Modeling knowledge sharing:

Enablers of the private-collective innovation model

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Abstract

Knowledge sharing in a competitive environment faces the problem of free riders and under-provision. In these situations, aversion and reciprocity are considerations that impact willingness to share. Particularly, in situations of mixed incentive schemes, such as private-collective innovation, the willingness to share knowledge need to be further understood (Gachter et al. 2010). This paper builds on the work of the private-collective innovation model on how incentives motivate actors to share knowledge in initial and recurring states. We consider and estimate social preferences, following the guidelines of Fehr and Schmidt (1999) and Gachter et al. (2010) using utility functions. In a second step, we simulate a private-collective knowledge sharing environment and compare our results with the extant and predicted results from previous studies. We investigate the role of incentives on aversion to share knowledge in a simulated reality, were actors' decisions depend on others, following a prisoner's dilemma structure. We provide evidence that incentives, as well as, previous decisions matter in knowledge sharing in the initial phase, as well as, in recurring states.

Keywords: private-collective innovation, knowledge sharing, simulation

Introduction

Knowledge sharing between actors is often seen as a utopic situation, which has no place in a competitive market, made of rational selfish. Many economic models assume that people will only pursue their self-interested goals, without considering the social benefit. However, other studies highlight the impact of fairness in firm's cooperation (Kahneman, Knetsch, & Thaler, 1986) or between individuals (Fehr & Schmidt, 1999).

The problem of cooperation has been investigated from multiple perspectives, including transaction-cost theory (Hill, 1990), resource-based theory (Combs & Ketchen, 1999; Mowery, Oxley, & Silverman, 1998) or game theory (Fehr & Schmidt, 1999; Gachter et al., 2010). One increasingly important type of collaborative setting is the private-collective innovation, coined by Eric von Hippel and Georg von Krogh (2003). This model is particularly interesting as it explains the creation and development of public goods through cooperation and how contributors to the public goods benefit more than the free-riders, only consuming the public good. The private-collective model is illustrated in the case of Open Source Software development, and has been further experimented in real settings (Gachter et al., 2010; Stuermer, Spaeth, & von Krogh, 2009).

Ostrom (1990) proposed that many contextual factors impact on the collaborators behavior in a collective action, affecting contributions over time. The identification and estimation of the parameters that enable knowledge sharing, such as aversion to advantageous and disadvantageous inequity, that leads to a private-collective model (Gachter et al., 2010) is of great importance and has not yet been done. This paper develops and investigates a framework in a simulation environment that accounts for the level and stability of knowledge sharing in public goods, where interactions between actors recur, as opposed to only initialize a knowledge-sharing environment

(Gachter et al., 2010). We draw on elements of game theory and private-collective theory (von Hippel & von Krogh, 2003) to develop a new framework that predicts actors' contributions. Our focus is on the social preferences of the actors’ impact on knowledge sharing, such as inequality aversion, reciprocity and other considerations, in the environment of knowledge sharing.

The organization of this paper is as follows. The next section briefly reviews existing literature on knowledge sharing and game theory, discusses core concepts of private-collective theory, and their embedding in the extant literature. Subsequently, we present our model. The fourth section describes the research design, followed by a discussion of the results. Next we discuss the implications of our work for the literature on private-collective theory, and collective action and conclude the paper.

Relevant literature

Knowledge has long been recognized as a valuable resource for organizational growth and sustained competitive advantage. Previous work argues that knowledge is a valuable resource because it represents intangible assets, operational routines, and creative processes that are hard to imitate (Grant, 1996), and strategically significant (Lee, 2001). We define knowledge sharing as "activities of transferring or disseminating knowledge from one person, group or organization to another" (Lee, 2001). Knowledge sharing actors have no assurances that those they are helping will ever reciprocate, and free-riders draw upon the knowledge of others without sharing anything in return. This leads to a very fragile environment, where considerations over previous actions play a determinant role.

Prior studies find that knowledge sharing is positively related to factors such as strong ties (Wellman & Wortley, 1990), awards, status similarity (Cohen & Zhou, 1991), and a history of prior relationship (Krackhardt, 1992). Fehr (1999) investigated how economic environments determine the actor types that dominate in equilibrium: fair types or the selfish. Next, Fischbacher, Gachter, & Fehr (2001) studied conditional cooperation in public goods, observing declining contributions in almost all experiments. They find a constant fraction of actors that are free riders, and a decrease on contributions from sharing-actors in repeated situations over time.

More recently, Gachter et al. (2010) use previous studies on knowledge sharing (Fehr & Schmidt, 1999; Fischbacher et al., 2001) to test the initialization of a private-collective model (von Hippel & von Krogh, 2003) using game theory propositions. Even though its findings are relevant to understand the initialization of communities, it does not highlight the issues, previously stated, that collaborative environments face: decrease of contributions over time and the free rider problem.

Game-theoretic background

Game theory is especially well suited for model development in this setting, since knowledge sharing is conceived as a decision process dependent on perceived costs and benefits, following a similar structure that can be found in strategic games. Some studies have examined the dynamics of knowledge sharing using the multi-person game-theoretic framework (Chua, 2003; Gachter et al., 2010). Chua (2003) proposes that an individual's knowledge sharing decision is driven by a set of contextualized concerns and interests, differing from the notion of payoff in game theory. Its empirical findings suggest that individual's perceived payoff of sharing knowledge is contingent on the knowledge sharing behavior of others, thus showing recurrent treats.

Private-collective theory

The term private-collective model of innovation was coined by von Hippel and von Krogh (2003). It combines model private investment and the collective-action innovation attributes. The collective-action innovation model explains the creation of public goods, which are characterized by the non-rivalry of benefits and non-excludable access to the good (Monge et al., 1998). Free riding occurs, since public goods innovations are exposed to problems of collective action (Ostrom, 1990). Ostrom (1990) argues that contributions to a public good are affected by environmental and social factors, such as competition among participants. She acknowledges the existence of several players that differ on their cooperative behavior, most of them being conditional cooperators and rational egoists (Ostrom, 1990). Conditional cooperators initiate a cooperative action when they estimate others will reciprocate, but free riders will, on the other hand, disappoint these initial contributors to the public good (Ostrom, 1998).

