Individual Behavior and Strategy in Favor Exchange and Online Content Contribution

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Abstract

Individual Behavior and Strategy in Favor Exchange and Online Content Contribution

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This thesis consists of three chapters. Chapter 1 theoretically studies a favor exchange model between two infinitely lived agents. Under private information, the efficient strategy is not incentive compatible. We propose a class of Markov strategies, which we call Bounded Favors Bank strategies (BFB hereafter). Within the class of BFB strategies, we consider two types of the BFB strategy. A type of BFB strategy which prescribes a form of reward for the agent who provided the most favors is referred to as BFBr strategy; another type of BFB strategy which prescribes a form of punishment for the agent who received the most favors is referred to as BFBp strategy. We show that the payoffs of BFBr and BFBp strategies can approximate the efficient outcome under private information and the BFBp strategy can achieve a higher long-term payoff.

Chapter 2 experimentally test the theoretical model in Chapter 1. In the experiment, we examine the behavior of subjects and infer the strategies subjects employ under complete information and incomplete information. Our experiment shows that subjects cooperate to exchange favors substantially less often under incomplete information, the most commonly employed strategy switches from the efficient one to the non-cooperative one, and the BFB strategies are played with a statistically significant probability only under incomplete information. In addition, the BFBr strategy is played more often than the BFBp strategy, implying that using a form of reward may have more compliance than using a form of punishment in a long-term bilateral relationship with private information.

Chapter 3 provides theoretical and empirical findings on the incentive effect of peer recognition on content provision. Our theoretical model illustrates how the incentive could be adversely affected by reputation and privacy concerns. Employing a unique data set from the largest Chinese Q&A platform, we analyze the content provisions of all the influencers with more than 10,000 followers on the platform over two years. Using an instrumental variable approach, we find that a simple OLS method is likely to underestimate the incentive of peer recognition due to the adverse effect of strategic behaviors of influencers.

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Contributions of Authors

Chapter 1: This paper is co-authored with Dr. Arianna Degan and Dr. Huan Xie. We conceived the research questions and conducted the literature review together. Dr. Arianna Degan provided the first stage of the theoretical model. I proved the further theoretical results and wrote the manuscript. I revised the paper with the comments and suggestions from Dr. Arianna Degan and Dr. Huan Xie.

Chapter 2: This paper is co-authored with Dr. Arianna Degan and Dr. Huan Xie. We conceived the research questions, reviewed the related literatures, and developed the experimental design and methodology together. Dr. Xie and I conducted the experimental sessions. I programmed the z-Tree interface for the experiment, conducted data analyses and wrote up the first draft. I did the main revision with the comments and suggestions from Dr. Arianna Degan and Dr. Huan Xie.

Chapter 3: This paper is co-authored with Dr. Xintong Han and Dr. Tong Wang. We conceived the research questions, reviewed the related literatures, and developed the theoretical model together. I provided the empirical results and wrote the manuscript. I revised the paper based on our discussions and comments.

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1 A Model of Favor Exchange

1.1 Introduction

Bilateral relationships are widespread in any society. Interactions in bilateral relationships are often repeated, such as, between business partners or rivals, countries, provinces, political parties, partnerships among practitioners, colleagues, couples, relatives and friends. We can also think of many instances where the interactions between agents in a bilateral relationship take the form of exchange of favors. A situation with favors emerges when one agent's benefit depends only on an action taken by the other agent. For example, baby sitting service between friends. In the political arena, the party in power could implement a "favor" policy that has high salience for the opposition party as long as it does not affect much the ruling party's main political program, the opposition party in exchange may abstain from opposing some policy proposed by the ruling party. Alternatively, the favor could be returned when political power changes hand. In many business or health care service, one agent may refer some of her clients to the other for a related service/good. Like a regular dentist that refers her patient to a specialist, or an architect refers her client to a contractor, and vice versa.

By and large, the literature has considered models where agents privately observe the possibility of making a favor to the other and only one agent at a time can have such possibility. Möbius (2001) and Hauser and Hopenhayn (2008) consider a continuous-time model where the possibility of making favor arises according to a Poisson distribution. Kalla (2010), Abdulkadiroglu and Bagwell (2012; 2013), Jeitschko and Lau (2017), Olszewski and Safronov (2018b) consider settings where interactions are in discrete time. Hauser and Hopenhayn (2008) are the first to allow for divisible favors. Kalla (2010) introduces private information about agent's discount factor and characterizes sufficient conditions under which the high type agents are able to separate themselves from the low type agents.[1] Abdulkadiroğlu and Bagwell (2013) propose a richer setting with divisible favors, trust, and immediate reciprocity. Jeitschko and Lau (2017) assume that in a given period the recipient can solicit a favor, the helper may be in the position to provide help, and allow for an accounting mechanism that keeps track of the net benefit of favors traded.[2]

One simple family of strategies that has been widely studied with indivisible favors is called chip strategies. In baseline chip strategies, agents behave as if they were endowed with a finite number of chips and when an agent receives a favor she has to give a chip to the favor provider. So that if an agent has no chip left, the strategy prescribes that she cannot receive any more favors until she gets a chip.

Different from the existing literature, where at any given point only one agent may be in the (privately observed) position of providing a favor, we propose a setting where each agent can provide a favor in each period and the source of private information is the cost of providing a favor.[3][4] In particular, the cost of providing a favor can be either low or high

[1]The low type agents who have lower discount factor do not find cooperation beneficial and the high type agents have benefits from cooperation.

[2]There are some applications of favor exchange in context of collusion (see Athey and Bagwell (2001), Skrzypacz and Hopenhayn (2004), Olszewski and Safronov (2012)) in which the accounting mechanism that keeps track of the net favors is also considered. Their accounts depend on the net benefit of the favor, the benefit and the cost of favor can vary over time.

[3]Jeitschko and Lau (2017) also allow the cost of favors to be privately observed but only one agent may be able to provide a favor with a probability $\alpha = 1/2$.

[4]For example, consider the situation where two single mothers with high school kids can share the task of bringing the kids to school and take them back. Kids are old enough that they could go to school with public transportation but it is not that safe and it takes more time, meaning that they would have to wake up earlier and come back later so that less time is available for other activities. Suppose that the parent's work schedule is such that one parent can never take them to school in the morning, while the other can never take them back at the end of the day. When one parent is not working, there are days in which taking the kids to school is not costly, but there are other days where taking them to school is too costly (due to a medical appointment or some other activity that the parent would like to take). For another example think of the referral of clients among associate practitioners. A practitioner may have private information about the condition of their patient. She could provide a specialize treatment himself, or refer the client to her associate specialist. The opportunity cost of referring the patient may depend on the specific condition of the patient

and the net benefit is positive only in the first case. Under private information, efficiently exchanging favors cannot be sustained as an equilibrium. Focusing on Perfect Public strategies, we consider a class of Markov strategies that we call Bounded Favors Bank (BFB). In such strategies, as in Möbius (2001), each agent has a maximum net number of favors she can provide (maximum debit) and receive (maximum credit). When no agent has yet hit this maximum, a Bounded Favors Bank strategy prescribes an efficient strategy to be played. When the maximum is achieved a Bounded Favors Bank strategy requires a form of reward for the agent who provided the most favors or a form of punishment for the agent who received the most favors. We refer to the BFB pure strategy, where the agent who reached her maximum net number of favors provided is exonerated from providing favors until she receives a favor back, as BFB with reward (BFBr). We refer to BFB pure strategy, where the agent who reached her maximum net number of favors received to provide a favor even if highly costly, as BFB with punishment (BFBp). We prove that both BFBr and BFBp strategies may constitute equilibria when the information about the cost of favor provision is privately observed.

Notice that our BFB strategies, where the state variable is the net number of favors received, are equivalent to chip strategies where agents are endowed with chips and an agent at the end of a given period must transfer a chip to the other if and only if she is the only one providing a favor in that period. In particular, our BFBr strategy corresponds to the baseline chip strategy considered in the literature, where an agent is supposed to provide a favor when it is efficient (when she has an opportunity to do so) if and only if she does not have all the chips. Our BFBp strategy would be equivalent to a chip strategy where an agent always provides a favor when it is efficient but has to provide it also when it is inefficient and she has all the chips.[5]

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and the ability of the specialist in dealing with such condition. Analogous arguments apply for the associate specialist refer some of her clients to the general practitioner.

[5]Our BFBp strategy has the flavor of the general chip strategy considered by Olszewski and Safronov

The contribution of our analysis is to propose a model of favors that allows for a strategy that, in order to reestablish a balance in 'Equality Matching' relationships (see Fiske (1992)), directly punishes the agent who benefits from many net favors.

To summarize, the novelty of this paper is to consider a different favor exchange model, where favors can be immediately reciprocated and where the cost of providing favors is private information, that allows considering a new strategy (BFBp) that could not be considered in the setting of the existing literature.

Olszewski and Safronov (2018b) have shown that the equilibrium chip strategy is asymptotically efficient.[6] Using the same arguments we show that in our setting both BFB with reward and with punishment are asymptotically efficient.[7] We then compare long-run payoffs within the class of Bounded Favors Bank strategies for a given maximum credit and debit and also compare the payoffs of Bounded Favors Bank strategies with those of Stationary Strongly Symmetric Strategies. We find that agents who employ Bounded Favors Bank strategy with punishment can obtain payoff that strictly dominate all payoffs of Stationary Strongly Symmetric strategies in the equilibrium. And agents can gain more in the long-term from punishing the ones who received the most favors than from rewarding the ones who provided the most when cost of favor provision decreases.

The rest of the paper is organized as follows. Section 1.2 presents the theoretical model. Section 1.3 describes the strategies and related properties. Results of payoff comparison are reported in Section 1.4. And Section 1.5 concludes.

(2018a). They consider a general setting with multiple agents who at each period report their types and have access to a public randomization device.

[6]Abdulkadiroğlu and Bagwell (2013) consider Highest Symmetric Self-Generating Line (HSSL) strategies analogous to the ones considered by Athey and Bagwell (2001), where firms in a duopoly collude use future market shares favors. In HSSL strategies, utility pair and continuation payoff must all be drawn from a given line.

[7]We show that long-term payoffs of two BFB pure strategies can approximate the efficient outcome under incomplete information if agents are patient enough.

1.2 The model

We consider the exchange of favors between two infinitely lived agents. Each agent $i \in \{1, 2\}$, obtains an instantaneous utility "x" from receiving a favor and faces a random cost "c_i" of providing a favor. This cost can take only two values: low or high, $c_i \in \{c_l, c_h\}$. We restrict attention to the case where there are potential gains from providing a favor only in presence of a low cost, that is when $0 < c_l < x < c_h$.[8] In addition, we assume that the joint cost distribution is independently and identically distributed across time. This assumption implies that the cost at any period t does not affect the cost at period $t + 1$ and hence allows using a recursive formulation of the problem. Let (c_k, c_j), $(k, j \in \{l, h\})$, be the cost realization at a generic period for the 2 agents, where the first element is the cost of agent 1 and the second is the cost of agent 2. The marginal probability an agent has a low cost is $\Pr(c_l) = p$ and the corresponding probability that she has a high cost is $\Pr(c_h) = 1 - p$. To simplify the analysis we assume a particular form of complementarity between agents, where only one agent in each period can have a low cost of providing a favor and hence $p < \frac{1}{2}$. The joint distribution of costs of favors is represented in Table 1.

The joint distribution implies that conditional on agent i having a low cost $c_i = c_l$, the other agent has a high cost with probability 1, $\Pr(c_{-i} = c_h | c_i = c_l) = 1$. Conversely, conditional on agent i having a high cost $c_i = c_h$, the other agent has a low cost with probability $\Pr(c_{-i} = c_l | c_i = c_h) = \frac{p}{1-p}$, and a high cost with the complement probability, $\Pr(c_{-i} = c_h | c_i = c_h) = \frac{1-2p}{1-p}$.

Let $Y^t = \{(F, F), (F, N), (N, F), (N, N)\}$ be the set of possible allocations of favors in period t. The generic element $y^t \in Y^t$ has two components: the first indicates whether agent 1 provided a favor or not (respectively F and N), and the second indicates the analogous for agent 2. In this context, a public history at time t is a sequence of realized allocations

[8] The other cases are of no interest.

c_1,c_2	Pr(c_1,c_2)
c_l, c_l	0
c_l, c_h	p
c_h,c_l	p
c_h,c_h	$1-2p$

	$c_2 = c_l$	$c_2 = c_h$	marginal prob for c_1
$c_1 = c_l$	0	p	p
$c_1 = c_h$	p	$1-2p$	$1-p$
marginal prob for c_2	p	$1-p$	1

Table 1: Distribution of costs of favors

until time $t-1$, $h^t = \{y^1, y^2, ...y^{t-1}\}$, and it is common to both agents. We denote the set of public histories at time t by H^t. We are interested in the situation where the allocations of favors are publicly observed but each agent's cost is private information. Thus agents' histories include not only the publicly observed actions but also the whole sequence of privately observed cost realizations and will therefore be different across agents. In addition there is no explicit commitment device available to agents. The repeated game we consider is therefore one with perfect monitoring and where the constituent game is a two-stage game with incomplete information. As common in the literature of dynamic and repeated games, we will consider only public strategies.

Definition 1. *A public strategy is a sequence of functions for each agent $i = 1, 2$, $\{s_i^t\}_{t=1}^{\infty}$ where each element of the sequence is a map from any public history and private cost at time t, to the set of actions. That is: $s_i^t : H^t \times \{c_l, c_h\} \rightarrow \{F, N\}$.*

We say that an allocation of favors in the stage game is (ex-post) *efficient* if it maximizes the sum of the utilities of the two agents after the costs have been realized at any period. We define a strategy of the infinitely repeated stage game as *efficient* if it induces the efficient allocation of favors in each period.

Definition 2. *An **Efficient Strategy** in our setting is a strategy such that, along the equilibrium path, an agent chooses F at time t if and only if her cost is low.*

The discounted payoff induced by the efficient strategy is $V = (x - c_l)p$ for each agent. An efficient allocation is therefore also Symmetric Pareto Optimal, that is, there is not another feasible symmetric allocation that makes both agents ex-ante better off. If the costs of providing favors were observable, this efficient allocation of favors could be supported by Grim-Trigger strategy, where the worst Nash equilibrium of the stage game is played ever after a deviation is detected, for discount factors $\delta \geq \frac{c_l}{(x-c_l)p+c_l}$.[9] However, under incomplete information, the efficient strategy is not incentive compatible, as the low type would find it profitable to mimic the high type in the current period without such deviation being detected by the public history.[10]

In the next section, we first analyze a classic type of strategies studies in the literature of repeated and dynamic games, which can support certain equilibria when the cost of providing a favor is private information. And then we propose a class of Markov strategies which we refer to Bounded Favors Bank Strategies.

1.3 Equilibrium strategies

A common practice in the literature of dynamic games with private information is to focus on *Perfect Public Equilibria (PPE)*, in which the strategy profiles are restricted to depend only upon the public history and where continuation strategies after every possible public history are themselves equilibrium strategies. PPE may be supported by very complicated strategies. For tractability and since in many real situations agents seem to follow simple strategies, in this paper we follow the literature and concentrate on some subsets of PPE.

[9]The grim-trigger strategy prescribes each agent in each period t to play F if and only if the cost is low and N if the cost is high, unless someone deviated, in which case N is played forever on. The efficient strategy gives a discounted expected payoff to each agent of $(x - c_l)p$. Given the recursive structure of the problem, the condition for the discount factor can be derived from the low type incentive constraint: $-c_l(1-\delta) + \delta(x - c_l)p \geq 0$.

[10]The efficient strategy prescribes that only the low cost type provides the favor. This strategy is incentive compatible if no agent of any type at any time is better off by behaving as a different type. The recursive formulation of the incentive constraint for the low type is $-c_l(1-\delta) + \delta V \geq \delta V$, which is never satisfied $\forall c_l > 0$.

1.3.1 Stationary Strongly Symmetric strategies

A *strongly symmetric strategy* profile prescribes that the strategy played at any period t, after any history h^t, is the same for all agents. Within this class, we consider stationary strategies.

Definition 3. *Stationary Strongly Symmetric equilibria (SSE) are equilibria where both players have the same continuation payoff after any possible history, and where on equilibrium path (normal regime) the same static strategy is played at each period t, while off-equilibrium (deviation regime) the worst static Nash equilibrium is played.*

In our context any possible stationary strategy must belong to the set, $S = \{(F, N), (N, F)$ $, (N, N), (F, F)\}$, where the first element inside a bracket is the action to be chosen when the cost is low and the second element is the action to be chosen when the cost is high. We let s^{qj}, $q, j \in \{F, N\}$, denote the strategy prescribed in the normal regime in which a player takes action q when she has a low cost and action j when she has a high cost. In any SSE, the strategy played in the deviation regime is (N, N).[11]

We now analyze the conditions under which SSE exist and the derived payoffs. We characterize a SSE by the prescribed strategy in the normal regime s^{qj}. Before imposing stationarity, an agent's payoff corresponding to each potential equilibrium strategy s^{qj} can be written, using the recursive payoff decomposition implied by symmetric public strategies, as:

$$
\begin{aligned}
v(s^{FF}) &= (1-\delta)[x - c_l p - c_h(1-p)] + \delta v_{FF};\\
v(s^{FN}) &= (1-\delta)(x - c_l)p + \delta 2 p v_F + \delta(1-2p)v_N;\\
v(s^{NN}) &= \delta v_N;\\
v(s^{NF}) &= (1-\delta)(x - c_h)(1-p) + \delta(1-2p)v_F + \delta 2 p v_N,
\end{aligned}
$$

[11] (N, N) is the unique and worst Nash Equilibrium of the stage game.

where v_{FF} is the continuation payoff after the current period realization of favors $y = (F, F)$ in which both players provide a favor; v_F is the continuation payoff after the current period realization in which only one player provides a favor; v_N is the continuation payoff after the current period realization in which none of the player provides a favor.

Imposing stationarity (i.e., the same strategy is played at every period, which implies that the payoff on the LHS of each equation should be equal to each of the continuation payoffs on the RHS of each equation), the expected payoff from the above strategies becomes:

$$\begin{aligned} v(s^{FF}) &= [x - c_l p - c_h(1-p)]; \\ v(s^{FN}) &= (x - c_l)p; \\ v(s^{NN}) &= 0; \\ v(s^{NF}) &= (x - c_h)(1-p). \end{aligned} \tag{1}$$

Lemma 1. *Among the set of Stationary Strongly Symmetric Strategies:*
(i) s^{NF} and s^{FN} cannot be an equilibrium;
(ii) s^{NN} is an equilibrium;
(iii) s^{FF} is an equilibrium if and only if the following two assumptions are satisfied:

$$\begin{aligned} &\text{A1: } [x - c_l p - c_h(1-p)] > 0 \\ &\text{A2: } \delta \geq \tfrac{c_h}{x + p(c_h - c_l)} = \delta_{SS}. \end{aligned}$$

The proof of Lemma 1 is in Appendix1.6.1. Note that by construction any (discounted) payoff of a SSE is independent of δ.

1.3.2 Bounded Favors Bank (BFB) strategies

A milder restriction than imposing Stationary Strongly Symmetric Strategies is to consider Markov strategies. These are public strategies where the strategy profile in each period t

depends only on the value of a state variable at the beginning of the period. In other words, a Markov strategy depends on time only through the value of the state variable at any period. The state variable acts as a sufficient statistic for all the strategically relevant information. In the context considered in this paper, as a state variable one can use a function (or a summary) of the public history that both agents use to condition their strategy upon.

A Bounded Favor Bank Strategy is a stationary Markov strategy that uses the net number of favors received by an agent as a state variable. Specifically, we denote by k the net number of favors received by agent 1, that is, the total number of favors received minus the total number of favors provided by agent 1. By definition, $k < 0 (k > 0)$ indicates that agent 1 provided more (less) favors than she received. We let $n_i \geq 0$ denote the maximum net number of favors that agent $i \in \{1, 2\}$ can receive, which implies that n_j, $j \neq i$, is the maximum net number of favors that agent j can provide. Our state variable when a deviation has not being detected takes value in $K = \{-n_2, -n_2 + 1, ...0, 1, ...n_1\}$, where each element denotes the net number of favors received by agent 1 at the beginning of a period, where $|K| = n_1 + n_2 + 1$.

To completely describe a strategy, we need to amend the state space so that agents can keep track of past *detectable* deviations. We let $\widetilde{K} = K \cup \{\emptyset\}$ denotes the extended state space, where $k = \emptyset$ means that a deviation has been detected from the public history. Notice that if an agent deviates from a specified strategy but her deviation is not detectable from the public history, then $k \in K$.

Definition 4. *A* ***Bounded Favors Bank (BFB) Strategy*** *is a stationary Markov strategy, with state variable* $k \in \widetilde{K}$*, where:*

(i) on the equilibrium path, the stage-game efficient strategy is played in all states except in the boundary states $k = n_1$ *and* $k = -n_2$*, where* $n_1, n_2 < +\infty$*;*

(ii) off the equilibrium path, the worst and unique Nash equilibrium of the stage game

is played forever on.

The term “Bank” denotes the fact that each agent in practice has an account of net number of favors, which can be in credit or in debit. The term “Bounded” comes from the assumption that there is a maximum finite net number of favors that each agent can provide or receive. It also implies a bound on the number of times that the efficient strategy can be played consecutively and on average.

We consider two possible types of BFB strategies: Bounded Favors Bank strategy with Reward (BFBr) and Bounded Favors Bank strategy with Punishment (BFBp). We analyze them in details in the following. Notice that the maximum net number of favors that agents can receive is an integrant part of a BFB strategy. To simplify the analysis, without loss of generality, in what follows we will consider symmetric BFB strategy, where $n_1 = n_2 = n$.

Bounded Favors Bank with Reward (BFBr) strategy

Definition 5. *A BFB strategy with reward prescribes that an agent in the negative boundary state $-n$ where she provided the maximum net number of favors, is exhonorated from providing favors, even if she has a low cost.*

The BFBr strategy for agent 1 at each period t is given by equation 2:

$$s_1^r(k, c_1) = \begin{cases} \text{F} & \text{if} \quad c_1 = c_l \text{ and } k \in K \backslash \{-n\} \\ \text{N} & \text{if} \quad c_1 = c_h \text{ or } k \in \{\emptyset, -n\} \end{cases} \tag{2}$$

The state variable of agent 1 in the next period depends on its value in the current period k and the realized allocation of favors in the current period y, according to the transition matrix illustrated on Table 2.[12] The strategy and the transition matrix for agent 2 is analogous and it is therefore omitted.

[12] At the beginning of a period when agent 1's state variable k is interior, (i) if only agent 1 provides a favor

y	$k \neq \{-n, n\}$	$k = n$	$k = -n$	$k = \emptyset$
(F, N)	$k - 1$	$n_1 - 1$	$\emptyset$	$\emptyset$
(N, F)	$k + 1$	$\emptyset$	$-n + 1$	$\emptyset$
(N, N)	k	n	$-n$	$\emptyset$
(F, F)	$\emptyset$	$\emptyset$	$\emptyset$	$\emptyset$

Table 2: Transition to state k' from state k in BFBr

The fact that an off-equilibrium allocation is observed allows agents to coordinate the punishment, which only happens on off-equilibrium path. The state variable moves to the deviation regime and stays there ever after, once a deviation is detected. This happens when an agent who should be rewarded does not abstain from providing a favor, or when both agents provide a favor in a period.[13]

Ergodic distribution of states under BFBr strategy

Given BFBr strategy and the corresponding transition matrix of the state variable, we can derive the transition probability matrix. Let Π be the one-state probability transition matrix in the normal regime. It has dimension $|K| \times |K|$ (i.e., $(2n+1) \times (2n+1)$) and is given by the matrix in (3):

in the current period, then she begins with state $k' = k - 1$ in the next period; (ii) if only agent 2 provides a favor in the current period, then she begins with state $k' = k + 1$ in the next period; (iii) if nobody provides a favor in the current period, then she starts with $k' = k$ in the next period. At the beginning of a period when agent 1's state variable k has reached the boundary of maximum net number of favors provided, $k = -n$, she is supposed to be exonerated from providing a favor. Therefore, on equilibrium, (iv) if agent 2 has high cost then agent 1 starts with $k' = k$ and (v) if agent 2 has low cost then agent 1 starts with $k' = k + 1$. However, when agent 1's state variable $k = -n$ and she deviates to provide a favor, then the state variable moves to the absorbing punishment state $k' = \emptyset$.

