest 0 ECU, every person with whom you will have formed reciprocal links in a later stage of the experiment will obtain 0 ECU and you will pay nothing. When you invest 5 ECU, every person with whom you formed reciprocal links will obtain 9 ECU and you will pay 5 ECU for each of those mutual connections.

All other members of your group also decide independently and without knowing your decision how much they want to invest.

DECISION 2:

In this stage, you need to decide if you want to give out your name to other members of your group. If you choose to do so, then please write your full name in the field provided. Then wait for an experimenter to come to you and compare the name you gave with the name on your ID card.

Please put your ID card on the table to the right of the computer keyboard with the face up if you decided to disclose your name, and face down if you chose not to disclose the name. Please do not talk to the experimenter about your decision when he / she comes to check your credentials. He / she will then enter a code so that you can move to the next decision in the experiment.

Your decision whether to disclose your name or not will be communicated to the other group members in the next stage. Your name itself will be shown to them only after they decided whether to add you to their personal list or not.

Your name will be deleted from our electronic record after the experiment, so that the experimenter will only know if you gave your name or not, but will not know your name.

DECISION 3:

In this stage, you see a list of the other members of your group, shown as "group member 1", "group member 2", "group member 3" and "Group Member 4". Each group member sees a different order of the group members, so that the person who appears on your personal list as "group member 1" may be displayed in the list of another person as "group member 3".

No one in your group can see how much you invested in decision 1. You also cannot see how much other group members have invested.

In addition to this, you can see next to the identifier of a group member whether he / she has decided to make his / her real name known. Other group members can also see if you decided in decision 2 to give out your real name.

You need to decide which members of the group you want to add your personal list, by making a check mark in the box next to the group member. If you change your mind, you can also remove the check mark.

Once you made your final decision, please click OK. All other members of your group also decide who they wish to add their personal list. The group members do not see at this stage who added who to his / her personal list.

Once you made decision 3, you will see the screen again together with your decision who you want to add and the names of those people who decided to give them. The other participants in your group also see your real name if you decided to do so (otherwise not). Please click OK when you are ready to proceed.

You will then be assigned to a new group and repeat the same steps as above. You will be assigned to 6 groups in total. You will never be more than once with the same person in the same group. In other words, the members of each group to which you are assigned are people with whom you were not in a group previously in this experiment.

Before your earnings are calculated for this experiment, we will ask you a series of questions regarding your decisions during the experiment, as well as some questions about yourself.

DETERMINATION OF PAYOUTS

At the end of the experiment the computer will randomly select one of the groups you were assigned to and you will be paid according to the results of your decisions and the decisions of the other participants in this group. Other participants in this group also get payoffs from their decisions in this group.

You do not know beforehand which group will be selected to determine the payout. You should therefore make your decisions in all six groups carefully since any of them could decide the amount of your payment at the end of the experiment. There is no connection between the groups since each group is composed of new participants and you do not know the results of the previous group.

Once a group is selected for payment, the program displays both the information that you had available at the time of decision 3, as well as who you added to your personal list and how much you invested in this group. Note that this time you not only see the names of people who decided to reveal them, but also, how much each group member invested. Likewise, the other group members will learn your real name (if you have decided in decision 2 to do so) as well as how much you invested.

You will also learn how many mutual connections you made. This is determined as follows: The program compares the people on your personal list to their own personal list:

- If a person on your personal list also has you on their own personal list, a mutual connection is made between the two of you.
  In this case you receive the amount that the person invested in Decision 1 (0 or 5 ECU) multiplied by 1.8 (so you get either 0 or 9 ECU). The other person receives the amount you invested in Decision 1 (0 or 5 ECU) multiplied by 1.8 (ie, they receive either 0 or 9 ECU). You also pay the cost of your investment (0 or 5 ECU) for each mutual connection.

- If either you did not list the other person or if the other person did not list you, then no connection is made.
  In this case, you get nothing from the other and the other gets nothing from you, and you do not pay anything.

Overall, you therefore get, for each group member with whom you established a mutual connection, their investment multiplied by 1.8 minus your investment. In addition, you get 5 ECU as a show up fee and ECU 10 as a starting amount.

SUMMARY:

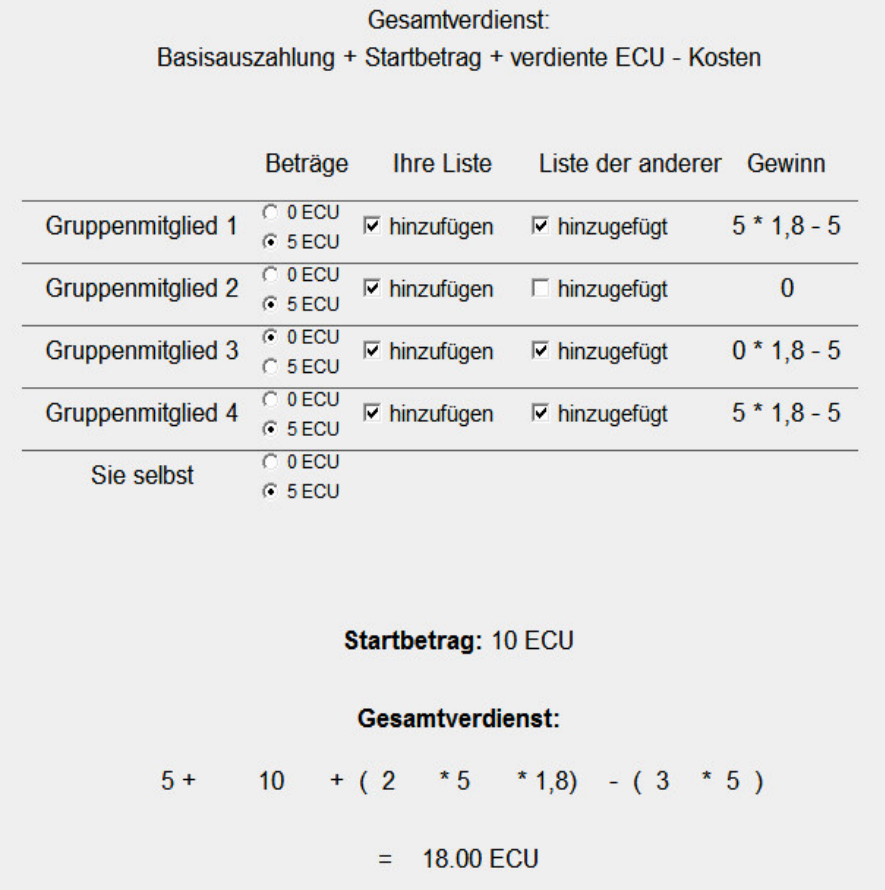
- You will be assigned to six group over the experiment. Each group is composed of different people. For each group, you will need to make a few decisions in succession.