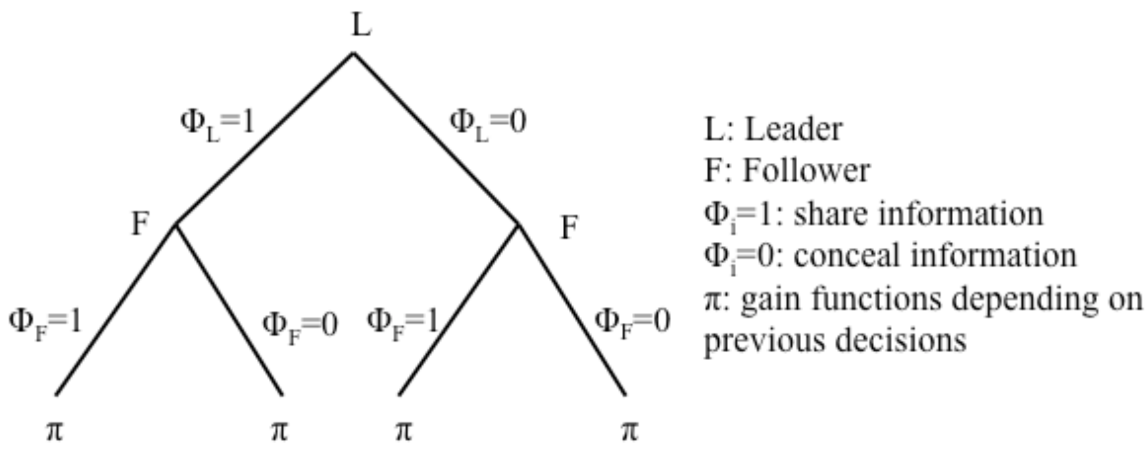
The private-collective model of innovation explains the creation of public goods through knowledge sharing, based on the assumption that it occurs when the process-related rewards exceed the process-related costs (Hippel, 2005). Gachter et al. (2010) traced the initiation of private-collective innovation to the first decision to share knowledge in a two-person game. They consider benefits and cost of sharing knowledge, and benefits of conceal knowledge. The results indicate that when individuals face opportunity costs to sharing their knowledge with others, these turn away from the social optimum of mutual sharing.

Some limitations apply to Gachter's study. Initial decisions might be affected by repeated interactions, which consequently bias initial and future collaborative behavior of the actors. Another limitation relates with on how the social aversion to disadvantage affects the fragility of knowledge sharing. We expect these two characteristics to affect the initial and consecutive states of a knowledge sharing environment.

Model

Previously mentioned by Fehr (1999), the most common equilibrium in cooperative environments is not to cooperate, unless there are advantages in doing so. Gachter et al. (2010) created a knowledge sharing model, where actors could share or conceal in couples interaction. i.e. actor "F", the follower, can chose whether to share or conceal knowledge, depending on what actor "L", the leader, has decided. The study on knowledge sharing game is based on the sequential prisoner's dilemma of game theory and Fehr and Schmidt (1999)'s model. On Figure 1, we have a representation of the decision process in the game of knowledge sharing, where decisions of followers depend on previous decisions made by a leader. The two possible decisions are always the same, share or conceal information (see Figure 1), and the pay-offs of each participant (L or F) will depend on the follower and leader choices.

Figure 1. Knowledge-sharing model based on Gachter et al. (2010)



Gachter et al., 2010 find that knowledge sharing equilibrium is fragile, and will depend on exclusivity payoffs that actors receive by not sharing knowledge. Their study mainly focuses on the initialization of knowledge sharing, empirically testing their hypotheses with a laboratory experiment.

In this paper we focus on two main extensions of the previous model: First, we use Gachter et al. (2010) results to estimate the coefficients of aversion to disadvantageous inequity ($\tilde{\alpha}$) and aversion against advantageous inequity ($\tilde{\beta}$) mentioned by Fehr (1999) and also assumed by Gachter, using previous literature on estimation of utility functions based on conditional probabilities (Blass, Lach, & Manski, 2010; Revelt & Train, 1998). Therefore, our first extension refers to validating an old assumption on the utility function in a knowledge sharing process (Fehr & Schmidt, 1999; Gachter et al., 2010) which conditional probability results. Second, using the previously estimated values, we simulate the long run in a private-collective knowledge-sharing environment, which will vary depending on the cost of concealing.

Research design

To simulate a knowledge-sharing game we use a two-step procedure. First, we calculate the utility function coefficients in a private-collective setting using the utility function and conditional probability duality (Revelt & Train, 1998). Second, we replicate Gachter et al. (2010) results using the previously mentioned utility function.

Utility function and conditional probability

We base our model on a utility function based on person (U_L or U_F) and choice situation (ϕ_L and ϕ_F). We use the results of Gachter et al. (2010), which give us the conditional probability of knowledge sharing in a private-collective environment. The utility that person obtains from alternative j in choice depends on the aversion coefficients, β and α, which varies in the population (Revelt & Train, 1998). Conditional on these parameters, the probability that L or F chooses to share or conceal knowledge follows a standard logit distribution (Revelt & Train, 1998), based on the utility function, of the form:

$$P_{ni}(\varphi_n) = \frac{e^{\varphi_n' X_{ni}}}{\sum_j e^{\varphi_n' X_{ni}}} \tag{1}$$

X_{ni} vector represents the observed variables for each individual n in choice situation i, such as pay-off or expenses of sharing knowledge, and φ_{ni} the unobserved variables, such as the aversion to disadvantageous inequity and aversion against advantageous inequity. We used the gathered probability by Gachter et al. (2010) that a person places on sharing knowledge versus concealing. Utility function based on Fehr–Schmidt (1999) and assumed by Gachter with $\pi_{F,L}$ as pay-offs, and α as measures of aversion to disadvantageous inequity and β measures aversion against advantageous inequity, is show in the following functions. First, the pay-offs functions vary depending on the decisions of both players:

$$\pi_F(\phi_L, \phi_F) = b + \phi_L \cdot v + \phi_L(1 - \phi_F) \cdot a_F \tag{2a}$$

$$\pi_L(\phi_L, \phi_F) = b + \phi_F \cdot v + \phi_F(1 - \phi_L) \cdot a_L \tag{2b}$$

$$\phi_i = \begin{Bmatrix} 1 & \text{if} & \text{i shares} \\ 0 & \text{if} & \text{i conceals} \end{Bmatrix} \text{ for i L and F}$$