[13]Because of the correlation of the cost, there is at most one agent in a period should provide a favor.

$$\underset{|K|\times|K|}{\Pi} = \begin{bmatrix} 1-p & p & & & & & \\ p & 1-2p & p & & & & \\ & p & 1-2p & p & & & \\ & & \ddots & \ddots & \ddots & & \\ & & & p & 1-2p & p \\ & & & & p & 1-p \end{bmatrix} \tag{3}$$

The first row and the last row of the matrix provide the probability for each possible k' in the next period given that $k = -n$ and $k = n$ in the current period, respectively.[14] Notice that only adjacent states communicate and there are no transient states. As well, in the matrix, not only each row sums up to 1, which is by the nature of probability matrix, but also each column sums up to 1, which is due to the symmetric structure of the cost realizations. Consider the row vector w of dimension $|K| = 2n+1$ whose elements are all constants α, i.e., $w = [\alpha, \alpha, \dots, \alpha]_{1\times|K|}$. It is easy to verify that $w\Pi = w$. Together with the restriction that $\sum_{i=1}^{K} \alpha = 1$, they imply that there exists a unique ergodic distribution for the state variable k which is given by the vector w when α is set to $1/|K|$. The following Lemma 2 summarizes this result of ergodic distribution for BFBr strategy.

Lemma 2. *The ergodic distribution of the $|K|$ states, for a BFBr strategy, assigns probability $1/(N+1)$ to each state, where $N = n_1 + n_2$.*

[14]Based on Table 2, conditions on $k = -n$, agent 1 should never do a favor in a normal regime, (1) $k' = -n$ when agent 2 does not do a favor neither, which occurs with probability $1-p$ when agent 2 has a high cost; (2) $k' = -n+1$ when agent 2 provides a favor which occurs with probability p. Similarly, conditions on $k = n$, agent 2 will never do a favor in a normal regime, (3) $k' = n-1$ when agent 1 has a low cost (with probability p) and (4) $k' = n$ when agent 1 has a high cost (with probability $1-p$). Finally, for $k \in (-n, n)$, $k' = k-1$ when agent 1 has a low cost and agent 2 has a high cost (with probability p), $k' = k+1$ when player 1 has a high cost and player 2 has a low cost (with probability p), and $k' = k$ when both players have a high cost (with probability $1-2p$).

Values of BFBr strategy

From the description of the strategy and the law of movement of the state variable, we can calculate the "value" (the average expected discounted payoffs) in each state k, v_k.[15] These values are represented, separately for the interior and boundary states, in the following formula.[16]

Value induced by BFBr strategy

$$
\begin{aligned}
&(4.1) \quad v_k = [(1-\delta)p(x-c_l) + \delta p(v_{k-1} + v_{k+1})]/[1-\delta(1-2p)] \\
&(4.2) \quad v_n = [-(1-\delta)pc_l + \delta p v_{n-1}]/[1-\delta(1-p)] \\
&(4.3) \quad v_{-n} = [(1-\delta)px + \delta p v_{-n+1}]/[1-\delta(1-p)]
\end{aligned}
\tag{4}
$$

Equation (4.1) is derived from the equation

$$v_k = (1-\delta)[px - pc_l + (1-2p)0] + \delta[pv_{k-1} + pv_{k+1} + (1-2p)v_k],$$

where the first part of the RHS is the normalized expected payoff from the current period and the second part is the normalized expected payoff from future periods.

Equation (4.2) is derived from the equation

$$v_n = (1-\delta)[p(-c_l) + (1-p)0] + \delta[pv_{n-1} + (1-p)v_n].$$

[15]As standard in repeated games the values are average expected discounted payoffs, that is, the expected discounted payoff is normalized by $(1-\delta)$, see book by Mailath and Samuelson (2006).

[16]The value $v_\emptyset$=0 and is omitted from the table.

Finally, Equation (4.3) is derived from the equation

$$v_{-n} = (1-\delta)[px + (1-p)0] + \delta[pv_{-n+1} + (1-p)v_{-n}].$$

The equations for the values in the BFBr strategy in state k are second order difference equations and the solution of the equation system is characterized by Lemma 3.

Lemma 3. *The analytical solution for the value in state k, from the reward strategy, is:*

$$v_k = (x - c_l)p + Az^k + Bz^{-k}, \tag{5}$$

where $z = \frac{(1-\delta+2p\delta)+\sqrt{(1-\delta)(1-\delta+4p\delta)}}{2\delta p} > 1$, and A and B are some constants (independent of n, k, c_h).

The reader can find the proof of the Lemma 3 and the details on the constants A and B in Appendix 1.6.2.

Individual rationality constraints of BFBr strategy

We also impose that agents are free to walk away from their bilateral relationship. In other words, in order to sustain an equilibrium we impose that a BFB strategy is individually rational so that the participation constraints hold. Let us assume that if a partner walks away she obtains a payoff of zero. The individual rationality (IR) constraints are that $v_k \geq 0$, for all $k \in \widetilde{K}$.

Lemma 4. *The value v_k is decreasing in k, $\forall k \in K$.*

According to Lemma 4 we have all individual rationality (IR) constraints are satisfied if and only if $v_n \geq 0$. Reader can find the proof of the Lemma 4 in Appendix 1.6.2.

Incentive constraints of BFBr strategy

In order for the proposed BFBr strategy to be an equilibrium, it must first of all be incentive compatible. Recall that when agent 1 is low type, $\Pr(c_j = c_h|c_i = c_l) = 1$. The incentive constraints for the low type (ICL) are shown in Table 3:

[1]	$-c_l(1-\delta) + \delta v_{k-1} \geq \delta v_k$	$k > -n$
[2]	$\delta v_{-n} \geq -c_l(1-\delta) + 0$	$k = -n$

Table 3: Incentive constraints for the low type in BFBr

Intuitively the IC for the low type is trivially satisfied in the reward state (i.e. $k = -n$). If the agent had to deviate she would have to pay an instantaneous cost and give up any future positive payoff. In other states (i.e. $k > -n$) where a low type agent is supposed to provide a favor, it must be that the instantaneous discounted cost of providing a favor plus the continuation payoff $v_{k'}$ with $k' = k - 1$ at the beginning of next period are higher than the payoff of pretenting being a high type by providing no favor plus the continuation payoff with the same net number of favors (i.e. $k' = k$) at the beginning of next period. The ICL in the other states can be written as follows: $(1-\delta)c_l < \delta(v_{k-1} - v_k)$. It follows that the more stringent ICL is the one in state $k = j$ where $(v_{k-1} - v_k)$ is minimized. Following Abdulkadiroglu and Bagwell (2012) in Appendix1.6.2, we show that $j = -n + 1$.

For the high type, recall that $\Pr(c_j = c_l|c_i = c_h) = \frac{p}{1-p}$ and $\Pr(c_j = c_h|c_i = c_h) = \frac{1-2p}{1-p}$. The incentive constraints for the high type (ICH) are presented in Table 4.

[1]	$(1-p)(1-\delta)c_h + p\delta v_{k+1} - (1-2p)\delta(v_{k-1} - v_k) \geq 0$	$k \in \{-n+1, \ldots. n-1\}$
[2]	$(1-\delta)c_h - \delta(v_{k-1} - v_k) \geq 0$	$k = n$
[3]	$(1-p)(1-\delta)c_h + p\delta v_{-n+1} + (1-2p)\delta v_{-n} \geq 0$	$k = -n$

Table 4: Incentive constraints for the high type in BFBr

In interior states (i.e. $k \in \{-n+1, \ldots. n-1\}$), following the BFBr strategy, the high type agent can receive a favor in the current period if the other agent is low type which occurs with probability $\frac{p}{1-p}$. In this case the high type agent will start next period with one more favors received (i.e. $k' = k + 1$). With the complement probability, $\frac{1-2p}{1-p}$, the high type agent will not receive a favor and start next period with the same net number of favors. If the high type agent deviates in the current period by pretending being a low type, with probability $\frac{p}{1-p}$ the other agent is low type and provides a favor as well, then the deviation of the high type agent will be detected and both agents will switch to no favor provision forever on (i.e. $k' = \emptyset$). However, with probability $\frac{1-2p}{1-p}$, the other agent is also high type. Then the deviation of pretending being a low type will not be detected by the public history and the agent will start next period with one more favor provided on her account (i.e. $k' = k - 1$).

In state $k = n$, the BFBr strategy prescribes that the high type agent can no longer receive favor. Thus she will simply start next period with the same net number of favors. If the high type agent deviates and provide a favor, a deviation would not be detected by the public history (although the other agent may privately detect it if she has low cost) and she would start next period with one more favor provided on her account, $k' = k - 1$. On the other hand, in state $k = -n$, on equilibrium the high type agent can receive a favor in current period if the other agent is low type and start next period with one more favor received on her account, $k' = k + 1$. If the other agent is also a high type, she will receive no favor and start next period with the same net number of favors, $k' = k$. It is easy to verify that the ICH in state $k = -n$ is always satisfied.

In Appendix1.6.2 we show that the more stringent ICH is the one in state $k = n$. Following Abdulkadiroglu and Bagwell (2012), we show in Appendix1.6.2 that given discount factor and n, the more stringent ICL is the one in state $k = -n + 1$. We also show that if this ICL in state $k = -n + 1$ is satisfied, then all the IR are satisfied. When all the IR are satisfied, all the incentive constraints for the high type (ICH) are satisfied. It follows that a necessary and sufficient condition for the BFBr strategy constitutes an equilibrium is that the incentive compatibility constraint of low type in state $k = -n+1$ to be satisfied. Lemma 5 below summarizes the result.

Lemma 5. *For every finite n, there is a $\bar{\bar{\delta}} < 1$ such that for every $\delta > \bar{\bar{\delta}}$, the most stringent constraint of low type in state $k = -n+1$, ICL_{-n+1}, can be satisfied and the BFBr strategy constitutes an equilibrium.*

Proof. The IC constraint of low type in the interior state k is $c_l\,(1-\delta) \le \delta(v_k - v_{k+1})$. When $\delta = 1$ it is satisfied because both the LHS and the RHS are zero. We want to see it is satisfied for discount factors close to 1. We re-write the constraint as :

$$c_l \le \frac{\delta}{(1-\delta)}(v_{k-1} - v_k),$$

In the RHS, both the numerator and the denominator go to zero as δ goes to 1. We can apply de l'Hôpital and obtain:[17]

$$\lim_{\delta\to 1}\frac{\delta}{(1-\delta)}(v_{k-1} - v_k) = \frac{\partial(v_{k-1} - v_k)}{\partial\delta} \Big/ \frac{\partial(\frac{1}{\delta})}{\partial\delta}\Bigg|_{\delta=1} = \frac{x(n+k+1) + c_l(n-k)}{2n+1}.$$

We show that the limit of $\frac{\delta}{(1-\delta)}(v_{k-1} - v_k)$ exists and it is finite. It is immediate to show that $\frac{x(n+k+1)+c_l(n-k)}{2n+1}$ is strictly greater than c_l for any $k = -n+1, \ldots .n$. We are interested in the more stringent constraint in state $k = -n+1$, ICL_{-n+1}. It follows that, fixing n, by continuity we can find a $\bar{\bar{\delta}} < 1$, such that for all $\delta \ge \bar{\bar{\delta}}$ the ICL_{-n+1} holds. ■

[17] Following Lemma 2 in Olszewski and Safronov (2018b) this derivative is calculated using the implicit function theorem around the system of equations defining the expressions for $(v_{k-1} - v_k)$, $k = -n+1, \ldots n$ evaluated at $\delta = 1$. Where the system of linear equations that follows, is solved using the Gauss-Jordan elimination method.

Payoff efficiency of BFBr strategy

Lemma 6. *For any given n and λ_1, there is a $\delta_1 < 1$ such that for every $\delta > \delta_1$, we have*

$$v_k > (x - c_l)\, p \frac{2n}{(2n+1)} - \lambda_1$$

for all $k \in K$.

Proof. The BFB strategies induce a stochastic Markov chain over states $k = \{-n, \ldots .n\}$. By the ergodic theorem (see the book by Jeffreys (1998)), there exists a probability distribution over states $\{\pi_k : k = -n \ldots n\}$ such that the probability of being in state k after a sufficiently large number of periods is arbitrarily close to π_k, independent of the initial state. This probability distribution is an eigenvector corresponding to eigenvalue 1 of the probability transition matrix (3). We have show in Lemma 2 that the eigenvector (probability distribution) corresponding to eigenvalue 1 is the ergodic distribution and the ergodic distribution has all its coordinates equal to $1/(2n+1)$ under BFBr.

Instantaneous payoff of each agent is $(x - c_l)\, p$ in any state other than $-n$ and n. Instantaneous payoffs are $-c_l p$ and xp in states n and $-n$, respectively. When δ is sufficiently close to 1, each agent's continuation payoff is bounded below by any number lower than $(x - c_l)\, p \frac{2n}{(2n+1)}$. $(2n-1)/(2n+1)$ is the limit occupation probability of states other than n and $-n$ and $1/(2n+1)$ is the probability of staying in n and $-n$. ■

We see that for discount factors close to 1, the payoff of a BFBr strategy is arbitrarily close to the efficient payoff when agent adjusts n accordingly.

It is important to point out that our BFBr strategy is isomorphic to a chip mechanism with $N = n_1 + n_2$ chips. Under the chip mechanism (see Möbius (2001), Hauser and Hopenhayn (2008), Abdulkadiroglu and Bagwell (2012), etc), each agent is endowed with a finite number of chips and the agent has to give a chip to the other when she receive a favor. But if an agent has no chips left she cannot receive any more favor. Having all the chips is equivalent to providing the maximum net number of favors. When the agent has all the chips, she is rewarded by providing no favor even when she can, until the other agent provides at least one favor back. The symmetric situation where agents are assigned n chips corresponds to a BFBr strategy where agents start with zero net number of favors and $n_1 = n_2 = n$. Similarly, the asymmetric situation where agents are assigned a different number of chips corresponds to a BFBr strategy where agents start with zero net number of favors and $n_1 \neq n_2$.

However, our BFB strategy with punishment is a new type of strategy as we do not limit the behavior of agents in each period. The BFBp strategy is defined below.

Bounded Favors Bank with Punishment (BFBp) strategy

Definition 6. *A BFB strategy with punishment prescribes an agent who reached the positive boundary state n (i.e. she received the maximum net number of favors), has to provide a favor independent of her realized cost.*

The BFBp strategy for agent 1, at each t, is equation (6):

$$s_1^p(k, c_1) = \begin{cases} \text{F} & \text{if} \quad (c_1 = c_l \text{ and } k \in K) \text{ or } (c_1 = c_h \text{ and } k = \{n\}) \\ \text{N} & \text{if} \quad c_1 = c_h \text{ and } k \in \widetilde{K} \backslash \{n\} \end{cases} \tag{6}$$

Similarly, Table 5 below describes the state variable of agent 1 in the next period and it depends on its value in the current period k and the realized allocation of favors in the current period y.[18] The strategy and the transition matrix for agent 2 is analogous.

[18]As in every BFB strategy, in the interior states, if only one agent provides a favor she starts next period with one less net number of favors received on her account. If no agent provides a favor, on equilibrium they start the next period with the same net number of favors received. However, if both provide a favor, the next

y	$k \neq \{-n, n\}$	$k = n$	$k = -n$	$k = \emptyset$
(F, N)	$k - 1$	$n - 1$	$\emptyset$	$\emptyset$
(N, F)	$k + 1$	$\emptyset$	$-n + 1$	$\emptyset$
(N, N)	k	n	$-n$	$\emptyset$
(F, F)	$\emptyset$	$\emptyset$	$\emptyset$	$\emptyset$

Table 5: Transition to state k' from state k in BFBp

The Definition 6 implies that when agent i has provided the maximum net number of favors (i.e. $k = -n$), in the BFBp equilibrium she will either provide and at the same time receive a favor or will only receive a favor. With a BFBp strategy, a deviation is detected by the following cases, (i) when the state variable of an agent is $k = n$ and the agent does not provide a favor and (ii) when state variable $k \in \{-n + 1, : -n + 2, \ldots, n - 1\}$ and outcome (F, F) is observed. And once a deviation is detected from the public history, the state variable moves to the deviation regime (i.e. $k = \emptyset$) where no agent provides a favor ever after.

Ergodic distribution of states under BFBp strategy

We can derive the transition probability matrix for state variable under the BFBp strategy. Let the transition probability matrix for the state variable be $\overline{\Pi}$, as the matrix in (7) below:

period start in the punishment regime, because someone clearly deviated. In state n a deviation is detected when agent 1 does not follow the strategy and does not make a favor. In state $-k$ a deviation is detected when agent 2 (who reached the maximum net number of favors received) does not provide a favor.

$$
\underset{K\times K}{\overline{\Pi}} = \begin{bmatrix} p & 1-p & & & & & & & & \\ p & 1-2p & p & & & & & & & \\ & p & 1-2p & p & & & & & & \\ & & .. & .. & .. & & & & & \\ \cdots & \cdots & .. & .. & .. & .. & .. & p & & .. \\ & & & & .. & & p & 1-2p & & p \\ & & & & & & & 1-p & & p \end{bmatrix} \tag{7}
$$

As before, only adjacent states communicates and that there are no transient states. The following Lemma 7 shows the property of ergodic distribution for BFBp strategy.

Lemma 7. *The ergodic distribution of the* $|K|$ *states, for a BFBp strategy, assigns probability* $p/[N(1-p)+3p-1]$ *to each boundary state and probability* $(1-p)/[N(1-p)+3p-1]$ *to each interior state, where* $N = n_1 + n_2$.

Values of BFBp strategy

From the description of the strategy and the law of movement of the state variable, we can calculate the "value"(the expected discounted payoffs) in each state k, $\overline{v}_k$. These values are represented, separately for the interior and boundary states, in the equation (8).

Value induced by BFBp strategies

$$
\begin{aligned}
&(8.1) \quad \overline{v}_k = [(1-\delta)p(x-c_l) + \delta p(\overline{v}_{k-1} + \overline{v}_{k+1})] + \delta(1-2p)\overline{v}_k \\
&(8.2) \quad \overline{v}_n = (1-\delta)[px - pc_l - (1-p)c_h] + \delta(1-p)\overline{v}_{n-1} + \delta p\overline{v}_n \\
&(8.3) \quad \overline{v}_{-n} = (1-\delta)(x - pc_l) + \delta(1-p)\overline{v}_{-n+1} + \delta p\overline{v}_{-n}
\end{aligned} \tag{8}
$$

Equation (8.1) is a second order difference equation, and equations (8.2) and (8.3) are the boundary conditions.

The solution of the equation system is characterized by Lemma 8.

Lemma 8. *The analytical solution for the value in state k, from the reward strategy, is:*

$$\overline{v}_k = C + \overline{A}z^k + \overline{B}z^{-k}, \tag{9}$$

where $z = \frac{(1-\delta+2p\delta)+\sqrt{(1-\delta)(1-\delta+4p\delta)}}{2\delta p} > 1$, *and* $\overline{A}$ *and* $\overline{B}$ *are some constants (independent of* n, k, c_h*).*

The form of the solution for the BFBp strategy is the same as for the BFBr strategy. The reader can find the proof of the Lemma 8 and the details on the constants $\overline{A}$ and $\overline{B}$ in Appendix 1.6.2. We also show that the value, $\overline{v}_k$, induced by the BFBp stratey can approximate the efficient payoff $v = (x - c_l)p$ as long as the discount factor δ and boundary n are large enough (see Appendix 1.6.2).

Individual rationality constraints of BFBp strategy

We also impose that agents are free to walk away from their bilateral relationship. In other words, we impose that a BFBp strategy is individually rational so that the participation constraints hold. Let us assume that if a partner walks away she obtains a payoff of zero. The individual rationality (IR) constraints are that $\overline{v}_k \geq 0$, for all $k \in \widetilde{K}$.

Lemma 9. *The value* $\overline{v}_k$ *is decreasing in* k, $\forall k \in K$.

According to Lemma 9 we have all individual rationality (IR) constraints are satisfied if and only if $\overline{v}_n \geq 0$ (For the proof of the Lemma 9, see Appendix 1.6.2).

Incentive constraints of BFBp strategy

In this subsection, we describe the incentive compatibility constraints for the BFBp strategy. First, the incentive constraints for the low type under the BFBp strategy are presented in Table 6

[1]	$-c_l(1-\delta)+\delta(\bar{v}_{k-1}-\bar{v}_k)\geq 0$	$k\in\{-n+1,\ldots n-1\}$
[2]	$-c_l(1-\delta)+\delta\bar{v}_{n-1}\geq 0$	$k=n$
[3]	$(x-c_l)(1-\delta)+\delta\bar{v}_{-n}\geq x(1-\delta)+\delta\bar{v}_{-n+1}$	$k=-n$

Table 6: Incentive constraints for the low type in BFBp

The ICL constraints of BFBp strategy in the interior states are the same as for the BFBr strategy. In state $k=n$ if agent 1 provides a favor, as prescribed to all types in state $k=n$, agent 1 will start next period with one less favor received on her account (i.e. $k'=k-1$). However, if the agent 1 does not provide a favor in state $k=n$, she would have a null instantaneous utility and she will have a zero continuation payoff because her deviation will be detected. In state $k=-n$, the low type agent 1 should always provide and receive a favor and start next period with the same continuation payoff. If she deviates and does not provide a favor in state $k=-n$, she obtains instantaneous utility of x and starts next period with one more favor received on her account (i.e. $k'=-n+1$). Even if agent 2 may privately detect the agent 1's deviation in state $k=-n$, it is not detected by the public history and it is therefore not punished. Notice that the ICL constraint in state $k=-n$ is mathematically the same as the constraint in state $k=-n+1$. This is because agent 1 behaves the same in the two states. It is only the behavior of agent 2 that changes, but its effect on agent 1's payoff is independent of whether agent 1 follows the equilibrium strategy or deviates. So the difference in agent 1's payoff appears both on the LHS and on the RHS of the incentive constraints and cancels. The result that we find in the BFBr strategy also applies to the BFBp strategy such that, $(\bar{v}_{k-1}-\bar{v}_k)$ is minimized for some $k\leq 0$. The proof is completely equivalent as the relevant properties of A and B also apply to $\overline{A}$ and

$\overline{B}$. Therefore, when all IR constraints are satisfied, the more stringent ICL constraint is the one in state $k \leq 0$, where $(\bar{v}_{k-1} - \bar{v}_k)$ is minimized.

Consider now the incentive constraints for the high type as in Table 7.