- At the end we will ask you to fill out a questionnaire about yourself.

- Once all decision-making situations are over and you have answered all questions, the computer determines which group will determine your payoff. Then, your payoff in this group is determined and displayed along with the details of its calculation. Other members of the group also get their payoff from this group.

CONTROL QUESTIONS

First, you are asked to try out how different combinations of your decisions and those of other group members affect your earnings. In the following exercise, you are asked to decide how much you want to invest and how much you think other participants invest. You are also be asked who you would add to your list and whether they would add you on their personal list.



Example (with reference to graph above): You established a mutual connection with GM 1, GM 3 and GM 4 but not with GM 2, who did not add you back. You invested 5 ECU. Two of the individuals with whom you made a mutual link invested 5 ECU while one of them invested 0 ECU. You therefore get 2 * 9 = 18 ECU and pay 3 * 5 ECU = 15 ECU. Your total earnings for this part of the experiment consists of 5 ECU (base payment), 10 ECU (starting amount) + 18 ECU (from the other group members) - 15 ECU (your contribution multiplied by the number of mutual links established). This means you would earn in this case a total of 18 ECU.

You are invited to try out at least 4 different scenarios by changing some parameters in your decisions and those of others before you can proceed to answer some questions to check your understanding of the experiment. The experiment will continues only once all participants answered all control questions correctly.

Control questions:

1. Assume that you invested 0 ECU and established a mutual relation with two other participant, only one of whom invested 5 ECU. What is your total payoff?
    a. 9+10+5=24 ECU
2. Assume that you invested 5 ECU and established a mutual relation with three other participant, only two of whom invested 5 ECU. What is your total payoff?
    a. 2*9-3*5+10+5=18 ECU
3. Assume that you invested 5 ECU and established a mutual relation with three other participant, none of whom invested 5 ECU. What is your total payoff?
    a. -3*5+10+5=0 ECU
4. Assume that you invested 0 ECU and established a mutual relation with two other participant, both of whom invested 5 ECU. What is your total payoff?
    a. 2*9+10+5=33 ECU

EXAMPLE OF THE TASK FOR EACH EURO LOSS:

Please fill out all A's and a's with a pen.

Ea quae est secuta hieme, qui fuit annus Cn. Pompeio, M. Crasso consulibus, Usipetes Germani et item Tencteri magna [cum] multitudine hominum flumen Rhenum transierunt, non longe a mari, Rhenus influit quo. Causa fuit quod transeundi from Suebis complures annos exagitati bello premebantur et Agri Cultura prohibebantur. Sueborum gens est longe maxima et bellicosissima Germanorum omnium. Hi centum pagos habere dicuntur, ex quibus quotannis Singula milia armatorum bell andi causa educunt ex finibus. Reliqui, qui domi manserunt, se atque Illos alunt; hi rursus in vicem anno post in armis sunt, illi domi-retentive. Sic neque nec Agri Cultura ratio atque usus belli intermittitur. Sed privatized ac separati agri apud eos nihil est, neque longius remanere anno uno in loco colendi causa licet. Neque frumento multum, sed partem maximam Lacte atque pecore vivunt multum sunt in venationibus; quae res et cibi genere et cotidiana exercitatione et libertate vitae, quod a nullo Pueris officio aut disciplina adsuefacti nihil omnino faciunt contra voluntatem, et vires alit et immani corporum magnitudine homines efficit. Atque in eam se consuetudinem adduxerunt ut neque locis frigidissimis vestitus praeter pelles habeant quicquam, quarum propter exiguitatem magna est pars corporis aperta et laventur in fluminibus.

Mercatoribus aditus est magis eo ut quae bello ceperint quibus vendant habeant, quam quo ullam rem ad se importari desiderent. Quin etiam iumentis, quibus maxime Galli delectantur quaeque impenso parant PRETIO, Germani importatis non utuntur, sed quae sunt apud eos nata, parva atque deformia, haec cotidiana exercitatione summi ut sint laboris efficiunt. Equestribus proeliis Saepe ex equis desiliunt ac pedibus proeliantur, equos Same date remanere Vestigio adsuefecerunt, ad quos se celeriter, cum usus est, recipiunt: neque eorum moribus turpius quicquam aut inertius habetur quam ephippiis uti. Itaque ad quemvis numerum ephippiatorum equitum quamvis pauci adire audent. Vinum omnino ad se non importari patiuntur, quod ea re ad laborem referendum remollescere homines atque effeminari arbitrantur.

"De Bello Gallico", Julius Caesar, Book IV