We formulate the pay-off functions in matrix form:

$$P_L = \begin{pmatrix} \pi_L(1,1) & \pi_L(1,0) \\ \pi_L(0,1) & \pi_L(0,0) \end{pmatrix},\ P_F = \begin{pmatrix} \pi_F(1,1) & \pi_F(1,0) \\ \pi_F(0,1) & \pi_F(0,0) \end{pmatrix} \tag{3a \& 3b}$$

$$P_L = \begin{pmatrix} 30 & 10 \\ 30 + a_L & 10 \end{pmatrix}, \qquad P_F = \begin{pmatrix} 30 & 30 + a_F \\ 10 & 10 \end{pmatrix}$$

Utility function of the leader: (4a)

$$U_L = P_L - \alpha_L \cdot \max[P_F - P_L, 0] - \beta_L \cdot \max[P_L - P_F, 0]$$

$$= \begin{pmatrix} 30 & 10 \\ 30 + a_L & 10 \end{pmatrix} - \alpha_L \cdot \max\left[\begin{pmatrix} 0 & 20 + a_F \\ -20 - a_L & 0 \end{pmatrix}, 0\right] - \beta_L \cdot \max\left[\begin{pmatrix} 0 & -20 - a_F \\ 20 + a_L & 0 \end{pmatrix}, 0\right]$$

$$U_L = \begin{pmatrix} 30 & 10 - \alpha_L(20 + a_F) \\ 30 + a_L - \beta_L(20 + a_L) & 10 \end{pmatrix}$$

Utility function of the follower: (4b)

$$U_F = P_F - \alpha_F \cdot \max[P_L - P_F, 0] - \beta_F \cdot \max[P_F - P_L, 0]$$

$$= \begin{pmatrix} 30 & 30 + a_F \\ 10 & 10 \end{pmatrix} - \alpha_F \cdot \max\left[\begin{pmatrix} 0 & -20 - a_F \\ 20 + a_L & 0 \end{pmatrix}, 0\right] - \beta_F \cdot \max\left[\begin{pmatrix} 0 & 20 + a_F \\ -20 - a_L & 0 \end{pmatrix}, 0\right]$$

$$U_F = \begin{pmatrix} 30 & 30 + a_F - \beta_F(20 + a_F) \\ 10 - \alpha_F(20 + a_L) & 10 \end{pmatrix}$$

We simplify the model by fixing the values on pay-off functions to replicate Gachter et al. (2010) experiment, which are:

$$\begin{aligned} k &= 0 \\ b &= 10 \\ v_{L,F} &= 20 \\ a_i &\in \{0,\ 10,\ 20,\ 30\} \end{aligned} \tag{5}$$

Consequently, the pay-off and utility functions with pre-fixed values on base pay-off (b), value for sharing knowledge (v_i) and expenses (k) are simplified, leaving the aversion parameters to estimate using the conditional probabilities (Revelt & Train, 1998). According to Fehr and Schmidt (1999)'s study, alpha and beta follow a discrete distribution, with values shown on Table 1.

Table 1. Discrete distribution of aversion parameters

	Alpha (α) (0.19375)		Beta (β) (0.105)	
	%	Value	%	Value
Discrete distribution	30%	0	30%	0
	30%	0.25	30%	0.25
	30%	1	40%	0.6
	10%	4		

Parameters based on Fehr et al. (1999), average shown between brackets

We build a system of equations to estimate α and β average for all individuals, the code can be found in the appendix. To our surprise, α' and β' estimations do not match the previously reported values on Table 1. In our case, we have higher values of β' (average of 0.56) and an undefined value of α'. This discovery induces us to think that the simulated values of the private-collective environment created by Gachter using Fehr and Schmidt (1999) parameters will not closely match their results. It is interesting to see, that even though Gachter et al. (2010) use Fehr and Schmidt (1999) utility functions to create their model, the aversion values (α and β) are not the same.

Simulation of a private-collective environment

Next, we simulate the knowledge-sharing environment of Gachter et al. (2010) using the aversion coefficients in Table 1. According to Fehr and Schmidt (1999)'s student participants, β is distributed as follows: 30 percent of the population has $\beta = 0$; additional 30 percent have $\beta = 0.25$

and the residuary 40 percent have $\beta = 0.6$. Following this assumption, we simulate the initiation of the knowledge sharing with hundred thousand agents, varying the incentive parameters a_L and a_F. The results are presented in the next section.

Results

Our results show communalities and differences with the experimental results of Gachter et al. In the following subsections, we will describe the differences in detail.

Followers

In Gachter et al.'s results, about 73 percent of the followers share, if the leader shares. In our results, 85 percent followers share, as 30 percent of the participants have a beta of 0 and are "indifferent toward the outcome". In addition, our results indicate that there is no difference in a_F being 20 or 30. This shows that beta should have a fourth value in its outcomes, possibly between 1/3 and 1/2. Moreover, the presumed distribution of beta is over adjusted, since on average the followers share more than the participants in the experiment of Gachter et al.

Our results show a significant less amount of followers who share if the leader conceals. This is due to the presumed distribution of alpha. Given that on average 45.3 percent share in case of leader's concealing, 10 percent of the population should have an alpha that is greater than zero.

Leaders

Leaders in our experiments share less with the increasing a_L. Yet, Gachter et al.'s experiment results show that leaders tend to share less with both, increasing a_L and a_F. Since a_F does not play a critical role in the utility function of the leaders, Fehr and Schmidt's model is insufficient to explain the experimental results.

Mutual sharing

Gachter et al. describes the results that "knowledge sharing is substantially more fragile in a_F than a_L. In contrary, our results indicate that mutual knowledge sharing is equally fragile in a_L and a_F.

Therefore the surface of the mutual knowledge sharing is symmetric in both directions. The following figures show our simulated results using probabilities (Gachter et al., 2010) and utility functions (Fehr & Schmidt, 1999) in a more visual way.