[1]	$(1-p)(1-\delta)c_h + p\delta\bar{v}_{k+1} - (1-2p)\delta(\bar{v}_{k-1} - \bar{v}_k) \geq 0$	$k \in \{-n+1, \ldots .n-1\}$
[2]	$(1-p)(1-\delta)(-c_h) + p\delta\bar{v}_n + (1-2p)\delta\bar{v}_{n-1} \geq 0$	$k = n$
[3]	$(1-\delta)c_h - \delta[\bar{v}_{-n} - \bar{v}_{-n+1}] \geq 0$	$k = -n$

Table 7: Incentive constraints for the high type BFBp

The explanation for incentive constraint of the high type in interior states, $k \in \{-n + 1, \ldots .n-1\}$, for the BFBp strategy is the same as for the BFBr strategy. In state $k = n$, the BFBp strategy prescribes that agent with any type has to provide a favor. With probability $\frac{p}{1-p}$ the other agent is low type and provides a favor, then the high type agent in state $k = n$ receives instantaneous utility, $x - c_h$ and starts next period with the same net number of favors. With probability $\frac{1-2p}{1-p}$ the other agent is also a high type, then the high type agent in state $k = n$ receives instantaneous utility, $-c_h$ and starts next period with one more favor provided on her account (i.e. $k' = n - 1$). To understand the incentive constraint of the high type in state $k = -n$, we need to remember that the strategy profile is public. Even if the high type provides the favor and at the same time she meets a low type (which happens with probability p), the two agents do not revert to the punishment regime. Because in state $k = -n$ the allocation (F, F) occurs with positive probability on equilibrium. It means that for the high type agent, even if her opponent may realize that there was a deviation, the deviant (the high type) does not know whether her deviation was detected (she met a low type) or not (she met a high type). Therefore, the reversion to the deviation regime cannot be perfectly coordinated.

For the incentive constraint of the high type in BFBp strategy, we show in the Appendix 1.6.2 that the most stringent ICH constriant is the one in state $k = n$ if the individual rationality constraint in state $k = n$ holds. In addition, we also show that the necessary and sufficient conditions for the BFBp strategy to constitute an equilibrium are the following constraints: (1) the individual rationality constraint in state $k = n$, (2) the incentive compatibility constraints for the high type in state $k = n$ and (3) the incentive compatibility constraint for the low type in state $k = j \leq 0$, where $(\bar{v}_{k-1} - \bar{v}_k)$ is minimized. Lemma 10 below show the result for BFBp strategy constitute an equilibrium.

Lemma 10. *For any finite n, if* $c_h \leq x + (x - c_l)\frac{(2n-1-2np+3p)}{1-p}$*, there is a discount factor* $\delta(n) < 1$ *such that for* $\forall \delta \geq \delta(n)$ *the BFBp strategy is an equilibrium strategy.*

For the proof of Lemma 10, see Appendix 1.6.2.

Payoff efficiency of BFBp strategy

Lemma 11. *For any given n and* λ_2*, there is a* $\delta_2 < 1$ *such that for every* $\delta > \delta_2$*, we have*

$$\bar{v}_k > \left[(x - c_l)\, p - \frac{(c_h - x)(1-p)p}{N(1-p) + 3p - 1} \right] - \lambda_2$$

for all $k \in K$.

Proof. The proof is similar as the proof of Lemma 6. By ergodic theorem we know that a probability of being in a state k after a sufficiently large number of periods is arbitrarily close to a component of the ergodic distribution in Lemma 7. From Lemma 7, we know that the ergodic ditribution under BFBp strategy given by a vector $w = \left[\frac{p}{N(1-p)+3p-1} \quad \frac{1-p}{N(1-p)+3p-1} \quad \cdots \quad \frac{1-p}{N(1-p)+3p-1} \quad \frac{p}{N(1-p)+3p-1} \right]$. Instantaneous payoff is $(x - c_l)\, p$ in interior states, instantaneous payoff is $(x - c_l)p - c_h(1 - p)$ in state $-n$ and instantaneous payoff is $x - c_l p$ in state n. When δ is sufficiently close to 1, the continuation payoff of each agent is bounded below by any number lower than $(x - c_l)\, p - \frac{(c_h - x)(1-p)p}{N(1-p)+3p-1}$, where $(1 - p)$ is the probability of having efficiency loss in the state n and $p/[N\,(1 - p) + 3p - 1]$ is the probability of staying in this state. ■

We see that for discount factors close to 1, the payoff of a BFBp strategy is arbitrarily close to the efficient payoff when agent adjusts n accordingly.

1.4 Payoff comparison

Based on the model set up, the symmetric Pareto optimal long-term payoff, $v = (x - c_l)p$, is given by the efficient strategy which prescribes the agents to provide a favor if and only if the cost received is low. However, this payoff cannot be achieved in the long-term when there is incomplete information, as the efficient strategy is not incentive compatible (see section 1.2). In this section we aim at comparing the long-term (ergodic) payoffs of the different strategies we have considered so far, BFB strategies and Stationary Strongly Symmetric strategies. We first calculate the long term payoff for each strategy and then discuss their comparisons without restricting them to be equilibrium payoff (i.e., does not combine with the equilibrium conditions). Next, we discuss their long-term payoff comparison on the equilibrium path.

From section 1.3.1 we can easily obtain the long-term payoff of each stationary strongly symmetric strategy, as the strategy prescribes the same strategy is played in each period. Here we only explicitly consider the long-term payoff of s^{FF} strategy as the comparison with the other stationary strongly symmetric strategies is of no interest. They either delivery 0 long-term payoff (s^{NN}), or are not individually rational (s^{NF}) or are not incentive compatible when agents are not infinitely patients (s^{FN}). The long-term payoff of s^{FF} strategy is provided in the following equation 10,

$$v^{FF} = x - pc_l - (1-p)c_h \tag{10}$$

We now consider the long-term payoffs for the BFBr and BFBp strategies for a given n, abstracting from the conditions under which they are an equilibrium. For the BFBr strategy, based on the Lemma 2 we have that each state occurs with probability, $\frac{1}{N+1}$, in the long term. In addition, the instantaneous payoff of each interior state is $v_k = (x - c_l)p$, where $k \in \{-n+1, ..., n-1\}$. Since the BFBr strategy prescibes agent to provide no favor when the state variable is $k = -n$. Instantaneous payoffs of two boundary states, $k = n$ and $k = -n$, are $v_n = -c_l p$ and $v_{-n} = xp$, respectively. Therefore, the long-term payoff of a BFBr strategy with boundary n is given by equation 11:

$$v_r = (N-1)(x-c_l)p\frac{1}{N+1} + (x-c_l)p\frac{1}{N+1} = (x-c_l)p[1 - \frac{1}{N+1}] \tag{11}$$

Similarly, for the BFBp strategy, based on the Lemma 7 we have each interior state occurs with probability $\frac{1-p}{N(1-p)+3p-1}$ and each boundary state occurs with probability $\frac{p}{N(1-p)+3p-1}$. In the $(N-1)$ interior states, $k \in \{-n+1, ..., n-1\}$, the instantaneous payoff is $\bar{v}_k = (x - c_l)p$. In the boundary state, $k = n$, where the BFBp strategy prescribes agent 1 to provide a favor independent of her cost, her instantaneous payoff is $\bar{v}_n = [(x - c_h)p - c_h(1-2p) - c_l p] = (x - c_l)p - c_h(1-p)$. Analogously, in the boundary state $k = -n$, where agent 1 always receives a favor but provides one only if her cost is low, the instantaneous payoff is $\bar{v}_{-n} = [(x - c_l)p + x(1-p)] = x - c_l p$. The following equation 12 provides the expression for the long-term payoff of the BFBp strategy.

$$
\begin{aligned}
v_p &= (x - c_l)p\frac{(2n-1)(1-p)}{N(1-p)+3p-1} - c_l p\frac{2p}{N(1-p)+3p-1} \\
&+ x(1+p)\frac{p}{N(1-p)+3p-1} - c_h(1-p)\frac{p}{N(1-p)+3p-1} \\
&= (x-c_l)p\left(1 - \frac{(c_h - x)(1-p)}{(x-c_l)(N(1-p)+3p-1)}\right) \qquad (12)
\end{aligned}
$$

Each BFB strategy introduces some inefficiency in the boundary states. Specifically, the inefficiency of the BFBr strategy comes from agents' providing no favor when it is efficient. The inefficiency of the BFBp strategy comes from providing a favor when it is costly. Differently from BFB strategies, the s^{FF} strategy introduces inefficiency in each period, because there is always at least one player who has to provide a favor even when she has a high cost. Still, when this expected loss is low enough, such strategy is an equilibrium. The following proposition summarizes the results of the payoffs comparisons.[19]

Proposition 1. *Consider v_r, v_p, and v^{FF}, the long-term payoffs of the two Bounded Favors Bank strategies, BFBr, BFBp, and the stationary strongly symmetric strategy s^{FF}, respectively:*

1. *When $(c_h - x) \in \left(0, \frac{p}{(N+1)(1-p)}(x - c_l)\right)$ we have $v_p > v^{FF} \geq v_r$.*
2. *When $(c_h - x) \in \left[\frac{p}{(N+1)(1-p)}(x - c_l), \frac{p}{(1-p)}(x - c_l)\right]$ we have $v_p \geq v_r \geq v^{FF} \geq 0$.*
3. *When $(c_h - x) \in \left[\frac{p}{(1-p)}(x - c_l), \frac{N(1-p)+3p-1}{(N+1)(1-p)}(x - c_l)\right]$ we have $v_p \geq v_r \geq 0 > v^{FF}$.*

[19] According to the asymptotic results in section 1.3, we can always find a discount factor big enough such that all such strategies are equilibrium strategies for high enough discount factor.

4. *When* $(c_h - x) \in \left[\frac{N(1-p)+3p-1}{(N+1)(1-p)}(x-c_l), \frac{N(1-p)+3p-1}{(1-p)}(x-c_l)\right]$ *we have* $v_r \geq v_p \geq 0 > v^{FF}$.

5. *When* $(c_h - x) > \frac{N(1-p)+3p-1}{(1-p)}(x-c_l)$ *we have* $v_r \geq 0 \geq v_p > v^{FF}$.

Proposition 1 shows that that whether the BFBr or the BFBp strategy provides a higher long-term payoff depends on the extent of the inefficiencies induced in the boundary states and the ergodic probabilities of being in such states. Particularly, using the BFBp strategy has a higher chance to obtain a higher payoff, ceteris paribus, when the value of the high cost decreases and the marginal probability of receiving a low cost increases.

In comparison to the BFBp strategy, the s^{FF} strategy induces a lower instantaneous payoff after any history (strictly when on interior states). This implies that the BFBp strategy provides a higher long-term payoff than the s^{FF} strategy. The inefficiency introduced by the BFBr strategy can instead be such that under a condition of lower value of high cost, the BFBr strategy delivers a lower long-term payoff than the s^{FF} strategy.

We then focus on the discussion for the comparison of long-term payoffs, conditional on all these strategies being equilibrium strategies.

Following Lemma 1, s^{FF} strategy can constitute an equilibrium if and only if (i) $x - pc_l - (1-p)c_h > 0$; (ii) $\delta > \frac{c_h}{x+p(c_h-c_l)}$. Given that the $\delta < 1$, it implies that $c_h < \frac{x-pc_l}{1-p}$.

Lemma 5 presents that the BFBr strategy can constitute an equilibrium if and only if the ICL in state $k = -n+1$ holds, $ICL_{-n+1} = \delta(v_{-n} - v_{-n+1}) - (1-\delta)c_l > 0$.

For the BFBp strategy to be an equilibrium, these are the necessary and sufficient conditions that (i) δ is large enough to imply $v_n > 0$ and $c_h \leqslant \frac{N(1-p)+3p-1}{1-p}(x-c_l) + x$; (ii) $ICH_n = p\delta v_n + (1-2p)\delta v_{n-1} - (1-p)(1-\delta)c_h > 0$; (iii) $ICL_j = \delta(v_{j-1} - v_j) - c_l(1-\delta) > 0$ where $j \in argmin_{k\in(-n,0)} v_{k-1} - v_k$.

Note that all the discussions of payoff comparisons assume that discount factor δ is large enough. Given that $p < 1/2$, $n > 0$ and $c_l < x$, we have $\frac{N(1-p)+3p-1}{1-p}(x - c_l) + x > \frac{x-pc_l}{1-p}$ when comparing the conditions of both s^{FF} and BFBp strategy being equilibrium strategy (condition (i)). This implies that the s^{FF} strategy requires smaller value of c_h to be an equilibrium than the BFBp strategy.

Considering the condition (i) of BFBp strategy being equilibrium strategy and the condition of $v_r > v_p$ (i.e., point.4 of Proposition 1), we have that upper bound of c_h of BFBp strategy being equilibrium strategy is strictly greater than the upper bound of c_h of $v_p > v_r$, as $\frac{N(1-p)+3p-1}{1-p}(x - c_l) > \frac{N(1-p)+3p-1}{(N+1)(1-p)}(x - c_l) > 0$. This suggests that on the equilibrium path, the long-term payoff of the BFBp strategy can be either higher or lower than the long-term payoff of BFBr strategy.

Incorporating the equilibrium conditions of s^{FF} strategy, from Proposition 1, we have that the s^{FF} strategy has a higher chance to obtain a higher payoff than the BFBr strategy condtional on both of them are equilibrium strategies, as $\frac{(N+1)p}{(N+1)(1-p)} > \frac{Np}{(N+1)(1-p)} > 0$.

In addition, when considering the equilibrium conditions of all the three strategies (i.e., BFBr, BFBp and s^{FF}) and the Proposition 1, the payoff of BFBp is strictly higher than the payoff of BFBr conditional on all the three strategies are equilibrium strategies. This is because the upper bound of c_h of s^{FF} being equilibrium is strictly smaller than the upper bound of c_h of $v_p \geq v_r$, $\frac{(x-c_l)p}{1-p} < \frac{N(1-p)+3p-1}{(N+1)(1-p)}(x - c_l)$.

Therefore, we can draw the conclusions stated in Proposition 2 below.

Proposition 2. *When all the three strategies, BFBr, BFBp, and s^{FF}, can be sustained as an equilibrium, the comparison of their long-term payoffs is:*

1. $v_p > v^{FF} \geqslant v_r$, *when* $(c_h - x) \in \left(0, \frac{p}{(N+1)(1-p)}(x - c_l)\right)$.
2. $v_p \geqslant v_r > v^{FF}$, *when* $(c_h - x) \in \left(\frac{p}{(N+1)(1-p)}(x - c_l), \frac{(x-c_l)p}{1-p}\right)$.

The Proposition 2 shows that the highest long-term payoff is given by the BFBp strategy when all the three strategies constitute an equilibrium.

1.5 Conclusion

We analyze the dynamic allocation of favors between two individuals in an infinite horizon and private information setting. Private information imposes some restrictions on the possible individually rational and incentive compatible allocations. Indeed, the efficient allocation is not incentive compatible. We discuss different class of public strategies and propose our new type of Bounded Favors Bank strategy with punishment. By comparing the long-term payoff among the relevant equilibrium strategies, we find that imposing a punishment rather than a reward in the boundary state of a bilateral relationship can achieve higher long-term payoff when the cost of favor provision is lower.

In current paper, we show that our asymptotically efficient strategies constitute an equilibrium so long as the discount factors are high enough. In the further study, one can analyze the impact of the degree of patience on the asymptotically efficient strategy. One one hand, characterizing the whole asymptotically efficient frontier allow us to better understand how close are the payoffs induced by our Markov strategies to the Pareto optimal payoff; on the other hand, what other properties, an asymptotically efficient strategy must satisfy to constitute an equilibrium.

1.6 Appendix A

1.6.1 Proof of equilibria for Stationary Strongly Symmetric Strategies

Proof. (i) It is easy to verify that s_{NF} $(u(\sigma_{NF}) < 0)$ is not individually rational (IR) while σ_{FN} is not incentive compatible (IC).

(ii) Strategy s_{NN} consists of the repetition of the unique static Nash Equilibrium, so the result follows.

(iii) Strategy s_{FF} is an equilibrium if and only if it satisfies individual rationality and incentive compatibility. The first is satisfied if and only if equation 1 holds. The second is satisfied if and only if equation 1 holds, which implies that the most stringent incentive constraint (the one for the high type, $(1-\delta)(x-c_h)+\delta\left[x-c_l p-c_h(1-p)\right] \geq x(1-\delta)$, with the LHS being the expected payoff from receiving $x-c_h$ this period and receiving $x-c_l p-c_h(1-p)$ in all the future periods, and the RHS being the payoff from receiving x this period and 0 in all the future periods) is satisfied. ■

1.6.2 Proof for Bounded Favors Bank Strategies

Proof for BFBr strategy

Proof of Lemma 3:

Equation (4.1), defining the values of exchanging favors in state k is a second order difference equation, that can be re-written as:

$$E.1\delta p v_{k+2} - (1-\delta(1-2p))v_{k+1} + \delta p v_k + (1-\delta)p(x-c_l) = 0$$

whose general solution has the form:

$$E.2 \quad v_k = C + Az_1^k + Bz_2^k$$

The term C is found as the solution of the equation $\delta pv - (1-\delta(1-2p))v + \delta pv + (1-\delta)p(x-c_l) = 0$, and it is given by $C = (x-c_l)p$. The two roots z_1 and z_2 are equal to the inverse of the solutions (λ_1,λ_2) to the following characteristic equation:

$$E.3 \quad 1 - \frac{(1-\delta(1-2p))}{\delta p}\lambda + \lambda^2 = 0$$

where $\lambda_1 + \lambda_2 = \frac{(1-\delta(1-2p))}{2\delta p}$ and $\lambda_1\lambda_2 = 1$. This implies that $\lambda_1 = \frac{1}{\lambda_2} = \lambda$; and that $z_1 = \frac{1}{\lambda} = z = \frac{(1-\delta+2p\delta)+\sqrt{(1-\delta)(1-\delta+4p\delta)}}{2\delta p} > 1$; $z_2 = z_1^{-1} = z^{-1}$. It follows that the solution for v_k can be written as:

$$E.4 \quad v_k = (x-c_l)p + Az^k + Bz^{-k}$$

where the constants A and B obtained using $E.4$ and the two boundary conditions (4.2) and (4.3).

$$E.5 \quad A = \frac{-(1-\delta)px}{z^{n-1}((1-\delta+p\delta)z-p\delta)} - \frac{Bz_1^{-n}((1-\delta+p\delta)-p\delta z)}{z_1^{n-1}((1-\delta+p\delta)z-p\delta)}$$
$$E.6 \quad B = \frac{c_l(1-\delta)p}{z^{n-1}((1-\delta+p\delta)z-p\delta)} - \frac{Az_1^{-n}((1-\delta+p\delta)-p\delta z_1)}{z_1^{n-1}((1-\delta+p\delta)z-p\delta)}$$

The solution of this system with respect to A and B is:

$$E.7 \quad A = \frac{-(1-\delta)p[xz^{n-1}((1-\delta+\delta p)z-\delta p)+c_l z^{-n}((1-\delta+\delta p)-\delta pz)]}{[z^{n-1}((1-\delta+\delta p)z-\delta p)]^2-[z^{-n}((1-\delta+\delta p)-\delta pz)]^2}$$
$$E.8 \quad B = \frac{(1-\delta)p[xz^{-n}((1-\delta+\delta p)-\delta pz)+c_l z^{n-1}((1-\delta+\delta p)z-\delta p)]}{[z^{n-1}((1-\delta+\delta p)z-\delta p)]^2-[z^{-n}((1-\delta+\delta p)-\delta pz)]^2}$$

Note that z does not depend on n or k, and A and B do not depend on k. Define $y_1 = (1-\delta+p\delta)z - p\delta$, $y_2 = (1-\delta+p\delta) - p\delta z$. Given $z\frac{(1-\delta+2p\delta)+\sqrt{(1-\delta)(1-\delta+4p\delta)}}{2\delta p} > 1$, we have $y_1 > 0$, $y_2 < 0$, $y_1 + y_2 > 0$, $(y_1)^2 > (y_2)^2$, which also implies $y_1 > -y_2$. We can rewrite A and B into

$$E.9 \quad A = \frac{-(1-\delta)p(xz^{n-1}y_1+c_l z^{-n}y_2)}{(z^{n-1}y_1)^2-(z^{-n}y_2)^2}$$
$$E.10 \quad B = \frac{(1-\delta)p(xz^{-n}y_2+c_l z^{n-1}y_1)}{(z^{n-1}y_1)^2-(z^{-n}y_2)^2}$$

$\blacksquare$

Properties of the constants A and B and v_k:

1. $A + B < 0$

From expressions E.9 and E.10 we have that $A + B \propto -(xz^{n-1}y_1 + c_l z^{-n}y_2) + (xz^{-n}y_2 + c_l z^{n-1}y_1)$. So $A + B < 0$ iff $c_l[z^{n-1}y_1 - z^{-n}y_2] < x[z^{n-1}y_1 - z^{-n}y_2]$, which is true $\forall x > c_l$, because $[z^{n-1}y_1 - z^{-n}y_2] > 0$,

1.1 $A + B < 0$ implies $v_o = (x - c_l)p + A + B < (x - c_l)p$.

Intuitively, the value of the BFBr strategy differs from the value of the efficient strategy for the fact that the efficient one-shot strategy is not played in the boundary states. So compared to the efficient one, the BFBr implies a loss of xp in state n, where the agent cannot receive favors, and a gain of $c_l p$ in state $-n$, where the agent cannot provide favors. Both states arise with equal probabilities so the net loss is positive.

1.2 $A + B < 0$ implies $-A > B$.

2.1 $A < 0$

From expression E.9, we have that $A \propto -[xz^{n-1}y_1 + c_l z^{-n}y_2] < 0$ because $[xz^{n-1}y_1 + c_l z^{-n}y_2] > xy_1 + c_l y_2 > c_l(y_1 + y_2) < 0$, given that $y_2 < 0$ and $y_1 > 0$ with $y_1 > -y_2$.

2.2 $B > 0$ iff $c_l > z^{-2n+1}x(-y_2)/(y_1)$ from E.10.

3 $B/A < 1$

This is clearly the case when $B > 0$, where using $A < 0$ we have $B/A < 0 < 1$.

It is also the case when $B < 0$. In this case $B/A = \frac{[xz^{-n}y_2 + c_l z^{n-1}y_1]}{-[xz^{n-1}y_1 + c_l z^{-n}y_2]}$. So $B/A < 1$ iff $[xz^{-n}(-y_2) - c_l z^{n-1}y_1] < [xz^{n-1}y_1 + c_l z^{-n}y_2]$, that is iff $z^{-n}(-y_2)(x + c_l) < z^{n-1}y_1(x + c_l)$, which is always satisfied because $(-y_2) < y_1$ and $z > 1$.

Proof of Lemma 4:

Consider $v_k - v_{k-1} = Az^k + Bz^{-k} - Az^{(k-1)} - Bz^{-(k-1)} = Az^{k-1}(z-1) + Bz^{-k}(1-z) = (z-1)(Az^{k-1} - Bz^{-k}) < 0$ iff $Az^{k-1} < Bz^{-k}$, that is, iff $Az^{2k-1} < B$ or $-Az^{2k-1} > -B$. This is always the case when $B > 0$, since by result 1.6.2, $A < 0$ and so $-Az^{2k-1} > 0 > -B$. It can also be the case, when $B < 0$ iff, $z^{2k-1} > B/A$ (condition [k]). Since $z > 1$ and, from result 1.6.2, $B/A < 1$, when $k > 1/2$, condition [k] holds, as $z^{2k-1} > 1 > B/A$. Condition [k] is more stringent for smallest (non positive) k. In fact if we want v_k to be decreasing for all k, we would need

$$z^{2(-n+1)-1} = z^{-2n+1} > B/A$$

Using E.7 and E.8 we would have:

$z^{-2n+1}[xz^{n-1}y_1 + c_l z^{-n} y_2] > z^{-n}x(-y_2) - c_l z^{n-1} y_1]$, where $y_1 = (1-\delta+p\delta)z - p\delta > 0$, $y_2 = (1-\delta+p\delta) - p\delta z < 0$, and $y_1 + y_2 > 0$.