Figure 2. Percentage of followers who share if the leader shares, based on Gachter et al. (2010)

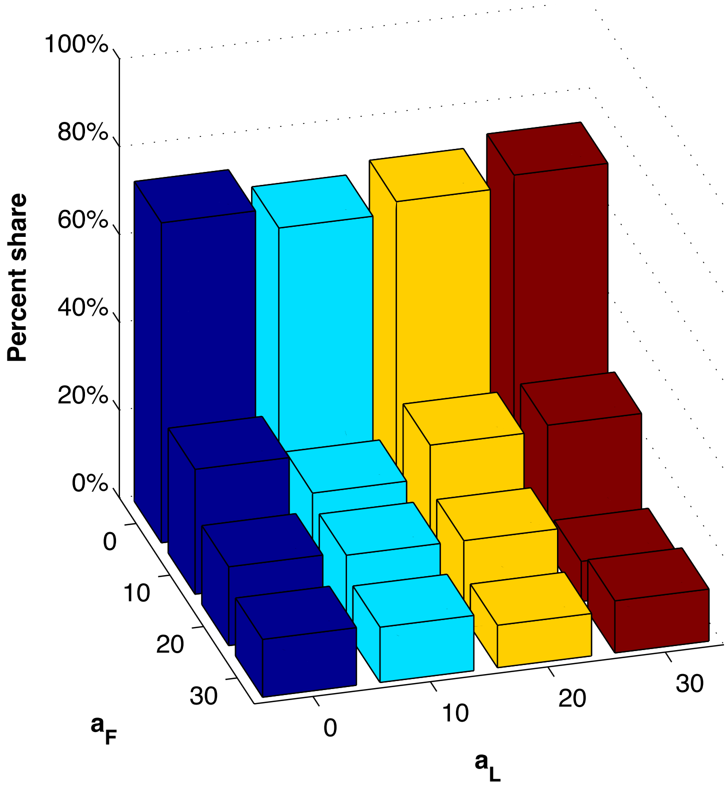


Figure 3. Percentage of followers who share if the leader shares, based on Fehr and Schmidt (1999)

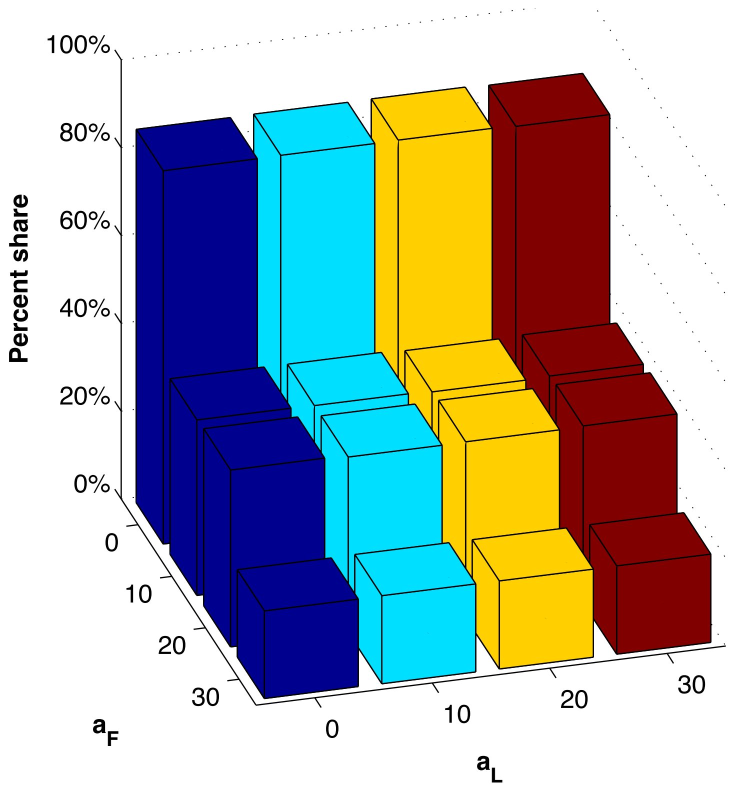


Figure 4. Percentage of followers who share if the leader conceals, based on Gachter et. Al (2010)

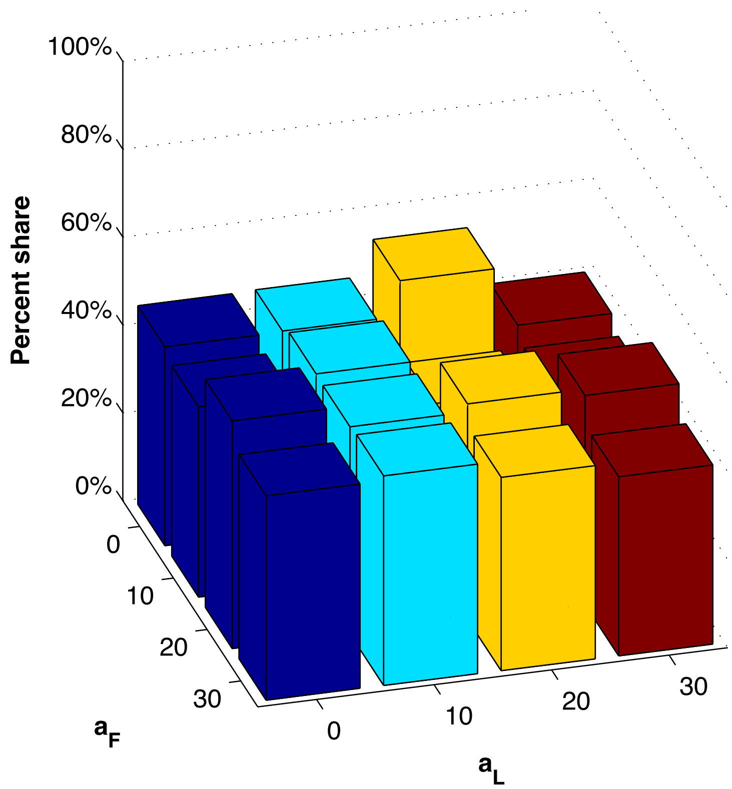


Figure 5. Percentage of followers who share if the leader conceals, based on Gachter et. Al (2010)

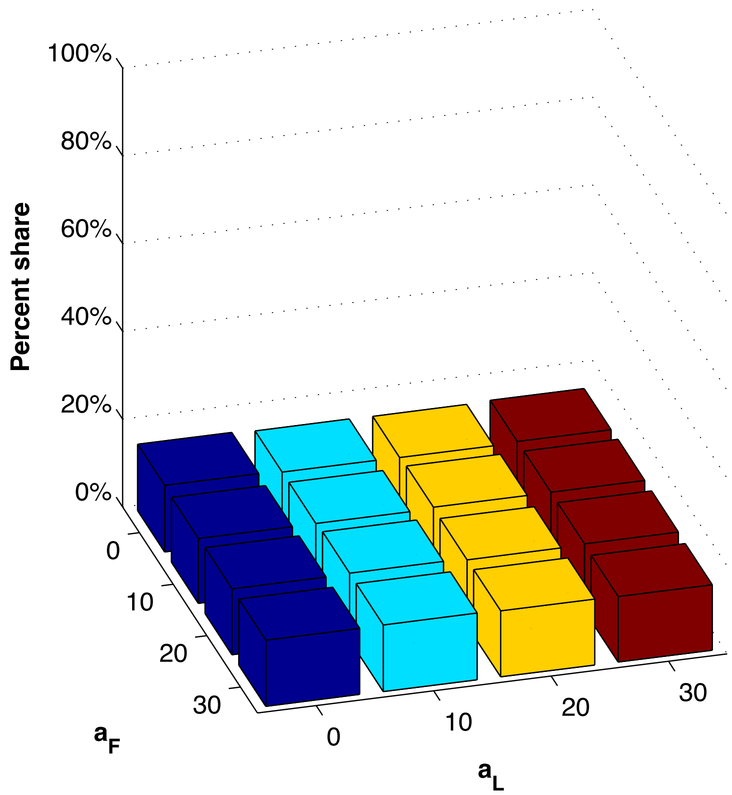


Figure 6. Percentage of leaders who share, based on Gachter et al. (2010)

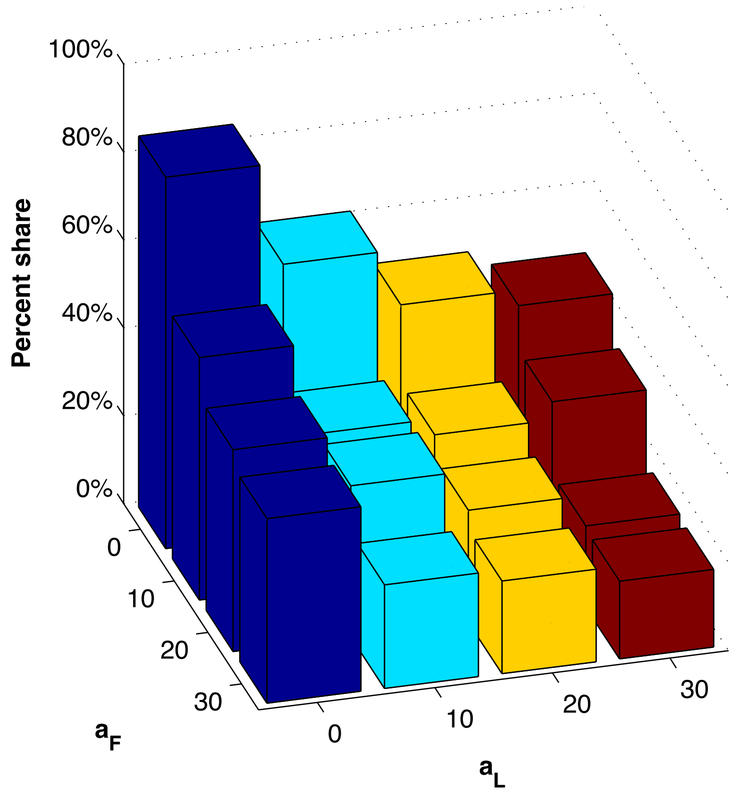


Figure 7. Percentage of leaders who share, based on Fehr and Schmidt (1999)

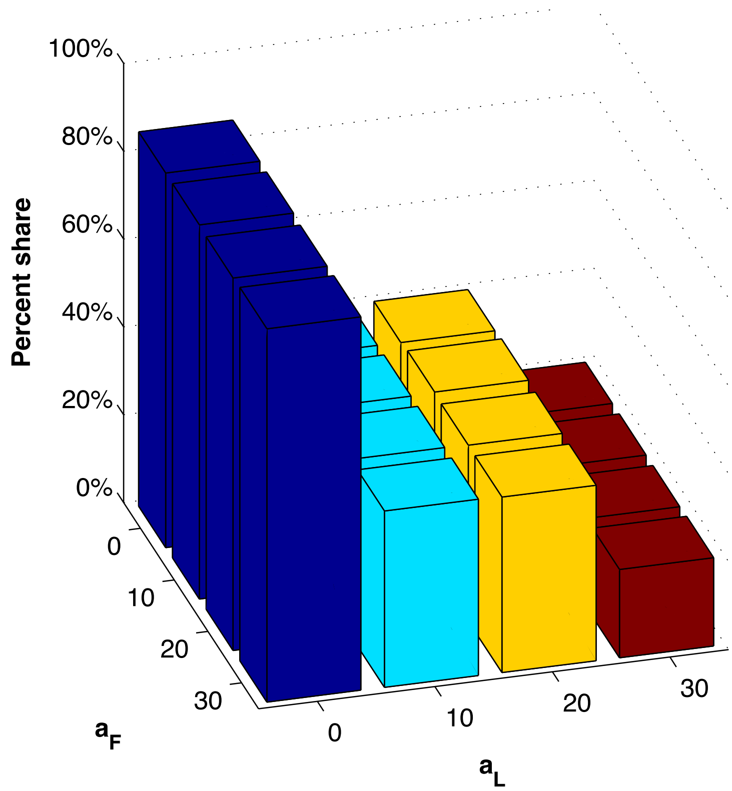


Figure 8. The fragility of knowledge sharing-percentage of mutual sharing, based on Gachter et al. (2010)