After rearranging, we have $[xz^{-n} + c_l z^{n-1}]y_1 > (-y_2)[z^{-n}x + c_l z^{-3n+1}]$, which is always satisfied.■

Proof of incentive compatibility and individual rationality for BFBr strategy:

Lemma 12. *If the IR constraint holds in state n, all the ICH constraints are satisfied*

Proof of Lemma 12:

Step.1: By lemma 4, if $v_n \geq 0$ then $v_k \geq 0$ for all $k \in K$.

Step.2: The ICH in state $-n$ is trivially satisfied, as by Step 1, when $v_k \geq 0$ for all $k \in K$, $(1-p)(1-\delta)c_h + \delta[pv_{-k+1} + (1-2p)v_{-k}] > 0$ for sure.

Step.3: The high cost constraints in interior states k are: $(1-\delta)(1-p)c_h + p\delta v_{k+1} \geq \delta(1-2p)(v_{k-1}-v_k)$.

If the IR constraints hold, $v_{k+1} > 0$, and given that $(1-p) > (1-2p)$, a sufficient condition for ICH$_k$ to be positive is that $(1-\delta)c_h \geq \delta(v_{k-1}-v_k)$.

Step.4: $(v_{k-1}-v_k)$ is minimized for some $k \leq 0$. We can write $(v_{k-1}-v_k)-(v_k-v_{k+1}) = (1-z^{-1})(z-1)[Az^k + Bz^{-k}]$. For $k \geq 0$, since $z > 1$, $A < 0$ and $A+B < 0$, we have $[Az^k + Bz^{-k}] < 0$, that is $(v_{k-1}-v_k) < (v_k - v_{k+1})$. For lower k the term $[Az^k + Bz^{-k}]$ is decreasing in k. Therefore $\min_{k\in\{-n+1,n\}}(v_{k-1}-v_k)$ is achieved at some $k \in [-n+1, 0]$.

Step.5: If ICH in state n holds, ICH in state k, $k \in (-n, n)$ holds as well.

From the previous Step, $(v_{k-1}-v_k)$ is minimized for some $k \leq 0$, before which (if any) it is decreasing and after which it is increasing. It follows that $\max_{k\in\{-n+1,n\}}(v_{k-1}-v_k)$ is achieved either in $k = -n+1$ or in $k = n$. From Step 3 we have that a sufficient condition for ICH$_k$ to be satisfied is that $(1-\delta)c_h \geq \delta \times \max_k(v_{k-1}-v_k)$. If we show that $(v_{n-1}-v_n) \geq (v_{-n}-v_{-n+1})$, we then can have that ICH in state n holds which implies ICH in the interior states to hold as well.

We can write $(v_{n-1}-v_n)-(v_{-n}-v_{-n+1}) = (z-1)[(-Az^{n-1}+Bz^{-n})-(-Az^{-n}+Bz^{n-1}) = (z-1)(-(A+B)(z^{n-1}-z^{-n}) > 0$.

Step.6: ICH in state n is always satisfied, which implies the result.

ICH$_n$ can be written as $c_h(1-\delta) \geq \delta[v_{n-1}-v_n]$. A sufficient condition is that $x(1-\delta) \geq \delta[v_{n-1}-v_n]$. Using equation (4.2) we can express $v_{n-1}-v_n = v_{n-1} - [-(1-\delta)pc_l + \delta p v_{n-1}]/(1-\delta(1-p) = (1-\delta)(v_{n-1}+pc_l)/(1-\delta+\delta p)$. Notice that $v_{n-1} < (x-c_l)p$ because $v_0 < C$ and v_k is decreasing in k. It follows that $v_{n-1} + pc_l < xp$. So a sufficient condition for $x(1-\delta) \geq \delta[v_{n-1}-v_n]$ is $x(1-\delta) > \delta(1-\delta)xp/(1-\delta+\delta p)$, that is if $(1-\delta+\delta p) > \delta p$, which holds for all $\delta < 1$. ■

Lemma 13. *If the ICL constraint in state n holds, then all the IR constraints hold.*

Proof of Lemma 13:

By Lemma 4, the more stringent IR constraint is the one in state n. We have to show that $-c_l(1-\delta)+\delta[v_{n-1}-v_n] \geq 0$ implies $v_n \geq 0$. Using equation (4.2), the LHS of the ICL constraint in state n can be rewritten as: $-c_l(1-\delta)+\delta[v_{n-1}-\frac{[-(1-\delta)pc_l+\delta p v_{n-1}]}{1-\delta+\delta p}] \propto -c_l(1-\delta+\delta p)+\delta v_{n-1}+c_l\delta p = -c_l(1-\delta)+\delta v_{n-1}$. If the ICL constraint in state n is satisfied, then $v_{n-1} \geq c_l(1-\delta)/\delta$. Consider now the expression of the equation (4.1), we have $v_n = \frac{[-(1-\delta)pc_l+\delta p v_{n-1}]}{1-\delta+\delta p} > \frac{[-(1-\delta)pc_l+\delta p c_l(1-\delta)/\delta]}{1-\delta+\delta p} = 0.$ ■

Lemma 14. [20]*If ICL_{-n+1} holds then $v_{-n} \leq p(x-c_l), \quad \forall n \geqslant 1$.*

Proof of Lemma 14:

Rewrite ICL_{-n+1} as

$$v_{-n+1} \leq v_{-n} - c_l\frac{(1-\delta)}{\delta}.$$

Combine it with the expression of the equation (4.3), we have,

$$\begin{aligned} v_{-n} \;\; = \;\; & p(1-\delta)x + p\delta v_{-n+1} + p\delta v_{-n} + (1-2p)\delta v_{-n} \leq \\ & p(1-\delta)x + p\delta v_{-n} - c_l p(1-\delta) + p\delta v_{-n} + (1-2p)\delta v_{-n}. \end{aligned}$$

Rearranging, we have $v_{-n}(1-\delta) \leq p(1-\delta)(x-c)$.■

Lemma 15. [21]*If ICL_{-n+1} holds, then ICL_k holds for all $k \in \{-n+2, -n+3, ..., n\}$.*

[20]This result is taken from Lemma 4 in Abdulkadiroglu and Bagwell (2012).
[21]This result is taken from Lemma 6 in Abdulkadiroglu and Bagwell (2012).

Proof of Lemma 15:

Suppose ICL_{-n+1} holds. From its expression we have

$$v_{-n} \geq c_l \frac{1-\delta}{\delta} + v_{-n+1} \tag{13}$$

A first step, that will be used later, is to notice that ICL_{-n+1} implies,

$$v_{-n+1} \leq (x - c_l)p - c_l \frac{1-\delta}{\delta}. \tag{14}$$

This is because from equation 13 we have $c_l \frac{1-\delta}{\delta} \leq (v_{-n} - v_{-n+1})$ and from Lemma 14 we have $c_l \frac{1-\delta}{\delta} \leq ((x - c_l)p - v_{-n+1})$.

Consider now the equation (4.1), when $k = -n + 1$

$$v_{-n+1} = (1-\delta)p(x - c_l) + p\delta(v_{-n} + v_{-n+2}) + \delta(1-2p)v_{-n+1}$$

From equation 13, we have

$$v_{-n+1} \geq (1-\delta)p(x - c_l) + p\delta(c_l \frac{1-\delta}{\delta} + v_{-n+1} + v_{-n+2}) + \delta(1-2p)v_{-n+1}$$

that is

$$v_{-n+1} \geq \frac{(1-\delta)px + p\delta v_{-n+2}}{(1-\delta+\delta p)} \tag{15}$$

We want to show that ICL_{-n+2} holds:

$$c_l\,(1-\delta) \leq \delta(v_{-n+1} - v_{-n+2}),$$

which we can re-write as

$$v_{-n+2} \leq v_{-n+1} - c_l \frac{(1-\delta)}{\delta}.$$

From equation 15, a sufficient condition for the above inequality to hold is

$$v_{-n+2} \leq \frac{(1-\delta)px + p\delta v_{-n+2}}{(1-\delta+\delta p)} - c_l \frac{(1-\delta)}{\delta}.$$

which implies

$$v_{-n+2} \leq p(x - c_l) - \frac{c_l(1-\delta)}{\delta}.$$

The above expression holds by equation 14 and the fact that $v_{-n+2} \leq v_{-n+1}$.

By the same steps, it can also be shown that when ICL_{-n+2} holds, then ICL_{-n+3} holds as well. And we can recursively show the ICL hold for all the remaining states. ■

Proof for BFBp strategy

Proof of Lemma 8 The proof is analogous to that of Lemma 3. Equation (8.1), defining the values of exchanging favors in state k is a second order difference equation, whose general solution has the form

$$\overline{v}_k = C + \overline{A}z^k + \overline{B}z^{-k},$$

which is the same as E.1. Therefore, the term C is $C = (x - c_l)p$, and $z = \frac{(1-\delta+2p\delta)+\sqrt{(1-\delta)(1-\delta+4p\delta)}}{2\delta p} > 1$. The constants $\overline{A}$ and $\overline{B}$ obtained using the solution for $\overline{v}_k$ and the two boundary equations (8.2) and (8.3),

$$\overline{E}.9 \qquad \overline{A} = \frac{(1-\delta)(1-p)[-c_h z^{n-1}\overline{y}_1 - xz^{-n}\overline{y}_2]}{[z^{n-1}\overline{y}_1]^2-[z^{-n}\overline{y}_2]^2}$$
$$\overline{E}.10 \quad \overline{B} = \frac{(1-\delta)(1-p)[c_h z^{-n}\overline{y}_2 + xz^{n-1}\overline{y}_1]}{[z^{n-1}\overline{y}_1]^2-[z^{-n}\overline{y}_2]^2}$$

where $\overline{y}_1 = (1-\delta p)z - \delta(1-p) > 0$ and $\overline{y}_2 = (1-\delta p) - z\delta(1-p)$. Notice that $\overline{y}_1 + \overline{y}_2 > 0$, which implies that $\overline{y}_1 > -\overline{y}_2$. It is also the case that $\overline{y}_1 > \overline{y}_2$, if $\overline{y}_2 > 0$. Thus the denominator of $\overline{A}$ and $\overline{B}$ is always positive.

Properties of the constants $\overline{A}$ and $\overline{B}$ and $\overline{v}_k$:

1. $\overline{A} + \overline{B} < 0$

From expressions $\overline{E}.9$ and $\overline{E}.10$ we have that $A + B \propto (c_h - x)(z^{n-1}\overline{y}_1 - z^{-n}\overline{y}_2) < 0$, $\forall x < c_h$, because $[z^{n-1}\overline{y}_1 - z^{-n}\overline{y}_2] > \overline{y}_1 - \overline{y}_2 > 0$, given that $\overline{y}_1 > -\overline{y}_2$.

1.1 $\overline{A} + \overline{B} < 0$ implies $v_o = (x - c_l)p + \overline{A} + \overline{B} < (x - c_l)p$.

Intuitively, the value of the BFBp strategy differs from the value of the efficient strategy for the fact that the efficient one-shot strategy is not played in the boundary states. So compared to the efficient strategy, the BFBp implies a loss of $c_h(1-p)$ in state n, where the agent always has to make favors, and a gain of $x(1-p)$ in state $-n$, where the agent always receives favors. Both states arise with equal probabilities so the net expected loss $\propto (c_h - x)$ is positive.

1.2 $\overline{A} + \overline{B} < 0$ implies $-\overline{A} > \overline{B}$.

2.1 $\overline{A} < 0$

From expression $\overline{E}.9$, we have that $\overline{A} \propto -[c_h z^{n-1}\overline{y}_1 + xz^{-n}\overline{y}_2] < 0$ because $c_h z^{n-1}\overline{y}_1 - xz^{-n}\overline{y}_2 > x(z^{n-1}\overline{y}_1 - z^{-n}\overline{y}_2) > 0$, given that $\overline{y}_1 > 0$ and $\overline{y}_1 > -\overline{y}_2$.

2.2. $B > 0$ iff $c_h z^{-n}\overline{y}_2 + xz^{n-1}\overline{y}_1 > 0$, from $\overline{E}$.10. When $\overline{y}_2 < 0$, this is the case iff $c_h < xz^{2n-1}\frac{\overline{y}_1}{-\overline{y}_2}$.

3 $\overline{B}/\overline{A} < 1$

This is clearly the case when $\overline{B} > 0$, given that $\overline{A} < 0$, we would have $\overline{B}/\overline{A} < 0 < 1$.
It is also the case when $\overline{B} < 0$. In this case $\overline{B}/\overline{A} = \frac{[c_h w_2 + xw_1]}{-[c_h w_1 + xw_2]}$, where $w_1 = z^{n-1}\overline{y}_1$ and $w_2 = z^{-n}\overline{y}_2$. So $\overline{B}/\overline{A} < 1$ iff $c_h w_2 + xw_1 > -[c_h w_1 + xw_2]$ (notice that$-c_h w_1 - xw_2 < -x(w_1 + w_2) < 0$), that is if $c_h(w_2 + w_1) > -[xw_1 + xw_2]$, which is always satisfied.

4. $\lim_{\delta\to 1} v_k = \lim_{\delta\to 1} v_o = (x - c_l)p + \lim_{\delta\to 1}(\overline{A} + \overline{B})$=$(x - c_l)p - \frac{(c_h - x)(1-p)p}{(2n-1-2np+3p)}$. Notice that the efficiency loss corresponds to the loss incurred in the boundary states, weighted by the long-run probability of staying in these states. Therefore the limiting values of a BFBp strategy are positive only if c_h is not too big. In particular:

$$c_h \leq x + (x - c_l)\frac{(2n - 1 - 2np + 3p)}{1 - p}.$$

5. $\lim_{\delta\to 1} \frac{\delta}{(1-\delta)}(v_{k-1} - v_k) = \left.\frac{\partial(v_{k-1} - v_k)}{\partial\delta}\right|_{\delta=1} = \frac{c_h(k(1-p)+n(1-p)+2p-1)+x(n(1-p)-k(1-p)+p)}{2n-2np+3p-1}$. For $k \in \{-n+1, n-1\}$, this term is positive and finite. In addition it is greater than c_l. A sufficient condition for this to hold, given that $c_h > x > c_l$, is that $(k(1-p) + n(1-p) + 2p - 1 + n(1-p) - k(1-p) + p) = 2n(1-p) + 3p - 1 \geq 2n - 2np + 3p - 1$.

Proof of Lemma 9:

The proof is equivalent to that of lemma 4. Consider $\overline{v}_k - \overline{v}_{k-1} = (z-1)(\overline{A}z^{k-1} - \overline{B}z^{-k})$. This is clearly negative when $\overline{B} > 0$. If we want it to be negative for all k when $\overline{B} < 0$, we would need

$$z^{-2n+1} > \overline{B}/\overline{A}$$

Using $\overline{E.9}$ and $\overline{E.10}$ we would have $z^{-2n+1} > \frac{c_h z^{-n}\overline{y}_2 + xz^{n-1}\overline{y}_1}{-[c_h z^{n-1}\overline{y}_1 + xz^{-n}\overline{y}_2]}$, which is always satisfied.

■

Lemma 16. [22]*If ICL_{-n+1} holds then $\overline{v}_{-n} \leq (x - c_l), \quad \forall n \geqslant 1.$*

Proof of Lemma 16:

Rewrite ICL_{-n+1} as

$$\overline{v}_{-n+1} \leq \overline{v}_{-n} - c_l\frac{(1-\delta)}{\delta}.$$

Combine it with the equation (8.3) for v_{-n}

$$\begin{aligned}\overline{v}_{-n} &= (1-\delta)(x - pc_l) + p\delta\overline{v}_{-n} + (1-p)\delta\overline{v}_{-n+1} \leq \\ &\quad (1-\delta)(x - pc_l) + p\delta v_{-n} + (1-p)\delta\overline{v}_{-n} - (1-p)c_l(1-\delta).\end{aligned}$$

Rearranging, we have $v_{-n}(1-\delta) \leq (1-\delta)(x - c_l)$.■

Proof of incentive compatibility and individual rationality for BFBp strategy:

Lemma 17. *If $v_n \geq 0$ then the most stringent ICH constraint is the one in state n.*

[22]This result is taken from Lemma 4 in Abdulkadiroglu and Bagwell (2012).

Proof of Lemma 17:

Step.1: Considering ICH_{n-1}, $(1-p)(1-\delta)c_h + p\delta\bar{v}_n - (1-2p)\delta(\bar{v}_{n-2} - \bar{v}_{n-1}) > 0$. Notice that, from the same argument of Step 5 of Lemma 12, we have that $\operatorname{argmax}_k(\bar{v}_{k-1} - \bar{v}_k) = n$, which implies $(\bar{v}_{n-1} - \bar{v}_n) > (\bar{v}_{n-2} - \bar{v}_{n-1})$. Therefore a sufficient condition for ICH_{n-1} to be satisfied is that $(1-p)(1-\delta)c_h + p\delta\bar{v}_n - (1-2p)\delta(\bar{v}_{n-1} - \bar{v}_n) \geq 0$.

Step.2: We want to show that $(1-p)(1-\delta)c_h + p\delta\bar{v}_n \geq (1-2p)\delta(\bar{v}_{n-1} - \bar{v}_n) > 0$. Since $v_n \geq 0$, a sufficient condition for it is that, $(1-\delta)c_h \geq \delta(\bar{v}_{n-1} - \bar{v}_n)$ [condition n-1]. Using equation (8.2), we have $\bar{v}_{n-1} - \bar{v}_n = \frac{(1-\delta)}{1-\delta p}(\bar{v}_{n-1} + pc_l - px + c_h(1-p))$. Recall that $\bar{v}_{n-1} + pc_l < px$ (this is because $v_0 < (x - c_l)p$ and values are decreasing). Therefore, $\bar{v}_{n-1} - \bar{v}_n < \frac{(1-\delta)}{1-\delta p}(c_h(1-p))$. We then have that a sufficient condition for [condition n-1] to be satisfied is that $\delta\left[\bar{v}_{n-1} - \bar{v}_n\right] < \delta\frac{(1-\delta)}{1-\delta p}c_h(1-p) \leq (1-\delta)c_h$. This is always the case, because $\frac{\delta(1-p)}{1-\delta p} \leq 1$ for all $\delta \leq 1$. It follows that ICH_{n-1} is satisfied.

Step.3: We want to show that ICH_k is satisfied all $k \in K\backslash\{-n, n\}$. Rewrite ICH_k as $(1-p)(1-\delta)c_h + p\delta\bar{v}_{k+1} - (1-2p)\delta(\bar{v}_{k-1} - \bar{v}_k) \geq 0$. From the previous steps we have $(1-p)(1-\delta)c_h + p\delta\bar{v}_{k+1} - (1-2p)\delta(\bar{v}_{k-1} - \bar{v}_k) \geq (1-p)(1-\delta)c_h + p\delta\bar{v}_n - (1-2p)\delta(\bar{v}_{n-1} - \bar{v}_n) \geq 0$.

Step.4: We want to show that ICH_{-n} is satisfied. Rewrite it as $(1-\delta)c_h \geq \delta\left[\bar{v}_{-n} - \bar{v}_{-n+1}\right]$. The result follows from the fact that $\left[\bar{v}_{-n} - \bar{v}_{-n+1}\right] < \left[\bar{v}_{n-1} - \bar{v}_{-n}\right]$ (Step 5 of Lemma 12) and Step 2, where we showed that [condition n-1] holds.

Proof of Lemma 10:

The more stringent constraints in the BFBp strategy are : the IR constaint in state n, the ICH constraint in state n, and the ICL constraint in state $j - \arg\min_{k\in\{-n+1\},0\}}(\bar{v}_{k-1} - \bar{v}_k)$. We show in turn that all these constraints hold for values of the discount factor close to 1.

Step.1: By result 1.6.2 for the BFBp strategy, for all k, $\lim_{\delta\to 1} v_k = \lim_{\delta\to 1} v_o = (x - c_l)p + \lim_{\delta\to 1}(\overline{A} + \overline{B})$=$(x - c_l)p - \frac{(c_h - x)(1-p)p}{(2n-1-2np+3p)}$, which is positive when $c_h \leq x + (x -$

$c_l)\frac{(2n-1-2np+3p)}{1-p}$. Therefore, by continuity there exists $\delta^1(n) < 1$ such that $v_n \geq 0$ for $\delta \geq \delta^1(n)$.[23]

Step.2: Consider ICH in state n, $(1-p)(1-\delta)c_h + p\delta\bar{v}_n - (1-2p)\delta(\bar{v}_{n-2} - \bar{v}_{n-1}) > 0$. When $\delta \geq \delta^1(n), \bar{v}_n \geq 0$, and since $\lim_{\delta\to 1}(\bar{v}_{n-2} - \bar{v}_{n-1}) = 0$, it follows that there exists $\delta^2(n) \in \left(\delta^1(n), 1\right)$ such that $(1-p)(1-\delta)c_h + p\delta\bar{v}_n - (1-2p)\delta(\bar{v}_{n-2} - \bar{v}_{n-1}) \geq 0$ for all $\delta \geq \delta^2(n)$.

Step.3: Consider the ICL constraint in the interior state k, $c_l\,(1-\delta) \leq \delta(v_k - v_{k+1})$. When $\delta = 1$ it is satisfied because both the LHS and the RHS are zero. We want to see it is satisfied for discount factors close to 1. We re-write the constraint as :

$$c_l \leq \frac{\delta}{(1-\delta)}(v_{k-1} - v_k),$$

and consider the RHS. Both the numerator and the denominator go to zero as δ goes to 1. We can apply de l'Hôpital and obtain :

$$\begin{aligned}\lim_{\delta\to 1}\frac{\delta}{(1-\delta)}(v_{k-1} - v_k) &= \left.\frac{\partial(v_{k-1} - v_k)}{\partial\delta}\right|_{\delta=1} \\ &= \frac{c_h(k(1-p) + n(1-p) + 2p - 1) + x(n(1-p) - k(1-p) + p)}{2n - 2np + 3p - 1}.\end{aligned}$$

As shown in the result 1.6.2 for the BFBp strategy, this term is positive and it is greater than c_l. If we consider the more stringent constraint, $k = j$, where $j -$ $\arg\min_{k\in\{-n+1\},0\}}(\bar{v}_{k-1} - \bar{v}_k)$, we can find a $\delta^3(n) < 1$ such that all ICL constraints in the interior states are satisfied for $\delta \geq \delta^3(n)$.

Overall, from all the previous steps we have that when $c_h \leq x + (x - c_l)\frac{(2n-1-2np+3p)}{1-p}$ and

[23]If $c_h > x + (x - c_l)\frac{(2n-1-2np+3p)}{1-p}$, the IR constraints are not satisfied at the limit, so by continuity they are not satisfied for very large discount factor. Notice that the higher n the higher the values of c_h for which the IR constraints are satisfied.

$\delta \geq \delta' = \max\{\delta^1(n), \delta^2(n), \delta^3(n)\}$, the BFBp strategy can constitute an equilibrium.

2 Favor Exchange: An Experiment

2.1 Introduction

Favor exchange is a simple principle of much of the cooperation among individuals in daily activities. Examples abound in various spheres of human relations. For instance, relatives pitch in to help one another when business is failing, employees cover for each other during the pandemic, and political parties support legislation introduced by other parties in the expectation of similar support when trying to pass their own. These behaviors not only generate mutual gains for self-interested individuals but also carry out a part of economic activities through long term cooperation without any explicit agreements.

Our theoretical framework is based on Chapter 1. In our stage game, the agents need to decide whether to provide a favor. Providing a favor is a costly action which only improves the well-being of the recipient but yields no direct benefit to the provider. We restrict the cost to take only two possible values (low cost and high cost). In the case of incomplete information, agents privately observe the realization of their cost and know the marginal and joint distribution of the cost of providing favors in the population in each period. In the other case of complete information, the costs of agents are publicly known when they make their decisions. The net benefit of receiving a favor is positive only when the cost of providing a favor is low. In infinitely repeated games, the set of strategies is infinite. We therefore focus on the strategies that we discussed in Chapter 1 when studying the strategies employed by individuals in our experiment. We consider the efficient strategy which is imposed by Grim Trigger Strategy. We also consider the class of Stationary Strongly Symmetric strategies which is commonly discussed in dynamic games with incomplete information. We mainly focus on a class of Markov strategies, which we call Bounded

Favors Bank (BFB) Strategy. Recall that the BFB strategies depend on time through the value of the state variable at any period. The state variable acts as a sufficient statistic for all the strategically relevant information. In the context of our model with incomplete information, a natural state variable is the net number of favors received by the players. In the BFB strategies each player has a maximum net number of favors she can provide and receive. When no player has yet hit this maximum, a BFB strategy prescribes an efficient strategy to be played. When the maximum is achieved, a BFB strategy requires a form of reward for the player who provided the most favors or a form of punishment for the player who received the most favors.[24] We then theoretically review whether those strategies described in Chapter 1 can constitute an equilibrium given our parametrization.

In the controlled experiment, our treatments mainly differ in the value of the game parameters and the information structure, which allows different equilibrium conditions to be satisfied. In one dimension, by varying the value of the cost, we alter the set of the BFB strategies that are sustained as equilibria, so as to investigate how subjects' behaviors and strategies change accordingly. Then, in the other dimension, we explore the effect of different information provided to subjects, where they play the indefinitely repeated favor exchange game. Specifically, in one treatment, we show the net number of favors received (state variable) to subjects in each decision round. The net number of favors received is endogenous in the BFB strategies, and in equilibrium the players choose different actions depending on the value of this state variable. Empirically, however, showing the value of the state variable explicitly may act as a device for the paired participants to coordinate on the BFB strategies, given the existence of multiple equilibria in infinitely repeated games. In another treatment, subjects are endowed with (payoff irrelevant) chips and are instructed about how their stock of chips change after receiving or providing a favor. The so

[24]As a robustness check, we also include other simple and popular strategies from infinitely repeated PD game when estimating individual strategy used.

called chip strategies are examined in several theoretical papers (Möbius (2001), Olszewski and Safronov (2018a,b), etc) in the literature and isomorphic to the BFBr strategies we proposed. We are interested in examining, first, whether providing chips can promote the use of the BFB strategies compared to the baseline treatment, and second, whether providing chips produces different results from the treatment that shows the net number of favors directly. Finally, we switch from the incomplete information setting to complete information setting, where the costs of favor provision are publicly observed by each pair of matched subjects in each decision round.

More clearly, our experimental study revolves around the following research questions. First, what is the behavior of subjects in the environment of the favor exchange model and how is their behavior affected by different payoff parameters and information structures? Second, what is the probability that subjects play the different strategies we consider? And finally, how do different payoff parameters and information structures affect the probability?

Our experimental results offer new understandings of long-term bilateral relationship in favor exchange. First, we find that subjects cooperate to exchange favors under complete information substantially more than under incomplete information. Then, employing the Strategy Frequency Estimation Method (see Dal Bó and Fréchette (2011, 2019), Camera et al. (2012), Jones (2014), Romero and Rosokha (2018), etc), we find that being a free rider (never providing favors) is the most prevalent strategy in treatments with incomplete information, but the efficient strategy turns out to be the most popular one and accounts for the largest proportion of individual behavior in the treatment with complete information. This result is striking because most subjects can succeed in coordinating on providing a favor when it is efficient to do so despite the fact that never providing favors is strictly dominant in the stage game and an equilibrium in the repeated game of favor exchange. Second, we find that one of our BFB strategy with reward (BFBr) is played with a statistically significant positive probability by subjects, which allows subjects to achieve a strictly positive expected payoff in the treatment with incomplete information. But our subjects' behavior cannot be explained by any BFB strategies with punishment (BFBp), even in the treatments where such strategies could provide a higher long term payoff than the BFBr strategy. Our experimental results suggest that when dealing with a bilateral relationship with private information, social norms based on rewards rather than punishments may be more likely to emerge. Meanwhile, our result shows that explicitly showing the net number of favors received enables the BFBr strategy to be more widespread. Finally, consistent with the related literature (see Fudenberg et al. (2012), Aoyagi et al. (2019)), we find that subjects choose complex strategies with long-memories more often under incomplete information than under complete information, but are more likely to choose simple strategies with memory one or zero under complete information than under incomplete information.

Our paper contributes to the literature in the following aspects. The favor exchange model has been extensively studied in the theoretical literature. Previous papers have considered models where agents privately observe the possibility of providing a favor to the other and only one agent at a time can have such possibility (e.g., Möbius (2001), Hauser and Hopenhayn (2008), Abdulkadiroglu and Bagwell (2012), Abdulkadiroğlu and Bagwell (2013), Olszewski and Safronov (2018a,b)). One simple family of strategies that has been widely studied with indivisible favors is called chip strategies (see Möbius (2001), Abdulkadiroglu and Bagwell (2012); Abdulkadiroğlu and Bagwell (2013), Olszewski and Safronov (2018a,b)), in which agents behave as if they were endowed with a finite number of chips and when an agent receives a favor she has to give a chip to the favor provider. If an agent has no chip left, she cannot receive any more favors. Olszewski and Safronov (2018b) apply the chip strategy not only in the favor exchange model but also in the repeated duopoly model and the model of repeated auctions. They show that the chip strategies can approximate the efficient outcomes in those models. Different from these papers, we consider a model where each agent can provide a favor in each period and the source of private information is the cost for each agent to provide a favor to the other player. Under this assumption on private costs, in our companion paper Degan et al. (2021), we derive the analytical equilibrium conditions for the BFBr and BFBp strategy, respectively. We find that the BFBr strategy can be mathmatically equivalent to the chip strategy, but the BFBp strategy is new in the literature and can achieve higher efficiency compared to other common strategies.[25]

Compared to the theoretical studies on favor exchange, however, empirical work on this topic remains largely unexplored. Using controlled lab experiments and econometric methods, we are the first that test the favor exchange model and show the impacts of information availability on subjects' behavior. To the best of our knowledge, Roy (2012) is the only paper that experimentally studies a model of favor exchange. His analysis is based on the continuous time model developed by Möbius (2001), where subjects can provide the matched player a favor at random times depending on whether or not she receives an opportunity to do so. But due to the feature of continuous time, estimation for individual strategies is beyond the scope of Roy (2012) and he has focused on comparative static analysis. Our study is the first one that sheds light on the strategies that subjects employ in this favor exchange environment. In particular, we provide an estimation of the frequency of individuals strategies played by subjects among a set of strategies that include our proposed BFB strategies and other strategies that are considered in the theoretical literature on favors.

Second, our paper contributes to the experimental literature on infinitely repeated games, especially those on repeated Prisoner's Dilemma (PD) games that aim to characterize the strategies subjects employ. In experiments on repeated PD games with complete

[25]Specifically, we compare the players' long-term payoffs in the BFBr strategy, BFBp strategy, and the stationary strongly symmetric strategy of always provide a favor independent of the cost.. When the parameters satisfy the equilibrium conditions for all the three strategies, the payoff from the BFBp strategy is always the highest.

information, using Strategy Frequency Estimation Method (SFEM) some papers find that Always Defect and Tit for Tat strategies are most often employed by subjects across treatments (e.g., Dal Bó and Fréchette (2011), Romero and Rosokha (2018), Dal Bó and Fréchette (2019), Romero and Rosokha (2019)). Jones (2014) explores an experimental setting where subjects played a series of 3-by-3 versions of the Prisoner's Dilemma with complete information and finds that subjects are more likely to use a simple selfish strategy of Always Defect in treatments with increased complexity of cooperative strategies. Breitmoser (2015) analyzes a metadata set of experiments on infinitely repeated PD games and introduces a class of mixed strategies, Semi-Grim strategies. Relying on SFEM, he finds that Semi-Grim strategies can summarize pattern of behavior well in experiments of other related literature as long as the discount rate exceeds the BOS-threshold. Similar to them, we use SFEM to estimate the individual strategy in the repeated game of favor exchange and find that the non-cooperative strategy is played with a large probability. Different from the experiments on PD games, the nature of favors and incomplete information of cost realization in the favor exchange model give rise to different types of strategies used in the experiment. In particular, in the treatment with incomplete information, we find that the BFB strategies are played with statistically significant probabilities. Another approach which trades off goodness-of-fit of a set of strategies versus a cost of adding more strategies is considered to select the best-fitting strategies in infinitely repeated game (see Engle-Warnick and Slonim (2004, 2006), Camera et al. (2012)). We follow the strategy-fitting procedure in Camera et al. (2012) and the results show that the strategy set we considered perform well on describing the individual behavior in the data. In addition, the results confirm that (i) the efficient strategy classifies the most individuals' behavior under complete information while the most of data is classified by never providing favors strategy and (ii) BFBr strategies are more likely to be played by subjects than BFBp strategies in all treatments.

Third, our paper also contributes to the understanding of the effects of information structure on the play of repeated games. There is a growing experimental literature that discusses the effects of different types of monitoring on repeated games (e.g., Green and Porter (1984), Aoyagi and Fréchette (2009), Ambrus and Greiner (2012), Deck and Nikiforakis (2012), Embrey et al. (2013), Rand et al. (2015), Aoyagi et al. (2019)). Many empirical evidences show that in the presence of imperfect monitoring, cooperation can be sustained. The level of cooperation under imperfect monitoring is comparable or even slightly greater than the level under perfect monitoring at the beginning of the experiment. Aoyagi and Fréchette (2009) investigate a classic PD game in infinite horizon where subjects only observe a random public signal of each other's action after each round. They find that the cooperation level decreases as noise increases. Fudenberg et al. (2012) introduce an infinitely repeated PD game with different imperfect monitoring where the choice of subjects made in each round would be altered to another choice with some probability (varying from 0 to $\frac{1}{8}$). They show that subjects can cooperate substantially despite imperfect monitoring and their strategies are considerably diverse. Aoyagi et al. (2019) compare the behavior of subjects in infinitely repeated PD game where monitoring is perfect, imperfect public and imperfect private. Their results are consistent with Fudenberg et al. (2012) and indicate that subjects sustain cooperation in every treatment, but their strategies under imperfect monitoring are both more complex and more lenient than those under perfect monitoring. In our paper, we examine subjects' behavior under complete information and incomplete information in the framework of favor exchange with an indefinite horizon. On one hand, different from the experimental designs of the papers above, since subjects do not observe the other player's cost of providing a favor under incomplete information (i.e., potential payoff of other players is private information), the efficient cooperative behavior can never be an equilibrium outcome. On the other hand, as usual, both the efficient equilibrium outcome (mutual cooperation) and the most inefficient equilibrium outcome (mutual non-cooperation) are supported under complete information. Our results show that the level of cooperation (in our setting providing a favor if and only if the cost is low) is significantly lower under incomplete information than under complete information. A consistent result with the literature (e.g., Fudenberg et al. (2012), Embrey et al. (2013), Aoyagi et al. (2019)) is obtained that the percentage of subjects who use complex strategies with longer memories is larger in the treatment with incomplete information than in the treatment with complete information.

The rest of the paper is organized as follows. Section 2.2 presents the theoretical predictions. Section 2.3 presents the experimental design and hypotheses. Main results are reported in Section 2.4. Section 2.5 concludes.

2.2 Theoretical predictions

The theoretical predictions are based on the work in Chapter 1. Our theoretical model is the favor exchange model described in section 1.2. Two players interact in an infinite horizon. They simultaneously and independently select an action of "Do a favor" or "Do not do a favor" to the other in each period. Each player obtains an instantaneous utility "x" from receiving a favor and faces a random cost "c_j" of providing a favor. This cost can take only two values: low or high, $c_j \in \{c_l, c_h\}$. As assumed in Chapter 1, conditional on player i having a low cost $c_i = c_l$, the other player has a high cost with probability 1, i.e., $\Pr(c_{-i} = c_h | c_i = c_l) = 1$. Conversely, conditional on player i having a high cost $c_i = c_h$, the other player has a low cost with probability $\Pr(c_{-i} = c_l | c_i = c_h) = \frac{p}{1-p}$, and a high cost with the complement probability, $\Pr(c_{-i} = c_h | c_i = c_h) = \frac{1-2p}{1-p}$. Each infinitely lived player discounts the future payoff according to the discount factor $\delta < 1$. As standard in infinitely repeated games, the set of strategies is infinite. We therefore restrict our attention to the set of "reasonable" strategies have been considered in section 1.3 of Chapter 1. Here we concisely present the relevant theoretical predictions; for additional details see sections 1.2 and 1.3 in Chapter 1.

In our experimental setting, we fix the utility of receiving a favor to $x = 10$, the low cost of making a favor to $c_l = 1$, the marginal probability of receiving the low cost to $p = 0.45$, and $\delta = 0.85$. We implement two values for c_h in different treatments, $c_h = 15$ or 11, for which different BFB strategies can be supported as an equilibrium. Our theoretical predictions below will focus on whether the three classes of strategies described in section 1.3 constitute an equilibrium given our choice of parameters.

We first consider the Efficient strategy such that a player in each period t provides a favor if and only if the cost is low when on the equilibrium path, and provides no favor forever on when off the equilibrium path. If the costs of providing favors were observable, the Efficient strategy could be supported by Grim-Trigger strategy, where the worst Nash equilibrium of the stage game is played ever after a deviation is detected, for discount factors $\delta \geq \frac{c_l}{(x-c_l)p+c_l}$.[26]

Proposition 3. *Given our parametrization, the Grim Trigger strategy (Efficient strategy)*

- *constitutes an equilibrium under complete information for both $c_h = 15$ and 11;*
- *cannot constitute an equilibrium under incomplete information for $c_h = 15$ or 11.*

Let now consider the Stationary Strongly Symmetric Strategies, s^{qj}, $q, j \in \{F, N\}$, where recall from Chapter 1 a player takes action q when she has a low cost and action j when she has a high cost. s^{NN} is an equilibrium as it plays the unique Nash equilibrium of the stage game in each period. For the strategy s^{FF} to constitute a Stationary Strongly Symmetric Equilibrium (Stationary SSE hereafter), it is necessary and sufficient that the average discounted payoff is individually rational and the long term payoff from both

[26]Given our parametrization, the threshold of δ is 0.198.

providing and receiving favors overcome the short term loss of favor provision with high cost (see Lemma 1). Notice that, the equilibrium conditions for s^{NN} and s^{FF} are exactly the same between complete and incomplete information, as they are independent of the cost realization. Furthermore, s^{FN} is an efficient strategy and it is therefore an equilibrium under complete information but not under incomplete information, as we described in Proposition 3. Conversely, s^{NF} can never be an equilibrium in either information setting as it is not individually rational.

Proposition 4. *Given our parametrization, Stationary Strongly Symmetric Strategies*

- s^{NN} *constitutes a Stationary SSE given* $c_h = 11$ *and* $c_h = 15$*, under both complete and incomplete information;*
- s^{FF} *constitutes a Stationary SSE given* $c_h = 11$ *but cannot constitute a Stationary SSE given* $c_h = 15$*, under both complete and incomplete information;*
- s^{FN} *constitutes a Stationary SSE given* $c_h = 11$ *and* $c_h = 15$*, under complete information but not under incomplete information;*
- s^{NF} *cannot constitute a Stationary SSE given* $c_h = 11$ *or* $c_h = 15$*, under either complete or incomplete information.*

Next we move to the predictions on the class of BFB strategies. Recall that, a BFB strategy is a stationary Markov strategy that uses the net number of favors received by a player as a state variable. We denote by $k \in Z$ the net number of favors received by player 1 (player 2 is analogous). The value of k is calculated by the total number of favors received minus the total number of favors provided. We consider a symmetric environment and let $K = [-n, ... - 1, 0, 1, ...n]$ be the state space, where each element indicates a possible number of net favors received at the beginning of each period. The element n

$(-n)$ represents the positive boundary state (negative boundary state). We let $\widetilde{K} = K \cup \{\emptyset\}$ denotes the extended state space, where $k = \emptyset$ means that a deviation has been detected from the public history. Notice that if an agent deviates from a specified strategy but her deviation is not detectable from the public history, then $k \in K$.

In the class of BFB strategies, we have two types of pure strategies. One of them is the BFBr strategy which prescribe that the player who reached her negative boundary state $-n$ is exonerated from providing favors (even if cost is low) until she receives a favor back. The BFBr strategy for player 1 at each t is given by the equation 16:

$$s_1^r(k, c_1) = \begin{cases} \text{F} & \text{if} \quad c_1 = c_l \text{ and } k \in K \backslash \{-n\} \\ \text{N} & \text{if} \quad c_1 = c_h \text{ or } k \in \{\emptyset, -n\} \end{cases} \tag{16}$$

The other type is the BFBp strategy, which prescribes that the player who reached her positive boundary state n to provide a favor even if the behavior is highly costly. The BFBp strategy for player 1 at each t is given by the following equation 17:

$$s_1^p(k, c_1) = \begin{cases} \text{F} & \text{if} \quad (c_1 = c_l \text{ and } k \in K) \text{ or } (c_1 = c_h \text{ and } k = \{n\}) \\ \text{N} & \text{if} \quad c_1 = c_h \text{ and } k \in \widetilde{K} \backslash \{n\} \end{cases} \tag{17}$$

To support a BFB strategy to be a (Perfect) Markov Equilibrium, all the values given any state variable k must satisfy the incentive rationality constraints. In addition, since types are not observable, the strategy must be incentive compatible for each type in each possible state. We delegate to section 1.3 of Chapter 1 the transition matrix of the state variable k, the recursive form of the value functions and the incentive constraints that respectively support BFBr and BFBp strategies as equilibria under incomplete information. For the complete proof of the theoretical results under incomplete information, refer to Appendices 1.6.2 and 1.6.2 in Chapter 1.

Notice that, the transition matrix of the state variable and the value functions for BFBr and BFBp strategies remain the same under complete information.[27] However, the incentive constraints of BFB strategies are different between complete and incomplete information, as players can observe each other's cost when making their decisions at each period.

Incentive constraints of the BFBr strategy under complete information

We discuss the incentive constraints for the BFBr strategy to support an equilibrium under complete information from the perspective of player 1, since the incentive constraints for player 2 are analogous. When player 1 receives a low cost, then player 2 must receive a high cost. The incentive constraints for the low type are presented in Table 8.

(1)	$-c_l(1-\delta)+\delta v_{k-1} \geqslant 0$	$k \in \{-n+1, \dots .n\}$
(2)	$-c_l(1-\delta)+\delta v_k \geqslant 0$	$k = -n$

Table 8: Incentive constraints for the low type in BFBr (complete information)

If player 1 is the high type, her incentive constraints depend on whether player 2 is the low type or high type, as presented in Table 9.

When player 2 receives a low cost		
(1)	$\delta v_{k+1} \geqslant -(1-\delta)c_h$	$k \in \{-n, \dots .n-1\}$
(2)	$\delta v_k \geqslant -(1-\delta)c_h$	$k = n$
When player 2 receives a high cost		
(1)	$\delta v_k \geqslant -(1-\delta)c_h$	$k \in \{-n, \dots .n\}$

Table 9: Incentive constraints for the high type in BFBr (complete information)

Incentive constraints of BFBp strategy under complete information

Similarly, when player 1 receives a low cost, then player 2 must receive a high cost. The incentive constraints for the low type of BFBp are presented in Table 10.

[27]Since the probability distribution of costs remains the same and the value functions are the average expected discounted payoffs, changing information about the cost to complete information should not alter

(1)	$-c_l(1-\delta)+\delta\bar{v}_{k-1} \geqslant 0$	$k \in \{-n+1, n\}$
(2)	$-(1-\delta)c_l+\delta\bar{v}_k \geqslant 0$	$k=-n$

Table 10: Incentive constraints for the low type in BFBp (complete information)

When player 1 receives a high cost, there are two possible cases for player 2: player 2 could either receive a low cost or a high cost. The incentive constraints for the high type of BFBp are presented in Table 11.

When player 2 receives a low cost		
(1)	$(1-\delta)x+\delta\bar{v}_{k+1} \geqslant -(1-\delta)c_h$	$k \in \{-n, \dots n-1\}$
(2)	$-(1-\delta)c_h+\delta\bar{v}_k \geq 0$	$k=n$
When player 2 receives a high cost		
(1)	$\delta\bar{v}_k \geqslant -(1-\delta)c_h$	$k \in \{-n+1, \dots n-1\}$
(2)	$-(1-\delta)c_h+\delta\bar{v}_{k-1} \geq 0$	$k=n$
(3)	$\delta\bar{v}_{k-1} \geq -(1-\delta)c_h$	$k=-n$

Table 11: Incentive constraints for the high type in BFBp (complete information)

We show in Appendix 2.6.1 that under complete information, the most stringent constraint for BFBr strategy is the incentive constraint for the low type in state n (ICL in state n). And the most stringent constraint for BFBp strategy is the incentive constraint for the high type in state n when the other player's cost is low (ICHL in state n) under complete information (see Appendix 2.6.2). On one hand, we prove that if a BFBr strategy is an equilibrium under incomplete information, then the BFBr strategy is also an equilibrium under complete informaion. On the other hand, we find that a BFBp strategy being an equilibrium strategy under incomplete information is neither a necessary nor a sufficient condition for the BFBp strategy to be an equilibrium strategy under complete information, vice versa. Reader can find the proof for BFBr and BFBp strategies to constitute equilibria under complete information in Appendices 2.6.1 and 2.6.2.

the form of the value functions and the form of transition matrix of the state k for the BFBr and BFBp strategies.

When fixing the value of δ and other parameters, if the BFB strategies are supported as an equilibrium strategy for a given bound on the net number of favors n'. It can be shown that a BFB, with any $n < n'$ is also an equilibrium.[28] Given the parametrization, we will only discuss the BFB strategies with $n = 1$ and $n = 2$. In fact, for any $n > 3$ the BFB strategies are not equilibrium strategies. Furthermore, for fixed parameters, there is a threshold c_h for which BFBp is an equilibrium. So for fixed δ and n, the BFBp strategy is an equilibrium for values of c_h lower than the threshold. Proposition 5 summarizes the theoretical predictions for the BFB strategies.

Proposition 5. *Given our parametrization of x, p, c_l, δ,*

- *the BFBr strategy, with $n = \{1, 2\}$, constitutes a Perfect Markov equilibrium given $c_h = 11$ and $c_h = 15$, under both complete and incomplete information setting;*
- *the BFBp strategy, with $n = 1$, constitutes a Perfect Markov equilibrium given $c_h = 11$ under both complete and incomplete information setting;*
- *the BFBp strategy, with $n = 2$, constitutes a Perfect Markov equilibrium given $c_h = 11$ under only incomplete information setting;*
- *the BFBp strategy, with $n = \{1, 2\}$, cannot constitute a Perfect Markov equilibrium given $c_h = 15$ under either complete or incomplete information.*

As a summary, Table 12 presents all the theoretical predictions we discussed above.