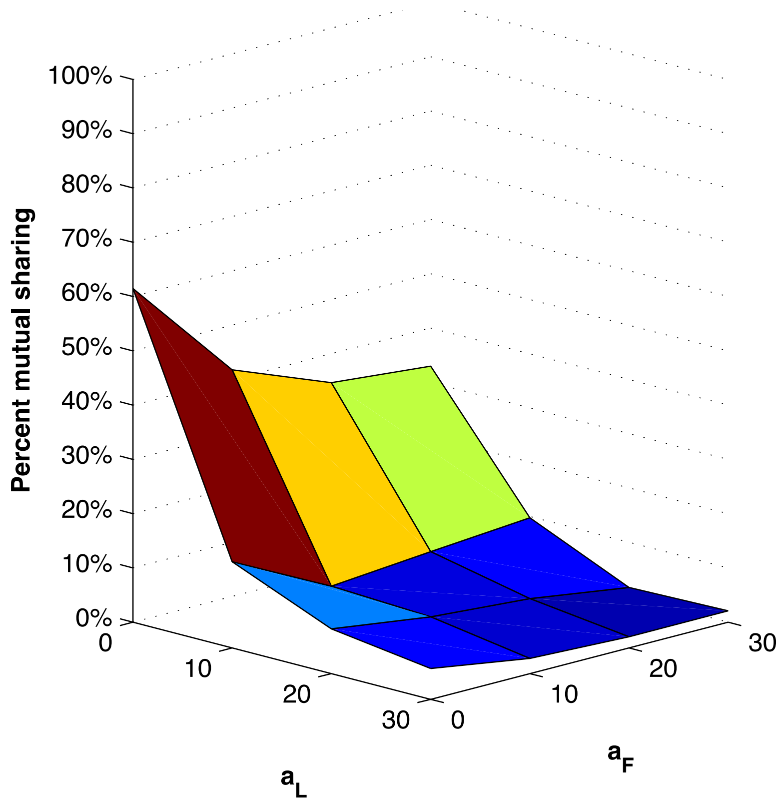
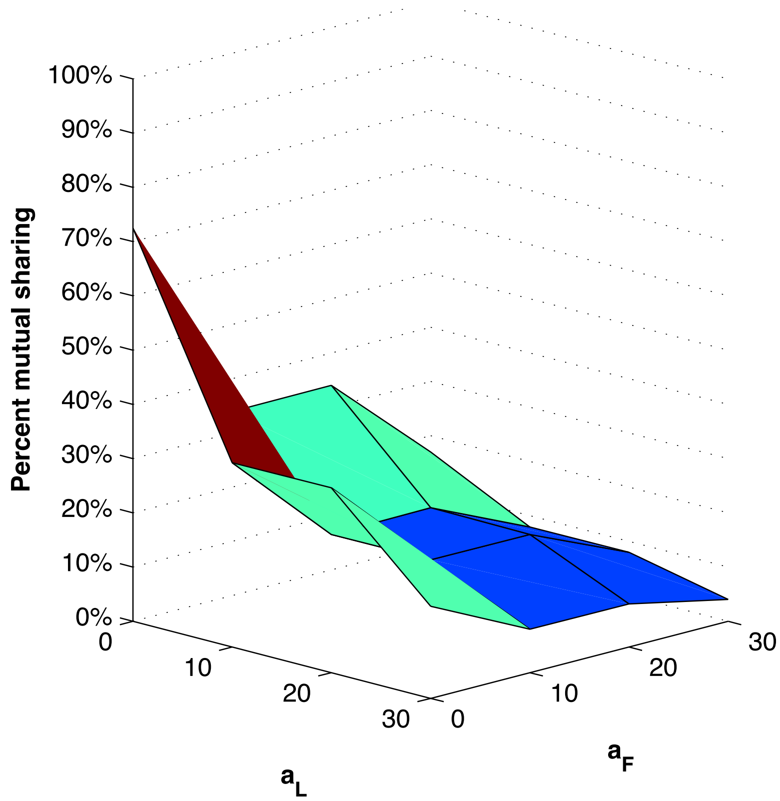


Figure 9. The fragility of knowledge sharing-percentage of mutual sharing, based on Fehr and Schmidt (1999)



Conclusion

In this paper we use the existence of a direct relationship between probabilities and utility functions (Revelt & Train, 1998) to model a Private-Collective innovation environment using results from previous research (Fehr & Schmidt, 1999; Gachter et al., 2010). Even though the results are challenging, as they do not explain all the social preferences of the individuals, it gives us an estimation of how close - or far - we are from understanding social behavior.

The implementation of Fehr and Schmidt's (1999) model on the knowledge sharing game proves the existence of some incompatibility with Gachter et al.'s (2010) lab-experiment results and the mathematical model behind. In many situations the presumed distribution of the aversion against advantageous and disadvantageous inequity is not entirely reflecting the reality, this being the lab results from Gachter et al. (2010). One possible explanation could be the simplicity of the discrete social distribution suggested by Fehr and Schmidt's (1999). It could be that these aversion parameters (α and β) are more dynamic that previous research has anticipated. Another plausible explanation lies in "hidden" social parameters that haven't yet been suggested or used in social games like knowledge sharing in Private-Collective environments. Overall, our results show the need to further investigate the individual behavior and better understand its incentives to share or conceal knowledge.

Next, we suggest to further look at the inner dependencies between utility functions. We show how leader's probability for sharing knowledge varies depending on followers parameters – from Gachter et al. (2010) replication (Figure 6), which wasn't previously explained by the functions used (Fehr & Schmidt, 1999). This indicates some dependencies between utility functions that were not explicitly formulated before. In other words: The leader will not only look at his utility function, when making his decision, he will also look at the followers utility functions to optimally decide.

This, of course, has a great effect on the willingness to share knowledge, and could potentially better explain our results and those of Gachter et al. (2010).