[28]The proof of the results for the BFBr strategies follows Abdulkadiroglu and Bagwell (2012). It is the case also for the BFBp strategies, for sure under our parmetrization. We do have asymptotic results with respect to the discount factor δ for both BFBr and BFBp strategies. In addition, while we do not have a formal proof, all numerical simulations indicate that when a BFB strategy is an equilibrium for a given δ, it is also true for higher discount factors.

Categories	Efficient	SSE				BFB			
Strategies	Grim	s^{NN}	s^{FF}	s^{FN}	s^{NF}	BFBr-1	BFBr-2	BFBp-1	BFBp-2
Complete Information									
$c_h = 11$	eqm	eqm	eqm	eqm	non-eq	eqm	eqm	eqm	non-eq
$c_h = 15$	eqm	eqm	non-eq	eqm	non-eq	eqm	eqm	non-eq	non-eq
Incomplete Information									
$c_h = 11$	non-eq	eqm	eqm	non-eq	non-eq	eqm	eqm	eqm	eqm
$c_h = 15$	non-eq	eqm	non-eq	non-eq	non-eq	eqm	eqm	non-eq	non-eq

Table 12: Theoretical predictions

2.3 Experimental design and hypotheses

2.3.1 Experimental design

The Stage Game — The stage game is a favor exchange game (Table 13) in which a pair of matched players determine independently and simultaneously whether "do a favor" or "do not do a favor" to the other player. There is a cost for favor provision and the cost can be either low ($c_i = c_l$) or high ($c_i = c_h$). The low cost is always set to $c_l = 1$. The high cost takes one of two possible values, $c_h = 11$ and $c_h = 15$, in different treatments. Finally, receiving a favor from the other player results in a benefit of $x = 10$.

player 1	player 2	
	Do a favor	Do not do a favor
Do a favor	$x - c_1, x - c_2$	$-c_1, x$
Do not do a favor	$x, -c_2$	0, 0

Notes: Value of cost, $c_i, i \in \{1, 2\}$, can be either $c_i = c_l$ or $c_i = c_h$.
x is 10 and c_l is 1. c_h can be either 11 or 15 for different treatments.

Table 13: The stage game

The Supergame — A supergame is an indefinitely repeated game induced by a random continuation rule (Roth and Murnighan (1978)).We set the probability of continuation $\delta = 0.85$ in all treatments, so in each round the supergame is expected to go on for around

7 (additional) rounds. We did not fix the number of supergames in advance. Instead, when the sessions lasted for 2 hours, the supergame ongoing was determined to be the last supergame for the session.

The Matching Protocol — Subjects were randomly and anonymously matched in each supergame. They were randomly rematched for a new supergame but played with the same partner within each supergame.

Treatments — The focus of our experiment is to examine the behavior of subjects and the strategies subjects employ under different payoff parameters and information structures of the indefinitely repeated favor exchange game. The experiment consists of two sets of treatments, as summarized in Table 14. In Set 1, the treatments differ in the payoff parameter and the amount of information available to subjects. In Set 2, the treatments differ in the information structure.[29]

Set 1.

In the baseline treatment, subjects play the game as in the theoretical model with private information of the cost received in each round. At the beginning of each round, subjects observe their private costs but not the matched players' costs. During each supergame, before making a decision in each round t, subjects can also observe their private histories up to round $t-1$.[30] But, there is no any summary information provided. We use Baseline-15 and Baseline-11 to denote the treatments with $c_h = 15$ and $c_h = 11$ in Set 1, respectively. As in Table 12 of theoretical predictions, by varying the value of c_h, different BFB strategies

[29]We do not compare the treatments in Set 1 with the treatments in Set 2 directly, since the incentive schemes are different between the two sets. In Set 1, we aim to implement the stage game as analogous as possible to that in the theoretical model. Specifically, doing a favor will result in a net loss and only benefit the other player. We therefore use the payoff of the stage game as in Table 13 and cumulative payoffs from all supergames, with a guarantee of a $15 show-up fee. In Set 2, we choose to give an endowment of 15 points in each round to avoid possible negative payoffs from the game and also downgrade the show-up fee to $10 to make the overall expected payments similar between Set 1 and Set 2. The final payoff in Set 2 relies on four randomly drawn supergames.

[30]Histories include their actions, their matched players' actions and their private costs received.

Treatment	c_h	Information	Equilibrium supported
		Set 1	
1 (Baseline-15)	15	Private information	s^{NN} BFBr-1, BFBr-2
2 (Baseline-11)	11	Private information	s^{NN}, s^{FF} BFBr-1, BFBr-2 BFBp-1, BFBp-2
3 (K-15)	15	Private information State variable k	s^{NN} BFBr-1, BFBr-2
		Set 2	
4 (Chip-15)	15	Private information Chip	s^{NN} BFBr-1, BFBr-2
5 (CompleteInfo)	15	Public information Chip	s^{NN}, Grim BFBr-1, BFBr-2

Table 14: Summary of treatments

can be supported as an equilibrium.

In Treatment K-15 , the computer program shows information on the net number of favors received, k, to each subject before he/she makes a decision in each round. Theoretically speaking, the information on the state variable k is part of the equilibrium and subjects can always calculate that variable since we also provide the full history of their past actions. However, explicitly showing the value of k can immediately reflect subjects' status and may help them coordinate on the BFB strategies.

Set 2.

In Treatment Chip-15, we introduce chips into the experiment, in which every subject receives two chips at the beginning of each supergame. Each pair of matched subjects always has 4 chips in total in each supergame. The chips can neither be carried over to the next supergame, nor can be redeemed for dollars, which means that the chips do not affect subjects' payoffs directly. In each round, a subject receives a chip from the matched player if the subject chooses "do a favor" and the matched player has at least one chip, otherwise there is no chip exchange. Notice that the introduction of chips does not directly affect the possibility of favor exchange. For example, between a pair of subjects, if subject 1 has 4 chips and subject 2 has 0 chip in a round, subject 1 can still choose "do a favor" but he/she will not receive any chip from subject 2.[31]

Theoretically speaking, the endowment of chips makes our BFBr strategy (with $n = 1$ and $n = 2$) equivalent to the Chip Strategy examined in other theoretical studies. The state variable k in our setting can be perfectly transformed to the number of chips when on the equilibrium path ($k = 0$ corresponding to the case that the subject has 2 chips, which is the endowment of chips, $k = 2$ corresponding to 0 chips and $k = -2$ corresponding to 4 chips). In the Chip Strategy, at the boundary on the equilibrium path, players will not choose "do a favor" if the other player has no chips available, which is similar to the behavior described in our BFBr strategy, i.e., do not "do a favor" even given a low cost if the player already reached the negative boundary (the maximum net number of favors provided in equilibrium). Notice that, by the definition of the BFB strategies, the boundary of the net number of favors is part of the equilibrium and players should not go beyond the boundary.

Consequently, given our model setup, introducing the chips in Treatment Chip-15 would play the same role as showing the state variable k in Treatment K-15 if players follow the BFB strategies. When on the equilibrium path, the number of chips will convey the same information as showing the value of k. When off the equilibrium path, the number of chips may not be perfectly transformed to the value of k. However, if players' behavior is consistent with the theory prediction, they will simply follow the Nash equilibrium of the stage game, which is not conditional on the net number of favors. Thus, the BFB strategies

[31]For details, please see the instruction of Treatment Chip-15 in Appendix 2.6.3.

still serve as the theoretical benchmark in Treatment Chip-15 as in Treatment K-15.

On the other hand, it is worth pointing out that, in our experiment, subjects can always choose to do a favor or not to do a favor, regardless of whether or not their matched player has chips. That is, in the implementation of the Chip-15 treatment, we do not restrict subjects' actions in the boundary state by the equilibrium strategy, since otherwise the choices we observe from the data will favor the predictions of the BFB strategy. Finally, different from the other favor exchange model (Möbius (2001), Abdulkadiroglu and Bagwell (2012), Olszewski and Safronov (2018b), etc), in our setting the BFBr and BFBp strategies are both possible to be played in the Chip-15 treatment, even though the parametrization does not support the BFBp strategy to be an equilibrium strategy.

In Treatment CompleteInfo, in addition to the chip endowment, the subjects can observe the actual costs of their matched players at the beginning of each decision round. This information will change the game from incomplete information to complete information and support the efficient equilibrium. Specifically, efficient strategy can constitute an equilibrium for both $c_h = 15$ and $c_h = 11$.

To summarize, the three treatments of Set 1 are characterized by incomplete information, i.e., subjects can observe past and current actions in their matched pair but not the actual cost of their matched player. By lowering the value of high cost c_h, Baseline-11 allows both BFBr strategy and BFBp strategy to constitute equilibria while only the BFBr strategy can be sustained as an equilibrium in Baseline-15. Meanwhile, an extra information is offered in Treaetment K-15 as the state k is directly showed to subjects. In Set 2, the Chip-15 treatment is characterized by incomplete information, but the CompleteInfo treatment is characterized by complete information. In Chip-15, subjects are endowed with chips, that serve as a tally for counting the number of favors received/provided. In CompleteInfo, subjects can perfectly observe past and current actions, payoffs and costs in their matched pair. In addition, subjects in CompleteInfo also receive chips which serve as the same role as in Chip-15.

The experiment was programmed with the z-Tree software (Fischbacher (2007)) and conducted at the CIRANO Experimental Economics Laboratory (Canada). We recruited subjects from a pool that mostly consists of undergraduate students. Participants have no prior experience in similar experiments. Instructions were read aloud and then subjects completed a brief comprehension quiz. To enable subjects to gain some experience with the play of the game, we had them play some trial periods prior to the official experiment in each session. All sessions were completed within 2.5 hours, including reading the instructions and completing the quiz.

2.3.2 Hypotheses

Based on our theoretical prediction in Table 12 and the experimental design in Table 14, we present the following hypotheses to test the behavior of subjects and their strategies used between treatments. Specifically, Hypotheses 1 and 2 focus on the treatments in Set 1, and Hypotheses 3 and 4 focus on the comparison between complete information and incomplete information settings in Set 2.

Hypothesis 1. *The prevalence of the BFBp strategy is higher in the Baseline-11 treatment than in the Baseline-15 treatment.*

Since explicitly showing state k may act as a device to help subjects coordinate on the BFB strategies, hypothesis 2 tests the prevalence of the BFB strategies.

Hypothesis 2. *The prevalence of the BFB strategies is higher in the K-15 treatment than in the Baseline-15 treatment.*

When moving from incomplete information to complete information, we expect that overall cooperation and favor provision will increase. Based on the theoretical prediction and previous experimental findings in the infinitely repeated Prisoner's Dilemma game, we conjecture that the Grim Trigger strategy will be more often used under the complete information setting than incomplete information. Correspondingly, under incomplete information, we expect to observe an increase in the frequencies of other types of strategies, such as the non-cooperative one and the BFB strategies.

Hypothesis 3. *The frequency of favor provision in the CompleteInfo treatment is greater than that in the Chip-15 treatment.*

Hypothesis 4. *The prevalence of the Grim Trigger strategy is higher in the CompleteInfo treatment than in the Chip-15 treatment. The prevalence of the non-cooperative strategy and the BFB strategies is higher in the Chip-15 treatment than in the CompleteInfo treatment*

Treatment	Number of sessions	Number of supergames	Number of rounds	Subject per session	Show-up fee	Average earnings
			Set 1			
Baseline-15	3	10	83	14	C$ 15	C$ 25.44
		15	74	14		C$ 24.31
		13	83	14		C$ 26.48
Baseline-11	3	18	106	10	C$ 15	C$ 25.66
		11	84	12		C$ 28.41
		11	72	14		C$ 26.79
K-15	2	11	79	14	C$ 15	C$ 22.95
		17	86	14		C$ 25.17
			Set 2			
Chip-15	3	18	86	14	C$ 10	C$ 21.27
		20	75	14		C$ 21.40
		8	76	14		C$ 31.61
CompleteInfo	2	11	89	12	C$ 10	C$ 35.72
		14	87	10		C$ 24.57

Table 15: Description of experimental sessions

2.4 Experimental Findings

Table 15 reports some details about all of our experimental sessions. As this table reveals, on average, each session involved 14 supergames and 83 rounds. In total, 120 subjects participated in our experiment, with an average earnings of CAD $26.

In the reminder of this section, we will begin with an aggregate data analysis, followed by data analysis at the individual level. In section 2.4.1, we first present descriptive statistics and graphical representations for general results on subjects' behavior across treatments and then provide comparisons between treatments. Section 2.4.2 provides a set of empirical results on individual strategies by using the estimation method of SFEM (Dal Bó and Fréchette (2011)). Section 2.4.3 provides statistical analyses on subjects' behavior in different boundary states.

2.4.1 The general description of behavior

Table 16 reports the average of individual frequency of favor provision across sessions of each treatment.[32] The results show that in every sessions, the frequency of favor provision conditions on low cost is significantly higher than that conditions on high cost ($p - value < 0.01$, two-tailed Wilcox signed rank test).[33] It indicates that subjects can clearly distinguish between the low cost and high cost and avoid providing a favor when it is too costly. This basic result is in line with Result 1 of Roy (2012).

Figure 1 report the frequency of favor provision over time (all supergames) by treatment and session. Figure 1 shows a decreasing trend over time in the CompleteInfo treatment. However, the trends of favors frequency in the other four treatments with incomplete

[32]The average of individual frequency of favor provision in a session is calculated by taking the average of every individual frequency in the session.

[33]For the test which is for each session, so the observation number is the number of subjects in each session.

Treatment	Session	Frequency	Frequency$\|C_l$	Frequency$\|C_h$
1 (Baseline-15)	1	0.268	0.562	0.075
	2	0.327	0.569	0.114
	3	0.305	0.460	0.176
2 (Baseline-11)	4	0.291	0.470	0.131
	5	0.244	0.444	0.098
	6	0.271	0.512	0.075
3 (K-15)	7	0.250	0.368	0.169
	8	0.311	0.607	0.069
4 (Chip-15)	9	0.358	0.693	0.093
	10	0.129	0.227	0.054
	11	0.347	0.501	0.244
5 (CompleteInfo)	12	0.390	0.580	0.202
	13	0.345	0.509	0.201

Table 16: Average frequency of "do a favor" - session level

information are somewhat ambiguous. For instance, in Baseline-15, K-15 and Chip-15, the trends of favors frequency of some sessions show a U shape, with an increase towards the end of the session. But in the other sessions of those treatments, the trends are flat or are slightly decreasing over time. These results indicate that the behavior of subjects is equivocal and strategies used could be complex under incomplete information. On contrast, subjects' behavior has a clearer pattern and the employed strategies may be simpler under complete information.

One important issue discussed in the literature is cooperation and efficiency. In our famework of favor exchange, to cooperate simply refers to choose "do a favor" if and only if the cost is low (cooperation rate = Frequency$|c_l$). Such a choice maximizes the sum of the match's benefits in a round. Figure 2 presents data of cooperation rate (the frequency of doing a favor given a low cost) in three blocks, separately for Set 1 and Set 2: In each figure (the left panel for Set 1 and the right one for Set 2), the frequency in the first

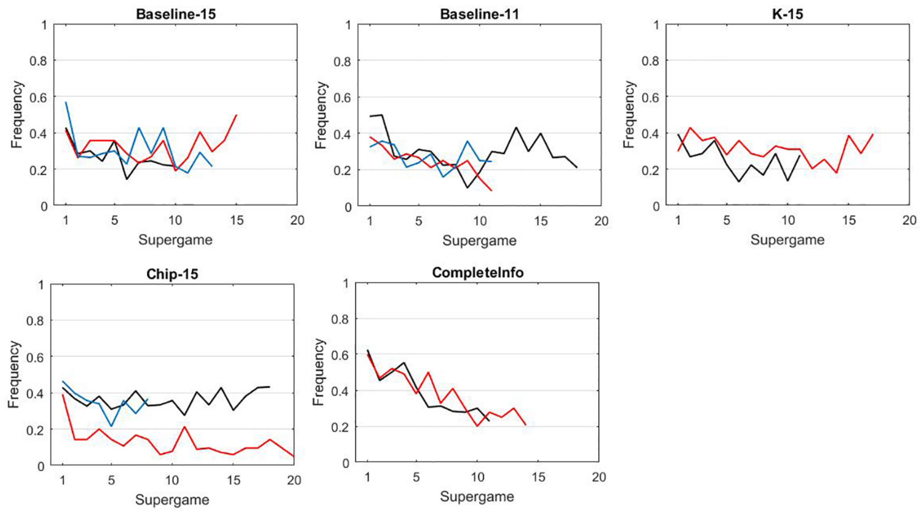


Figure 1: Frequency of favor provision over supergame
Notes: The black solid, red solid and blue solid lines denote the cooperation rate in session 1, 2 and 3 of each treatment.

three supergames are in the first block, the last three supergames in the third block, and a single point in the middle block (labeled "others") for the average of the rates in all other supergames.[34]

We see that there is markedly less cooperation in the beginning of the experiment (first three supergames) when the information is incomplete (Chip-15 versus CompleteInfo, $p = 0.049$). Conversely, we see little difference regarding the cooperation level in the last part of the experiment (last three supergames) between incomplete information and complete information (Chip-15 versus CompleteInfo, $p = 0.275$). Between the three treatments with incomplete information of Set 1, we do not find any difference in the beginning of the experiment (Baseline-15 versus Baseline-11, $p = 0.827$; Baseline-15 versus K-15, $p = 0.513$). There is also no difference between treatments of Set 1 in the last

[34]For each pairwise cooperation rate comparison, we report the results of a logistic regression over all individual decisions conditional on having a low cost, with a treatment dummy as the independent variable, clustered on session level.

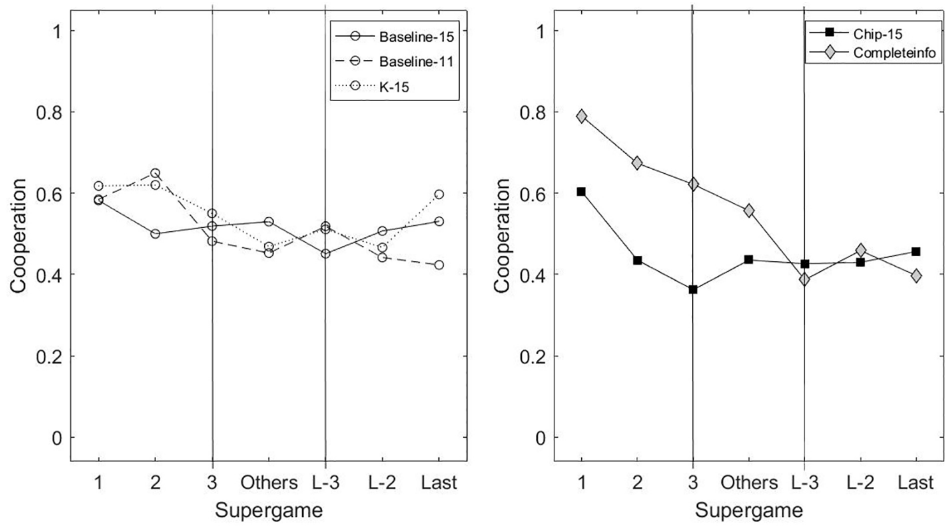


Figure 2: Cooperation Level By Treatment Over Supergames

three supergames (Baseline-15 versus Baseline-11, $p = 0.275$; Baseline-15 versus K-15, $p = 0.513$).

As Lugovskyy et al. (2017), we construct the data for each treatment as a panel, with subjects as the cross-sectional dimension and supergames as the time dimension. We consider below a regression model for three pairs of treatments and report the results in Table 17. The regression model is,

$$Frequency_i^S = \beta_0 + \beta_{T_k} D_{T_k,i}^S + \epsilon_i^S$$

Where $Frequency_i^S$ is the average frequency of individual i in supergame S, $D_{T_k,i}^S$ is a dummy variable for Treatment k and ϵ_i^S is an error term. In the model specification we use cluster-robust standard errors by session level. We control for the random sequence of supergames in the regression since the realized lengths of supergames has been shown to have an effect on choices (see Dal Bó and Fréchette (2011), Embrey et al. (2019)).[35] The

[35]According to our model specification, the random sequence of supergames is controlled by adding a series of dummy variable for the series of supergames in each session. The idea is similar to control the time fixed effect as in the other empirical studies.

regression also includes the fixed individual effect as in Engle-Warnick and Slonim (2006).

Treatment	N. Obs.	Mean Frequency	Sign	Mean Frequency	N. Obs.	Treatment	R^2
Chip-15	644	0.256	$<^{***}$	0.366	272	CompleteInfo	0.448
Baseline-15	532	0.303	$>$	0.287	392	K-15	0.356
Baseline-15	532	0.303	$>$	0.271	466	Baseline-11	0.388

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Subject-sequence as unit of observation.

Cluster robust standard errors by session.

Table 17: Panel data analysis of individual frequency of favor provision

Results of Table 17 show that on average, the frequency in the CompleteInfo treatment is significantly higher than that in the Chip-15 treatment at 1 percent level ($0.366 >^{***} 0.256$). However, there is no significant difference between the three treatments with incomplete information in Set 1 (Baseline-15 versus K-15, $0.303 > 0.287$; Baseline-15 versus Baseline-11, $0.303 > 0.271$). [36]

We extend the treatment comparison for the frequency of favor provision by conditioning on low cost c_l and high cost c_h, respectively (see Appendix 30 and Appendix 31). We find that when conditional on low cost c_l, on average, the frequency of favors is significantly higher in the CompleteInfo treatment than in the Chip-15 treatment ($0.545 >^{***} 0.463$). Meanwhile, the frequency is also significantly higher in the CompleteInfo treatment when conditional on high cost c_h ($0.202 >^{***} 0.101$). It could be due to that subjects can accurately observe the others' costs and they can count on their behavior in previous rounds without suspiciousness. This result is also in line with the results from other experimental studies on infinitely repeated PD game where the cooperative behavior

[36]See Appendix 2.6.4 for a series of robustness checks for these results. In the robustness check, we report the results with subject-random effect and the results by using Subject-period as a unit of observation in a panel data. of observation in a panel data.

increases as the information becomes more complete.[37] Again from the conditional results, we find no significant difference between the first three treatments in Set 1 regarding the frequency conditional on c_l and c_h, respectively.

We summarize the effects of changing the value of the high cost and providing the extra summary information on the state variable k (i.e., the net number of favors received), on the frequency of favor provision in Finding 1. Finding 2 summarizes the effect of information structure on the play of favor exchange game.

Finding 1. *There is little difference in the frequency of favors provision in the three treatments in Set 1, where the treatments differ in the value of the high cost and the availability of the net number of favors received.*

Finding 2. *The frequency of favor provision is higher under the complete information setting than under the incomplete information setting.*

Finding 2 supports Hypothesis 3. We conclude that in the framework of our favor exchange game, there is a statistically significant difference in the frequency of favor provision and of cooperation between complete and incomplete information treatments (Chip-15 and CompleteInfo). There is little difference between the three treatments in Set 1 indicating that the differences in the values of the cost parameter across treatments does not affect much the behavior of subjects. Similary, their behavior is not affected when we provide them some possible coordination devices (the net number of favors).