Finally, simulating real settings using Matlab or any other available software has its limitations. Real settings' results include factors and effects that are not reported – that belong to the individual or the environment, as it is imperfect – which could lead to biases when interpreting the data. Furthermore, it could lead to unexplainable results when simulating these settings with small variations. These should be considered when doing research and experiments of social behavior virtually, as we might underestimate the human complexity.

Appendix

System of equations to estimate aversion parameters (Matlab code)

Filename: alphabeta.m

```
% Solving the linear system of equations using probability values from Gachter
et al (2010) and Utility functions from Fehr et al (1990)


x0 = [1; 1];            % Make a starting guess at the solution
options=optimset('Display','iter');    % Option to display output
[x,fval] = lsqnonlin(@myfun,x0,[0; 0],[4; 0.999])  % Call solver
```

Filename: myfun.m

```
function F = myfun(x)
 a=0;
%
 F = [0.84211 * (exp(30) +exp(10) + exp(10-x(1)*(20+a)) + exp(30+a-x(2)*(20+a)))
- exp(30);
     0.65789   *   (exp(10)   +exp(10)   +   exp(10-x(1)*(20+10))   +   exp(30+10-
x(2)*(20+10))) - exp(30);
     0.25439   *   (exp(30)   +exp(10)   +   exp(10-x(1)*(20+20))   +   exp(30+20-
x(2)*(20+20))) - exp(30);
     0.17544   *   (exp(30)   +exp(10)   +   exp(10-x(1)*(20+30))   +   exp(30+30-
x(2)*(20+30))) - exp(30)

     %Follower
     0.73214  *  (  exp(30)  +  exp(10)  +  exp(30+a  -  x(2)*(20+a))  +  exp(10-
x(1)*(20+a)) )  - exp(30);
      0.19643  *  (  exp(30)  +  exp(10)  +  exp(30+10  -  x(2)*(20+10))  +  exp(10-
x(1)*(20+10)) )  - exp(30);
      0.25439  *  (  exp(30)  +  exp(10)  +  exp(30+20  -  x(2)*(20+20))  +  exp(10-
x(1)*(20+20)) )  - exp(30);
      0.11607  *  (  exp(30)  +  exp(10)  +  exp(30+30  -  x(2)*(20+30))  +  exp(10-
x(1)*(20+30)) )  - exp(30)
     ];
```

System of equations to simulate the private-collective environment (Matlab code)

```
Filename: main.m

close all
clear all
clc

%% simulation

%initiate agents
n=10^5;
alpha_L=[0*ones(1,n*0.3) 0.25*ones(1,n*0.3) 1*ones(1,n*0.3) 4*ones(1,n*0.1)];
alpha_F=[0*ones(1,n*0.3) 0.25*ones(1,n*0.3) 1*ones(1,n*0.3) 4*ones(1,n*0.1)];
beta_L=[0*ones(1,n*0.3) 0.25*ones(1,n*0.3) 0.6*ones(1,n*0.4)];
beta_F=[0*ones(1,n*0.3) 0.25*ones(1,n*0.3) 0.6*ones(1,n*0.4)];

%decision statistics
d_stat=zeros(2,2,4,4);
d_stat_ss=zeros(4,4);
d_stat_cc=zeros(4,4);

d_stat_L=zeros(2,4,4);
d_stat_F2=zeros(2,4,4);
d_stat_F1=zeros(2,4,4);

d_stat_sL=zeros(4,4);
d_stat_sF_sL=zeros(4,4);
d_stat_sF_cL=zeros(4,4);

%initiate payoff matrix
aL=0;
aF=0;

P_L= [30, 10 ; 30+aL , 10];
P_F= [30, 30+aF ; 10 , 10];

%vary parameters

%aL
for l=1:4
    aL=l*10-10;

    %aF
    for k=1:4
        aF=k*10-10;

        P_L= [30, 10 ; 30+aL , 10];
        P_F= [30, 30+aF ; 10 , 10];

        %decision round
        for j=1:1

            %shuffle pairs
            pair_matrix=randperm(n);

            %make decision
            for i=1:2:n;

                %decision leader and decision follower
                dL = 0; %reset decisions
```

```
                dF = [0,0];

                %[dL, dF] = make_decision_ks(aL,aF);
                   [dL, dF] = make_decision_FS_v2(P_L, P_F,
                  alpha_L(pair_matrix(i)), alpha_F(pair_matrix(i+1)),
                  beta_L(pair_matrix(i)), beta_F(pair_matrix(i+1)));

                %save decisions
                d_stat_L(dL,k,l)      = d_stat_L(dL,k,l) + 1;
                d_stat_F1(dF(1),k,l)  = d_stat_F1(dF(1),k,l) + 1;
                d_stat_F2(dF(2),k,l)  = d_stat_F2(dF(2),k,l) + 1;
                d_stat(dL,dF(dL),k,l) = d_stat(dL,dF(dL),k,l) + 1;

                if (mod(i+1,n/1) == 0)

                    d_stat_sL(k,l)=d_stat_L(1,k,l)/sum(sum(d_stat_L(:,k,l)));
                    d_stat_sF_sL(k,l)=d_stat_F1(1,k,l)/sum(d_stat_F1(:,k,l));
                    d_stat_sF_cL(k,l)=d_stat_F2(1,k,l)/sum(d_stat_F2(:,k,l));
                    d_stat_ss(k,l)=d_stat(1,1,k,l)/sum(sum(d_stat(:,:,k,l)));

                end
            end
        end
    end
end

plot_results(d_stat_sF_sL , d_stat_sF_cL , d_stat_sL , d_stat_ss)
```