2.4.2 The individual strategy estimation

In this subsection, we employ Strategy Frequency Estimation Method (SFEM) as in Dal Bó and Fréchette (2011) and Fudenberg et al. (2012) to assess which strategies are used more

[37] In PD game, cooperate behavior does not have explicit costs and it provides a lower instantaneous payoff compared to no cooperate behavior but they are both positive.

often in the favor exchange game. As in the literature of repeated Prisoner's Dilemma game, we focus on a subset of the infinitely many repeated game strategies. We begin with a set of reasonable strategies that have been discussed in section 2.2 and which have also been commonly considered in the related theoretical literature. To verify our results and provide a robustness check, we then extend the set of strategies by including other strategies that have received particular attention in the literature of infinitely repeated PD game.

The set of strategies that we consider includes four BFB strategies (i.e., BFBr-1, BFBr-2, BFBp-1 and BFBp-2), s^{NN} strategy (Always provides no favor), efficient strategy (Grim) and s^{FF} strategy (always provide a favor until the other deviates) as in Table 18. The Table 18 reports the estimation results using all the data separately for each treatment.[38] From column 1 to column 4, we see that s^{NN} is the most prevalent strategy which explains around 50% of all subjects' behavior in the treatments with incomplete information. This result is in line with most of the experimental studies on infinitely repeated PD game where Always Defection (fully non-cooperative strategy) is an unique pure Nash equilibrium and is strategy most likely to be played.[39] It is also consistent with Jones (2014) who finds that subjects are more likely to use a simpler selfish strategy when the complexity of game is higher.

Interestingly, in the CompleteInfo treatment, the efficient strategy becomes the strategy that accounts for the highest proportion of the data (34%) followed closely by the s^{NN}

[38]Even though our game is implemented by random continuation method by which subjects should not realize the end of each supergame. However, the total duration of each session was informed to each subject prior to the experiment. We can expect there is always an ending effect at the last part of each session as the subjects can count the time themselves. Therefore, instead of using the second half of all the data of each session, we insist on using all the data of each session which at least can fairly present the actual behavior of the subjects during the experiment and avoid a potential selection bias for selecting the data to use.

[39]Dal Bó and Fréchette (2011) find that subjects use only Always Defection (AD) or TFT. In 4 out of 6 treatments, they find that AD can account for more than 60 percent of all the data (Table 7 of Dal Bó and Fréchette (2011)). Fudenberg et al. (2012) estimate the importance of 11 strategies and find that AD can account more than 20 percent of all the data in each treatment (Table 3 of Fudenberg et al. (2012)).

strategy (33%). This is consistent with Finding 2, as subjects are more cooperative in the treatment with complete information.

Since the results inevitably depend on the number and types of strategies that are considered in the estimation, we add in the set of strategies considered two strategies, "Tit-for-Tat" strategy and "Suspicious Tit-for-Tat" strategy.[40] TFT and STFT have received particular attention in the theoretical literature and accounted large proportion of subjects' behavior in the previous papers (see Dal Bó and Fréchette (2011), Fudenberg et al. (2012)).[41] Column 1 to column 4 in Table 19 show that the s^{NN} strategy is estimated to account for the larger proportion of behaviors (ranging from around 45% to almost 50%), with estimates that are statistically significant.

Meanwhile, in the CompleteInfo treatment, most of the data is still explained by the efficient strategy (around 30%). Therefore, our results in Table 18 are robust with respect to the inclusion of TFT and STFT strategies. These results, that support Hypothesis 4, are summarized in the following Finding 3.

Finding 3. *The efficient and the s^{NN} strategies are estimated to be played with equal probability under the complete information setting, while the s^{NN} strategy is clearly the strategy that is played with the higher probability in the incomplete information setting.*

Finding 3 also has inner coherence with Finding 2 as the more subjects follow the efficient strategy, the higher the frequency of favor provision in the treatment.

In addition, the results of Table 18 and Table 19 show that there is little change across the three treatments in Set 1 regarding the probabilities that the s^{NN} and the efficient strategies are played.[42] This may explain Finding 1 that no significant difference can be found

[40]Given our parametrization, TFT and STFT can constitute equilibria only if the high cost is 11. Since $x - pc_l - (1-p)c_h > 0$ only if $c_h = 11$.

[41]In Dal Bó and Fréchette (2011), Table 7 reports that TFT accounts for 35% of the data among 6 strategies. In Fudenberg et al. (2012), Table 3 reports that TFT accounts for 15% of the data among 11 strategies.

[42]Although the proportion of the efficient strategy between Baseline-15 and k-15 is 10%, but the proportion

	(1)	(2)	(3)	(4)	(5)
	Baseline-15	Baseline-11	K-15	Chip-15	CompleteInfo
BFBr-1	0.076*	0.214***	0.139*	0.070	0
	(0.044)	(0.071)	(0.074)	(0.049)	(0)
BFBr-2	0.087	0.045	0.053	0.111**	0
	(0.054)	(0.046)	(0.047)	(0.055)	(0.020)
BFBp-1	0	0	0.071	0	0.084
	(0)	(0.005)	(0.051)	(0.008)	(0.083)
BFBp-2	0.050	0	0	0	0.071
	(0.041)	(0)	(0)	(0.010)	(0.078)
s^{NN}	0.445***	0.471***	0.535***	0.497***	0.326***
	(0.078)	(0.083)	(0.097)	(0.079)	(0.107)
Efficient	0.257***	0.188***	0.158**	0.210***	0.337***
	(0.077)	(0.071)	(0.073)	(0.067)	(0.128)
s^{FF}	0.085*	0.081	0.044	0.112**	0.171**
	(0.046)	(0.052)	(0.045)	(0.048)	(0.081)
Beta	0.848***	0.841***	0.829***	0.836***	0.773 ***
	(0.022)	(0.019)	(0.018)	(0.022)	(0.032)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Boostrapped standard errors in parentheses.

Table 18: Estimation of strategy used

between the three treatments in Set 1 regarding the frequency of favors and cooperation. Furthermore, we also find that when taking the s^{NN} and the efficient strategies together, they account for 70% of the observed behavior across all treatments. The other 30 percent of the data is mostly explained by other strategies with longer memories. These results are consistent with Result 2 in Romero and Rosokha (2018), where subjects used memory-zero and memory-one strategies two-third of the time and longer strategies one-third of the time.[43]

of subjects who following the s^{NN} is higher than the proportion of subjects who following the efficient strategies in these two treatments.

[43]In Romero and Rosokha (2018), it manifest that strategies with longer memory which are not commonly studied in the experimental literature are used by subjects and are existent in the game with indefinitely repeated period.

	(1)	(2)	(3)	(4)	(5)
	Baseline-15	Baseline-11	K-15	Chip-15	CompleteInfo
BFBr-1	0.070*	0.206***	0.113*	0.072	0
	(0.040)	(0.070)	(0.061)	(0.049)	(0)
BFBr-2	0.088	0.043	0.040	0.123**	0
	(0.055)	(0.042)	(0.042)	(0.058)	(0.020)
BFBp-1	0	0	0.032	0	0.084
	(0)	(0)	(0.036)	(0.008)	(0.079)
BFBp-2	0.051	0	0	0	0.071
	(0.041)	(0)	(0)	(0.008)	(0.071)
s^{NN}	0.431***	0.442***	0.536***	0.438***	0.310***
	(0.078)	(0.089)	(0.093)	(0.081)	(0.107)
Efficient	0.252***	0.189***	0.151**	0.218***	0.313***
	(0.077)	(0.067)	(0.069)	(0.070)	(0.112)
s^{FF}	0.044	0.014	0.035	0	0.033
	(0.034)	(0.023)	(0.035)	(0.022)	(0.046)
TFT	0.064	0.030	0.092	0.094**	0.189**
	(0.042)	(0.030)	(0.059)	(0.045)	(0.094)
STFT	0	0.077	0	0.055	0
	(0)	(0.048)	(0.005)	(0.040)	(0.013)
Beta	0.851***	0.848***	0.836***	0.848***	0.779 ***
	(0.021)	(0.018)	(0.016)	(0.019)	(0.031)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Boostrapped standard errors in parentheses.

Table 19: Estimation of strategy used

In following findings, we report some other important treatment effects. In Table 18, the results indicate that in all the treatments with incomplete information, the hypothesis that a positive proportion of subjects follow the BFBr strategy cannot be rejected at the 10 percent significance level (Baseline-15, 8%; Baseline-11, 21%; K-15, 14%; Chip-15, 11%). Conversely, there is no significant proportion of subjects' behaivor can be explained by the BFBp strategy. On the other hand, results from the CompleteInfo treatment show that 0 percent of the data can be explained by the BFBr strategies. Same results are confirmed in Table 19. Table 19 shows that around 10% ~ 20% of the data can be significantly accounted by the BFBr strategy in the treatments with incomplete information. Meanwhile, no data can be significantly explained by any BFB strategy in the treatments with complete information. Therefore, we conclude that the BFBr strategy is employed by the subjects only in the incomplete information setting.

Finding 4. *Around 10% to 20% of subjects' behavior can be significantly explained by the BFBr strategy in the treatments with incomplete information, but no significant proportion of subjects' behavior can be explained by any BFB strategy in the treament with complete information.*

In addition, in Table 18, we find that the BFBr strategy in the Baseline-11 treatment can account for a larger proportion of the data than that in the Baseline-15 treatment (21% v.s 8%). This result is robust to the inclusion of the TFT and STFT strategies, as shown in Table 19 and the difference is slightly bigger in the Table 19 (21% v.s 7%). In fact, maybe surprisingly, the BFBp strategy does not seem to be played by any positive proportion of subjects even in the Baseline-11 treatment, where BFBp-1 and BFBp-2 are equilibria. We summarize these results in the following Finding 5.

Finding 5. *In the treatment with incomplete information, a strategy based on reward rather than punishment is more likely to be played by subjects.*

Between treatments, the results of Table 18 show that the proportion of BFBr strategy in K-15 treatment is 75% higher than that in the Baseline-15 treatment (14% v.s 8%). The Table 19 shows that 7% of subjects' behavior can be explained at a statistically significant level by the BFBr strategy in the Baseline-15 treatment. Meanwhile, we cannot reject at 10 percent level that 11% of subjects' behavior is explained by the BFBr strategy in the K-15 treatment. We conclude that the BFBr strategy explains a larger proportion of subject's behavior in the treatment where the state variable k is directly shown than in the treatment where the state variable k is not shown. This result supports Hypothesis 2.

Table 18 shows that the s^{FF} strategy can account for 9%, 11% and 17% of the data in the Baseline-15, Chip-15, and CompleteInfo treatment, respectively. This result goes against the comparative statics suggested by the theory. s^{FF} should explain more in the Baseline-11 treatment than the Baseline-15 treatment. In addition, from Table 18, the proportion of the s^{FF} strategy in the CompleteInfo treatment is larger than that in the Chip-15 treatment (17% > 11%). This result makes sense as subjects tend to use a simple and straightforward strategy when they observe all information. In Table 19, there is no data can be significantly accounted by the STFT strategy in any treatment. From Table 19, we see that the proportion of subjects following the s^{FF} strategy is much smaller in all treatments and is not statistically significant. It is worth noting that in the CompleteInfo treatment, the TFT strategy takes the place of the s^{FF} strategy and significantly accounts for 19% of the data.[44] Notice that both s^{FF} and TFT strategies are simple memory-one strategies and are easy to follow. However, there is only 9% of the data that can be explained at a statistically significant level by the TFT strategy in the Chip-15 treatment, where the BFB strategies are more popular than the TFT strategy. These results suggest that only simple strategies with memory-one or lower explain the behavior of the subjects in the treatment with complete information, while strategies with longer memories exist and those complex strategies seem to explain a statistically significant proportion of behaviors in the treatments with incomplete information. These results are in line with the results of other experimental studies in repeated games that under incomplete information subjects tend to use more complex strategies than under complete information (Romero and Rosokha (2018, 2019), Aoyagi et al. (2019)). We summarize these last set of results in our last Finding 4.

[44]It is difficult to explicitly distinguish between the behavior of following the TFT strategy and of following the s^{FF} strategy as they both prescribe continuously provide a favor if no one deviated before, otherwise stop providing a favor in next round. Although s^{FF} strategy requires subjects stop providing a favor forever if the others deviate, following TFT strategy can also lead to the same behavior especially when the game is indefinitely repeated in the experiment.

Finding 6. *When subjects play our favor exchange model, they follow only simple strategies, with memory-one or lower, under complete information. However, they follow more complex strategies more often under incomplete information.*

Percentage of classified observation

To empirically identify the strategies employed by each individual in the experimental data, one can formalize the individual strategy used by means of the estimation procedure in Engle-Warnick and Slonim (2006) and Camera et al. (2012). In this subsection, we employ their strategy-fitting procedure to classify individuals by the strategy used and to provide a robustness check. The strategy-fitting procedure is a mapping from the experimental data into the set of strategies of Table 18. We follow the procedure in Camera et al. (2012) to check the performance of our set of strategies on explaining the behavior of subjects. This procedure in Camera et al. (2012) differs from SFEM because it imposes a maximal number of making errors (i.e., playing wrong actions) rather than estimating the prevalence of errors in implemented actions. The results of this classification procedure are highly consistent with the results of SFEM. For details of this procedure and its implementation with our data, see Appendix 2.6.7. Here we provide the main results only. Figure 3 shows the marginal gain in the total fit as one varies p_ε, which is defined as subjects' probability of making an error when following a particular strategy.[45]

We vary the probability p_ε from 0 to 50%. The total fit is 68% when we do not allow subjects to make any mistake (i.e. $p_\varepsilon = 0$). If we increase the probability of incorrect behavior to $p_\varepsilon = 0.1$, then the total fit of the entire strategy set improves drastically to 83%. The fit then gradually tapers out. With $p_\varepsilon = 0.30$ we classify 94% of subjects. Thus ,we want to conclude that our strategy set which includes BFBr1, BFBr2, BFBp1, BFBp2,

[45] The unit of observation is all choices of a subject in a supergame in Figure 3. Since the unit of observation is all choices of a subject in a session in SFEM, we report the results of the strategy-fitting procedure by using all choices of a subjects in a session as one observation in Figure 11 of Appendix 2.6.7.

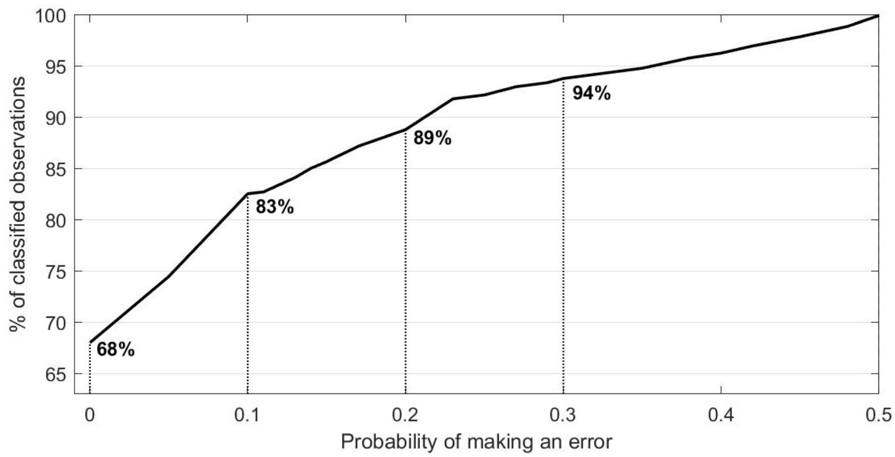


Figure 3: Percentage of classified observations

s^{FF}, Grim, s^{NN}, are able to classify around three-fourth of all subjects' behavior in the favor exchange game even when making an error is not allowed.[46]

2.4.3 The individual behavior in different boundary states

The most specific characteristic of the BFB strategies is that players make decisions based on the state variable k. Recall that the BFBr and BFBp strategies have their own specific rules in the boundary states–players should stop providing a favor in the negative boundary state in the BFBr strategy and provide a favor in the positive boundary state in the BFBp strategy, regardless of the realization of the cost. In this subsection, we use reduced-form approaches to study the behavior of subjects in different boundary states and provide empirical evidence of the use of the BFB strategies in the experiment.

Frequency of favor provision in negative and positive boundary states

Table 20 reports treatment comparisons regarding the frequency of favor provision when

[46]In Camera et al. (2012), Figure 3 shows that when $p = 0$, the total fit is 53.0% of individuals' behavior. If they increase p to 0.05, then the total fit of the entire strategy set reaches 81.0%.

the state variable k reaches negative boundary states.[47] The results show that in negative boundary states the frequency of favor provision in CompleteInfo is significantly higher than that of Chip-15 ($0.392 >^{***} 0.321$). This is in line with the previous findings that the BFBr strategies are played with a significant proportion in the incomplete information treatment but not in the complete information treatment, coupled with a larger proportion of data explained by the efficient strategy in the complete information treatment, since the BFBr strategies require players not to provide a favor in the negative boundary states. However, in positive boundary states, we do not see significant difference of the frequency of favor provision between the Chip-15 treatment and CompleteInfo treatment, as shown in Table 21. This is again consistent with the theoretical predictions since in the positive boundary states the player should do a favor given a low cost in the both BFBr strategies and efficient strategy.

Treatment	N. Obs.	Mean $\|-n$	Sign	Mean $\|-n$	N. Obs.	Treatment	R^2
Chip-15	200	0.321	$<^{***}$	0.392	111	CompleteInfo	0.410
Baseline-15	194	0.283	$>^{**}$	0.193	167	K-15	0.449
Baseline-15	194	0.283	$>$	0.224	182	Baseline-11	0.305

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Subject-sequence as unit of observation.

Cluster robust standard errors by subject and session.

Table 20: Panel data analysis of frequency of favor Provision - on negative boundaries

[47]The reasons why we choose to condition on $n \leqslant -1$ rather than a fixed point (i.e. $n = -1$, $n = -2$, etc) are (1) the dimension of the state space, 2n+1, is an equilibrium element, (2) there may be a heterogeneity in the 'n' chosen by subjects. Thus, instead of focusing on a point, we decide to consider the frequency of favors for positive and negative net number of favors.

Treatment	N. Obs.	Mean $\|n$	Sign Comparison	Mean $\|n$	N. Obs.	Treatment	R^2
Chip-15	200	0.324	$>$	0.303	111	CompleteInfo	0.500
Baseline-15	194	0.318	$<^{***}$	0.385	167	K-15	0.433
Baseline-15	194	0.318	$<$	0.329	182	Baseline-11	0.537

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Subject-sequence as unit of observation.

Cluster robust standard errors by subject and session.

Table 21: Panel data Analysis of Frequency of Favor Provision - on positive boundaries

Effect of reaching negative and positive boundary states on the probability of favor provision

As a complementary exercise to study whether subjects use the BFBr strategies we run a panel logit regression for each treatment, where we control for a number of variables. Table 22 reports the regression results.[48]

The results of column 1 to 4 show that in the treatments with incomplete information, reaching negative boundary states significantly decrease the probability of favor provision when the cost received is low.[49] It means that subjects in the treatments with incomplete information have significantly less incentive to provide a favor in negative states even conditional on having a low cost. It is coherent with a BFBr strategy which prescribe subjects to stop providing a favor in the negative boundary states even if the cost is low. The effect of reaching negative boundary states is insignificant conditional on the cost being high. This is coherent with the frequencies of providing favors that are shown in Table 16, unconditional on the net number of favors. Notice that the other strategies do not

[48]Appendix 2.7 reports the regression results of the impact of reaching the positive boundary states on the probability of favor provision across the treatment.

[49]The effect of the cross-term is significantly negative and larger, while the effect of $Net\ Favor\ Negative_t$ is smaller and insignificant.

Dependent variable: $Decision_t$					
	(1)	(2)	(3)	(4)	(5)
	Baseline-15	Baseline-11	K-15	Chip-15	CompleteInfo
	Logit	Logit	Logit	Logit	Logit
$Net\,Favor\,Negative_t$	0.031	-0.032	0.057	0.002	0.051
	(0.035)	(0.035)	(0.041)	(0.041)	(0.036)
$Cost_t$	0.504***	0.436***	0.432***	0.467***	0.406***
	(0.021)	(0.020)	(0.032)	(0.023)	(0.049)
$Net\,Favor\,Negative_t \times Cost_t$	−0.123***	−0.080**	−0.145***	−0.065*	0.077
	(0.040)	(0.040)	(0.049)	(0.038)	(0.048)
$Other\,Decision_{t-1}$	0.223***	0.181***	0.225***	0.119***	0.256***
	(0.033)	(0.038)	(0.037)	(0.031)	(0.037)
$Profit_{t-1}$	-0.014***	-0.011***	-0.005*	-0.003	-0.005**
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
$Time$	0.002	-0.002	0.001	-0.004	-0.003***
	(0.002)	(0.002)	(0.001)	(0.003)	(0.001)
Sequence Indicator	√	√	√	√	√
N	2556	2461	1918	2305	1593
$LR\,chi2$	756.20	646.13	466.49	776.10	447.86
$Log\,likelihood$	-836.36	-895.52	-671.53	-715.71	-578.73

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, standard errors in parentheses.

Cluster robust standard errors by subject and session.

$Decision_t$ is dummy binary variable which is equal to 1 when “Do a Favor”.

$Net\,Favor\,Negative_t$ is dummy binary variable which is 1 when state $k < 0$, otherwise is 0.

$Cost$ is dummy binary variable which is 1 when low cost, otherwise is 0.

$Other\,Decision_{t-1}$ is dummy binary variable which is equal to 1 when “Do a Favor”.

$Time$ is the series of the number of the round.

Table 22: Panel data analysis of effect of boundaries

depend on a state variable to make a choice. If subjects were playing is the other strategies we considered, the cross-term should not be significant.

Interestingly, in column 5 for the CompleteInfo treatment, we do not see a significant result for either the cross-term or the $Net\,Favor\,Negative_t$. It confirms that there is no significant effect of reaching negative boundary states on the probability of favor provision in CompleteInfo. The result is consistent with the previous finding from strategy estimation that the probability that subjects follow the BFB strategies is not statistically different from zero in the CompleteInfo treatment. These results are consistent with the idea that (at least a proportion of) subjects use the BFBr strategies in a favor exchange game, but only under incomplete information.

2.5 Conclusion

While a substantial theoretical literature studies favor exchange models and suggests the importance of understanding self-interested individual's behavior in the repeated interaction with private information, experimental work on the subject is still limited. The experiment presented in this paper shed light on behavior and strategy choice in the favor exchange game. By conducting the experiment, we are able to (i) analyze the behavior of subjects in this application; (ii) estimate the strategies subjects employ under different payoff parameters and information structures of the favor exchange game.

In the situation where dynamic incentives emerge, we find a difference in behavior between complete information and incomplete information. In particular, reduced form approach based on panel data analysis and strategy frequency estimation both reveal that the pattern of behavior is more clean and subjects are more cooperative in complete information than in incomplete information. We also see that never providing favors prevails in all the treatments we examined; however, when the cost realizations are publicly observed, the strategy of efficiently exchanging favor becomes the most popular strategy. The evidence presented suggests that, to sustain a long-term cooperative relationship with private information, subject's behavior may change when reaching a boundary after exchanging favors. While being a free rider (i.e. provides no favor) is a strictly dominant strategy of the stage game in theory, a certain level of efficiency can be achieved in reality as people are willing to reward the one who sacrifices more. Although punishing the one who benefits more can theoretically result in a higher long-run payoff, it is difficult for people to coordinate on the punishment in the experiment or in reality. Such finding indicates that when dealing with a long-term bilateral relationship (between individuals, institutes, governments, etc.), social norms based on rewards rather than punishments may be more likely to emerge.

Several possible directions might be profitably extended for future research. First, one could consider to directly elicit strategies employed by subjects during the experiment. A distinct advantage of strategy elicitation is that it is capable of considering many more strategies than the strategy frequency estimation method. Second, it would be of interest to consider a setting where subjects are allowed to communicate with each other. On the one hand, the communication could improve the efficiency. On the other hand, when the cost of favor provision is private information, it would be interesting to know whether subjects tell lies in order to receive more favors. We leave such extensions to future research.