Filename: make_decision_ks.m

```
function [decision_leader, decision_follower] = make_decision_ks(aL, aF)

%% assigning parameters

if (aL == 0 & aF == 0)

    sL = 0.84211;
    sF_sL = 0.73214;
    sF_cL = 0.45536;

elseif (aL == 10 & aF == 0)

    sL = 0.61404;
    sF_sL = 0.67857;
    sF_cL = 0.45536;

elseif (aL == 20 & aF == 0)

    sL = 0.48246;
    sF_sL = 0.71429;
    sF_cL = 0.53571;

elseif (aL == 30 & aF == 0)

    sL = 0.44737;
    sF_sL = 0.74107;
    sF_cL = 0.40179;

elseif (aL == 0 & aF == 10)

    sL = 0.55263;
    sF_sL = 0.28571;
    sF_cL = 0.42857;

elseif (aL == 10 & aF == 10)

    sL = 0.34211;
    sF_sL = 0.19643;
    sF_cL = 0.47321;

elseif (aL == 20 & aF == 10)

    sL = 0.30702;
    sF_sL = 0.26786;
    sF_cL = 0.37500;

elseif (aL == 30 & aF == 10)

    sL = 0.35088;
    sF_sL = 0.28571;
    sF_cL = 0.37500;

elseif (aL == 0 & aF == 20)

    sL = 0.45614;
    sF_sL = 0.17857;
    sF_cL = 0.51786;

elseif (aL == 10 & aF == 20)

    sL = 0.34211;
```

```
    sF_sL = 0.16964;
    sF_cL = 0.47321;

elseif (aL == 20 & aF == 20)

    sL = 0.25439;
    sF_sL = 0.16964;
    sF_cL = 0.49107;

elseif (aL == 30 & aF == 20)

    sL = 0.18421;
    sF_sL = 0.08929;
    sF_cL = 0.47321;

elseif (aL == 0 & aF == 30)

    sL = 0.42105;
    sF_sL = 0.13393;
    sF_cL = 0.46429;

elseif (aL == 10 & aF == 30)

    sL = 0.23684;
    sF_sL = 0.12500;
    sF_cL = 0.47321;

elseif (aL == 20 & aF == 30)

    sL = 0.21053;
    sF_sL = 0.09821;
    sF_cL = 0.43750;

elseif (aL == 30 & aF == 30)

    sL = 0.17544;
    sF_sL = 0.11607;
    sF_cL = 0.41071;

end

%% decision for leader

decision_leader = (rand() > sL) + 1; % 1 share, 2 conceal
%% decision for follower

decision_follower(1) = (rand() > sF_sL) + 1;
decision_follower(2) = (rand() > sF_cL) + 1;
```

Filename: make_decision_FS_v2.m

```
function [decision_leader, decision_follower] = make_decision_FS_v2(P_L, P_F,
alpha_L, alpha_F, beta_L, beta_F)

%Utility function of the leader
U_L = P_L - alpha_L * max(P_F-P_L,0) - beta_L * max(P_L-P_F,0);

%Utility function of the follower
U_F = P_F - alpha_F * max(P_L-P_F,0) - beta_F * max(P_F-P_L,0);

%% Decision of the leader
[x1,y1] = find(U_L==max(U_L(:)));

if length(x1) == 1
    decision_leader = x1;
else
    decision_leader = (rand() < 0.5) + 1; %1 share, 2 conceal
end

%% Decision of the follower

[x2,y2] = find(U_F==max(U_F(1,:)));
[x3,y3] = find(U_F==max(U_F(2,:)));

if length(y2) == 1
    decision_follower(1) = y2;
else
    decision_follower(1) = (rand() < 0.5) + 1;
end

if length(y3) == 1
    decision_follower(2) = y3;
else
    decision_follower(2) = (rand() < 0.5) + 1;
end
```

Filename: plot_results.m

```
function plot_results (d_stat_sF_sL , d_stat_sF_cL , d_stat_sL , d_stat_ss)

view_angle_bar=[[-16,26]];
view_angle_surface=[[45,15]];
data_aspect_ratio=[[0.8 0.8 0.2]];

figure
bar3(d_stat_sF_sL)
grid off
set(gca,'ZGrid','on')
set(gca,'DataAspectRatio',data_aspect_ratio)
title('Percentage of followers who share if the leader shares.')
xlabel('a_L','FontWeight','bold')
ylabel('a_F','FontWeight','bold')
zlabel('Percent share','FontWeight','bold')
set(gca,'XTickLabel',[0 10 20 30])
set(gca,'YTickLabel',[0 10 20 30])
set(gca,'ZTickLabel',['  0%';' 20%';' 40%';' 60%';' 80%';'100%'])
view(view_angle_bar)
axis([0.5 4.5 0.5 4.5 0 1])


figure
bar3(d_stat_sF_cL)
grid off
set(gca,'ZGrid','on')
set(gca,'DataAspectRatio',data_aspect_ratio)
title('Percentage of followers who share if the leader conceals.')
xlabel('a_L','FontWeight','bold')
ylabel('a_F','FontWeight','bold')
zlabel('Percent share','FontWeight','bold')
set(gca,'XTickLabel',[0 10 20 30])
set(gca,'YTickLabel',[0 10 20 30])
set(gca,'ZTickLabel',['  0%';' 20%';' 40%';' 60%';' 80%';'100%'])
view(view_angle_bar)
axis([0.5 4.5 0.5 4.5 0 1])

figure
bar3(d_stat_sL)
grid off
set(gca,'ZGrid','on')
set(gca,'DataAspectRatio',data_aspect_ratio)
title('Percentage of leaders who share')
xlabel('a_L','FontWeight','bold')
ylabel('a_F','FontWeight','bold')
zlabel('Percent share','FontWeight','bold')
set(gca,'XTickLabel',[0 10 20 30])
set(gca,'YTickLabel',[0 10 20 30])
set(gca,'ZTickLabel',['  0%';' 20%';' 40%';' 60%';' 80%';'100%'])
view(view_angle_bar)
axis([0.5 4.5 0.5 4.5 0 1])

figure
set(gca,'ZGrid','on')
set(gca,'DataAspectRatio',data_aspect_ratio)
surface(d_stat_ss')
title('The fragility of knowledge sharing-percentage of mutual sharing')
xlabel('a_L','FontWeight','bold')
ylabel('a_F','FontWeight','bold')
zlabel('Percent mutual sharing','FontWeight','bold')
set(gca,'XTickLabel',[0 10 20 30])
```

```
set(gca,'YTickLabel',[0 10 20 30])
set(gca,'ZTickLabel',['  0%';' 10%';' 20%';' 30%';' 40%';' 50%';' 60%';' 70%';'
80%';' 90%';'100%'])
axis([1 4 1 4 0 1])
view(view_angle_surface)
```

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