2.6 Appendix B

2.6.1 Proof for the BFBr strategy to be Markov equilibrium under complete information

We see that when all the individual rational constraints are satisfied, all the incentive constraints for high type are trivially satisfied, as the RHS of each constraint is strictly less than 0. Given that the value function is the same between complete and incomplete information, the Lemma 4 that v_k is decreasing in k still holds under complete information. Thus the more stringent IR is the one in state n, v_n.

The Lemma 13 in Appendix 1.6.2 can be directly applied to the situation of complete information. Becuase the ICL constraint in state n holds can immediately imply $v_{n-1} \geq c_l(1-\delta)/\delta$. According to equation (4.2), we have $v_n = \frac{[-(1-\delta)pc_l+\delta p v_{n-1}]}{1-\delta+\delta p} > \frac{[-(1-\delta)pc_l+\delta pc_l(1-\delta)/\delta]}{1-\delta+\delta p} = 0$. Therefore, we have that if the ICL constraint in state n hold, then all the individual rational constraints (IRs) hold under complete information.

We know that the value function v_k is decreasing in k, hence the most stringent constraint of BFBr strategy is ICL in state n, $ICL_n = -c_l(1-\delta) + \delta v_{n-1}$ under complete information.

Lemma 15 in chapter 1 show that under incomplete information, If ICL in state $-n+1$ holds, then ICL in state k holds for all $k \in \{-n+2, -n+3, ..., n\}$. Conditional on all the IR constraints are satisfied, the ICL in state n under incomplete information is more binding than under complete information, as v_k is decreasing in k. And Lemma 5 in chapter 1 presents that the most stringent constraint of BFBr is the ICL in state $-n+1$ under incomplete information. Therefore, we can conclude that if BFBr strategy constitute an equilibrium under incomplete information, then it also constitute an equilibrium under complete information.

2.6.2 Proof for the BFBp strategy to be Markov equilibrium under complete information

Under complete information, suppose ICHH in state n (incentive constraint of high type in state n when the other player's cost is high) holds, then $\bar{v}_{n-1} \geq \frac{(1-\delta)c_h}{\delta}$. From the value function at state n, we have, $\bar{v}_n = \frac{1-\delta}{1-\delta p}[px - pc_l - (1-p)c_h] + \frac{\delta(1-p)}{1-\delta p}\bar{v}_{n-1} \geq \frac{1-\delta}{1-\delta p}[px - pc_l - (1-p)c_h + \frac{\delta(1-p)}{1-\delta p}\frac{(1-\delta)c_h}{\delta} = \frac{1-\delta}{1-\delta p}(px - pc_l) + (1-p)c_h(\frac{1-\delta}{1-\delta p} - \frac{1-\delta}{1-\delta p}) > 0$. Therefore, if ICHH in state n holds, then all the IR constraints hold as well under complete information. Accordint to all the incentive constraints in Tables 10 and 11, we have if ICHL in state n (incentive constraint of high type in state n when the other player's cost is low) holds, then all the other constraints hold as well. This is because v_k is decreasing in k. Hence, the most stringent constraint for BFBp strategy is the ICHL in state n when information is complete. By the property 1.6.2 of value function for BFBp, we have $\lim_{\delta\to 1}\bar{v}_n - \frac{1-\delta}{\delta}c_h = (x - c_l)p - \frac{(c_h-x)(1-p)p}{(2n-1-2np+3p)}$, which is positive when $c_h \leq x + (x - c_l)\frac{(2n-1-2np+3p)}{1-p}$. Therefore, by continuity there exists $\bar{\delta} < 1$ such that $\bar{v}_n - \frac{1-\delta}{\delta}c_h \geq 0$ for $\delta \geq \bar{\delta}$.

Under incomplete information, ICH in state n is one of the more stringent constraints. And $ICH_n = -(1-p)(1-\delta)c_h + p\delta\bar{v}_n + (1-2p)\delta\bar{v}_{n-1}$. We have $\bar{v}_{n-1} > \bar{v}_n$, thus $ICH_n = -(1-p)(1-\delta)c_h + p\delta\bar{v}_n + (1-2p)\delta\bar{v}_{n-1} > -(1-p)(1-\delta)c_h + p\delta\bar{v}_n + (1-2p)\delta\bar{v}_n = (1-p)ICHL_n$. Conditional on BFBp strategy constitute an equilibrium under incomplete information, it is not sure whether the BFBp strategy also constitute an equilibrium or not when information is complete. Because it is possible that $ICH_n > 0 > (1-p)ICHL_n$ and it implies that $ICHL_n < 0$. In addition, for a BFBp strategy, if ICHL in state n holds under complete information, it is neither a necessary nor a sufficient condition to imply all the ICL constraints hold under incomplete information.

Overall, under complete information, the BFBp strategy could be more difficult to be sustained as an equilibrium than under incomplete information. The equilibrium conditions of a BFBp strategy under incomplete information cannot imply the BFBp strategy to be an equilibrium under complete information, and vice versa.

2.6.3 Instruction for Treatment Chip-15

Welcome

This is an experiment in the economics of decision-making. A research foundation has provided funds for conducting this research. You will be paid a show up fee of $10 for sure. In addition, you will receive additional earnings which depend partly on your decisions, partly on the decisions of the others, and partly on chance. The additional earnings from the experiment are calculated in points, which will be converted to Canadian dollars at the end of the experiment. If you follow the instructions and make careful decisions, you can earn a CONSIDERABLE AMOUNT OF MONEY. Please do not talk or in any way try to communicate with other participants. Please also do not use your mobile device during the experiment.

We will start with a brief instruction period. During the instruction period you will be given a description of the main features of the experiment. If you have any question during this period, raise your hand and your question will be answered.

General Instructions

1. The experiment consists of multiple sequences. Each sequence consists of multiple rounds. At the beginning of each sequence, you will be randomly matched with another participant in the room. Your matched player will not change during the sequence.

2. During the sequence, you will be asked to make decisions over a sequence of rounds. The length of a sequence, i.e. the number of rounds in a sequence, is randomly determined as follows:

   After each round, there is 85% probability that the sequence will continue for at least another round. Specifically, after each round, whether the sequence continues for another round will be determined by a random number between 1 and 100 generated by the computer. If the number is lower than or equal to 85, the sequence will continue for at least another round, otherwise it will end. For example, if you are in round 9, the probability that there will be a tenth round is also 85%. That is, at any point in a sequence, the probability that the sequence will continue is 85%.

3. Once a sequence ends, you will be randomly paired with someone again if a new sequence begins. You will not be able to identify whom you have interacted with in previous or future sequences.

Specifics

Cost Realizations

In each round, you and your matched player will each observe a random cost privately. The cost may be low (equal to 1 point) or high (equal to 15 points). The random costs realize by the following probabilities:

- The probability for each of you to receive a low cost is p=45%;
- The probability for each of you to receive a high cost is 1-p=55%;
- The probability for both of you to receive a low cost is 0%;

- The probability for both of you to receive a high cost is 1-2p=10%;

The table below summarizes the joint probabilities:

		Your matched player's cost	
		cost is low (=1)	**cost** is high (=15)
Your cost	**cost** is low (=1)	0%	45%
	cost is high (=15)	45%	10%

Table 23: Joint probability

Notice that in each round, your random cost and your matched player's random cost are not independent. Specifically,

- Conditional on you receiving a low cost, your matched player will receive a low cost with probability 0 and will receive a high cost with probability 1;
- Conditional on you receiving a high cost, your matched player will receive a low cost with probability $\frac{45\%}{55\%} = \frac{9}{11}$ and will receive a high cost with probability $\frac{10\%}{55\%} = \frac{2}{11}$.

However, the realization of the random costs is independent across different rounds in a sequence. That is, in each round, your random cost and your matched player's random cost will be drawn from the same probability table as shown above. Your cost or your matched player's cost in any previous round will not affect the realization of the cost in any future round.

Choices and Payoffs

In each round, after you and your matched player observe the private cost, each of you need to make a decision between "Do a favor" or "Do not do a favor" simultaneously. All subjects will receive 15 points endowment in each round. Your payoff in each round, beside your endowment, will depend on your decision, your matched player's decision, and your private cost. If you choose "Do a favor", your matched player will receive 10 points and you need to pay your private cost. Vice versa, if your matched player chooses "Do a favor", you will receive 10 points and your matched player needs to pay his/her private cost.

The payoffs corresponding to the possible choice pairs in each round are summarized in the following table. Denote **cost** as your own cost, and **cost'** as your matched player's cost.

Your decision	Your matched player's decision	
	Do a favor	Do not do a favor
Do a favor	25 – **cost**, 25 – **cost'**	15 – **cost**, 25
Do not do a favor	25, 15 – **cost'**	15, 15

Table 24: Payoff table

Each cell in the table represents a choice pair for you and your matched player. The first entry in each cell represents your payoff, while the second entry represents the payoff of the person you are matched with. Therefore, the payoff associated with each choice pair are as follows:

- (Do a favor, Do a favor): when you choose "Do a favor" and your matched player chooses "Do a favor", you earn (25 – **cost**) points and your matched player earns (25 – **cost'**) points. (notes that (25 – **cost**) = (10 – **cost** + 15))

- (Do a favor, Do not do a favor): when you choose "Do a favor" and your matched player chooses "Do not do a favor", you earn (15 – **cost**) points, and your matched player earns 25 points. (notes that 25 = 10 +15)

- (Do not do a favor, Do a favor): when you choose "Do not do a favor" and your matched player chooses "Do a favor", you earn 25 points, and your matched player earns (15 – **cost'**) points.

- (Do not do a favor, Do not do a favor): when both of you choose "Do not do a favor", you each earn 15 points. (notes that 15 = 0 +15)

Chips exchange

In the first round of each new sequence, each participant will receive two chips.

- Chips can neither be redeemed for dollars nor can be carried over to the next sequence.
- Within the same sequence, the number of chips you have at the end of each round will be carried over to the beginning of the next round.
- You and your matched player will always have four chips in total.

Within each round, chips will be exchanged by the following rules.

- If both you and your matched player choose "Do a favor" or both of you choose "Do not do a favor", there will be no chips exchange.
- If you have at least one chip at the beginning of the round, and your matched player is the only one who chooses "Do a favor", then one chip will be transferred from you to your matched player.
- Vice versa, if your matched player has at least one chip at the beginning of the round, and you are the only one who choose "Do a favor", then one chip will be transferred from your matched player to you.

- Finally, if a participant has four chips at the beginning of the round and is the only one who chooses "Do a favor", then there will be no chips exchange.

Please note that

- The chips exchange will not affect your payoffs in the round. Your payoffs in the round will be decided by your decision and your matched player's decision as well as your private cost.
- The screen will show the chips exchange table in each round when you make a decision whether to do a favor.

Information shown at the computer screen

The following screenshots give you examples of the information you will see on the screen before making a decision in each round. In addition to observing your private cost, you will also observe the current information on the number of chips you have and the number of chips your matched player has. You will also observe a chips exchange table which shows the possible net number of chips you and your matched player could receive based on your joint decisions in this round. Specifically, "0" means no chip exchange, "1" means receiving a chip from your partner, and "-1" means giving a chip to your partner. There are three possible chips exchange tables as follows based on the exchange rules we described before.

(1) When both you and your matched player has at least one chip,

(2) When you have 0 chip,

(3) When your matched player has 0 chip,

Before you make a decision in each round, a History Table will provide information on the history of all previous rounds and sequences, which includes your private cost, your

You now have 2 chips

Your matched player now has 2 chips

Chips Exchange Table

Your decision	Matched player's decision			
	Do a favor		Do not do a favor	
Do a favor	0	0	1	-1
Do not do a favor	-1	1	0	0

Figure 4: Both you and your matched player have at least one chip

You now have 0 chips

Your matched player now has 4 chips

Chips Exchange Table

Your decision	Matched player's decision			
	Do a favor		Do not do a favor	
Do a favor	0	0	1	-1
Do not do a favor	0	0	0	0

Figure 5: You have 0 chip

You now have 4 chips

Your matched player now has 0 chips

Chips Exchange Table

Your decision	Matched player's decision			
	Do a favor		Do not do a favor	
Do a favor	0	0	0	0
Do not do a favor	-1	1	0	0

Figure 6: Your matched player has 0 chip

decision, the decision made by your matched player, your total number of favors provided in the sequence, your total number of favors received in the sequence, the points you earned in the round, and the total points you earned in the sequence. The information of previous sequences will not be wiped off by a new sequence. Please pay attention to the sequence number when you check the history information of the previous rounds. The following screenshot gives you examples.

History in Previous Rounds

Sequence	Round	Your cost	Your decision	Your matched player's decision	Total number of favors provided in the sequence	Total number of favors received in the sequence	Points earned in the round	Total points in the sequence
1	1	15	Do a favor	Do a favor	1	1	10	10
1	2	1	Do a favor	Do not do a favor	2	1	14	24

Figure 7: History Table

The following two screenshots give you examples of the information you may see on the screen at the end of each round, after you submit your decision. In addition to your own information (your cost, your decision, number of chips you received/gave in this round), you will also observe the decision made by your matched player. However, you will never observe the cost of your matched player.

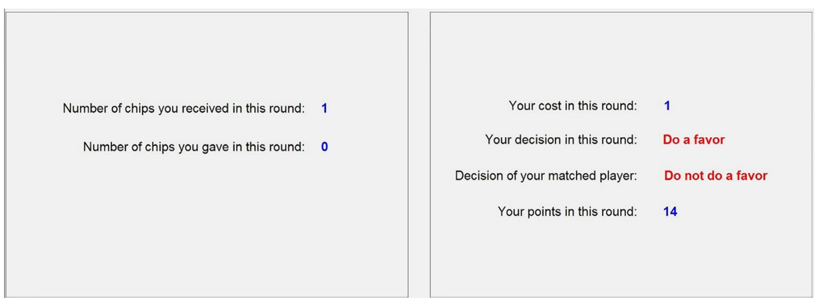


Figure 8: At the end of decision round-1

Final Earnings

Your payoff for each sequence will be the accumulated points you earn from all the rounds of that sequence. At the end of the session, the computer will randomly choose four sequences to calculate your total points from playing the game. The points will be converted to Canadian dollars at the exchange rate of 25 point=$1.

Your final earnings will be equal to the payoffs from playing the game plus $10 show-up fee.

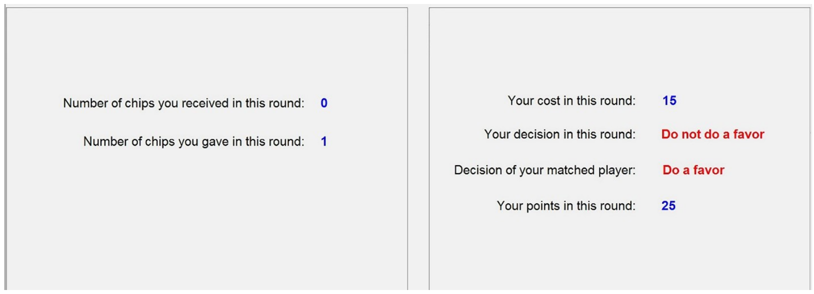


Figure 9: At the end of decision round-2

Duration of the experiment

The experiment will last for around two hours.

Before we start, let me remind you that:

- In each round, you will randomly receive either a low cost (equal to 1) or a high cost (equal to 15) with probability p = 0.45 and 1-p = 0.55, respectively. There are three possible cases: case 1) your cost is 1 and your matched player's cost is 15; case 2) your cost is 15 and your matched player's cost is 1; or case 3) both of your costs are 15. Only one case will incur in each round, with probability 45%, 45% and 10%, respectively. The value of the cost you receive is your private information. Cost realizations are independent across different rounds.
- The length of a sequence is randomly determined. After each round there is 85% probability that the sequence will continue for another round.
- When a new sequence begins, you will be randomly matched again with another anonymous participant in the room. You will never know the identity of your matched player.

2.6.4 Frequency of favor provision-robustness check

Treatment	N. Obs.	Mean	Sign	Mean	N. Obs.	Treatment	R^2
Chip-15	644	0.256	$<^{***}$	0.366	272	CompleteInfo	0.436
Baseline-15	532	0.303	$>$	0.287	392	K-15	0.475
Baseline-15	532	0.303	$>$	0.271	466	Baseline-11	0.449

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Subject-sequence as unit of observation. Cluster robust standard errors by session.

Table 25: Panel data analysis of individual frequency of favor provision - subject random-effect

Following Dal Bó and Fréchette (2011), we construct the data as panel with Subject-period as unit of observation. The Tables 26 and 27 below report the results.

Treatment	N. Obs.	Mean	Sign	Mean	N. Obs.	Treatment	R^2
Chip-15	644	0.256	$<^{***}$	0.366	272	CompleteInfo	0.303
Baseline-15	532	0.303	$>$	0.287	392	K-15	0.016
Baseline-15	532	0.303	$>$	0.271	466	Baseline-11	0.023

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Subject-period as unit of observation. Cluster robust standard errors by session.

Table 26: Panel data analysis of individual frequency of favor provision - time fixed effect

Treatment	N. Obs.	Mean	Sign	Mean	N. Obs.	Treatment	R^2
Chip-15	644	0.256	$<^{***}$	0.366	272	CompleteInfo	0.438
Baseline-15	532	0.303	$>$	0.287	392	K-15	0.153
Baseline-15	532	0.303	$>$	0.271	466	Baseline-11	0.154

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Subject-period as unit of observation. Cluster robust standard errors by session.

Table 27: Panel data analysis of individual frequency of favor provision - individual fixed effect

Instead of treating the data as panel, Table 28 reports the results of pooling regression as another robustness check.

Treatment	N. Obs.	Mean	Sign	Mean	N. Obs.	Treatment	R^2
Chip-15	3318	0.256	$<^{***}$	0.366	1938	CompleteInfo	0.288
Baseline-15	3360	0.303	$>$	0.287	2310	K-15	0.265
Baseline-15	3360	0.303	$>$	0.271	3076	Baseline-11	0.014

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Cluster robust standard errors by session.

Table 28: Pooling regression analysis of individual frequency of favor provision - session level

Treatment	N. Obs.	Mean	Sign	Mean	N. Obs.	Treatment	R^2
Chip-15	3318	0.256	$<^{***}$	0.366	1938	CompleteInfo	0.288
Baseline-15	3360	0.303	$>$	0.287	2310	K-15	0.265
Baseline-15	3360	0.303	$>$	0.271	3076	Baseline-11	0.014

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Cluster robust standard errors by Subject.

Table 29: Pooling regression analysis of individual frequency of favor provision - subject level

The Tables 30 and 31 below reports the results of comparison regarding the frequency of favor provision conditions on low cost and high cost, respectively.

Treatment	N. Obs.	Mean $\|c_l$	Sign	Mean $\|c_l$	N. Obs.	Treatment	R^2
Chip-15	521	0.463	$<^{***}$	0.545	229	CompleteInfo	0.546
Baseline-15	434	0.530	$>$	0.509	342	K-15	0.526
Baseline-15	434	0.530	$>$	0.477	389	Baseline-11	0.598

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Subject-sequence as unit of observation. Cluster robust standard errors by session.

Table 30: Panel data analysis of individual frequency of favor provision - condition on low cost

Treatment	N. Obs.	Mean $\|c_h$	Sign	Mean $\|c_h$	N. Obs.	Treatment	R^2
Chip-15	554	0.102	$<^{***}$	0.202	239	CompleteInfo	0.492
Baseline-15	463	0.123	$>$	0.109	357	K-15	0.440
Baseline-15	463	0.123	$>$	0.103	398	Baseline-11	0.568

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Subject-sequence as unit of observation. Cluster robust standard errors by session.

Table 31: Panel data analysis of individual frequency of favor provision - condition on high cost

2.6.5 Cooperation level at the beginning of and at the end of the session

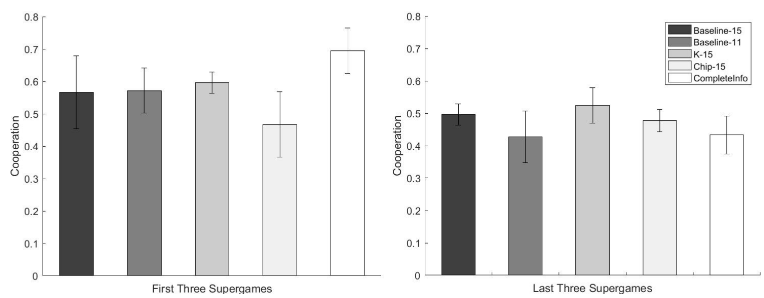


Figure 10: Average cooperation level by treatment over first three supergames and the last three supergames

2.6.6 Strategy estimation through maximum likelihood

We assume that subject i chooses strategy k with probability ϕ^k for all supergames in a session (if the strategy is selected to be used, the subject does not change the strategy between supergames within a session). In each round the subject plays according to the chosen strategy with probability $\beta \in (\frac{1}{2}, 1)$ and makes a mistake with probability $1 - \beta$, which means we assume subjects may make mistakes and choose an action that is not recommended by the strategy. By s^k_{imr} , denotes the choice that subject i would make in round r of supergame m if she followed strategy k. s^k_{imr} is coded as 1 for "do a favor" and 0 for "do not do a favor". The choice that subject i actually made in that round and supergame is denoted by c_{imr} (also coded 1 for "do a favor" and 0 for "do not do a favor"), and the indicator function taking value 1 when the two are the same and 0 otherwise is $I^k_{imr} = 1\{s^k_{imr} = c_{imr}\}$. The likelihood that the observed choices were generated by strategy k is

$$Pr_i(s^k) = \prod_{M_i} \prod_{R_{im}} (\beta)^{I^k_{imr}} (1-\beta)^{1-I^k_{imr}} \tag{18}$$

where β is a parameter need to be estimated. And when β is close to $\frac{1}{2}$, choices are almost random, when β is close to 1, choices are almost perfectly predicted.
Finally we need to maximum the following log likelihood function,

$$LL = \sum_{i \in I} ln \left(\sum_{k \in K} \phi^k Pr_i(s^k) \right) \tag{19}$$

where K represents the set of strategies we consider, labeled s^1 to s^k, and ϕ^k is the parameter of interest — namely, the proportion of the data attributed to strategy s^k.

To be clear about this method, one can think about the case that include only three strategies which are BFBr-n, Grim, and s^{NN}, and estimated proportion are one third for each of them with β is equal to 0.8. If the subject's cost in round 1 is low i.e. $cost = 1$, it implies that in round 1 of a supergame, the estimated model predicts a 60% rate of choosing "do a favor".

2.6.7 Detail of strategy-fitting procedure in Camera et al. (2012)

Specifically, each subject's behavior in each session can be described by one of these seven strategies or some of these seven strategies by the following procedure.[50] The strategy-fitting procedure is a mapping from the experimental data into the strategy set of seven proposed strategies. The unit of observation is all choices of a subject in a supergame. We say that strategy A fits a subject of a supergame if it can generate a series of actions consistent with behavior of the subject in the supergame. The definition of consistency is $x_{A,t} = 1$ if a subject's action in period t of a supergame corresponds to the outcome generated by a correct implementation of strategy A, and let $X_A(T) = \sum_{t=1}^{T} \frac{x_{A,t}}{T}$ denotes the consistency score of strategy A, in a supergame of duration T(T rounds). The score ranges from 0 (no action taken is consistent with strategy A) to 1 (100% correct implementation of A). For each subject in each supergame, we select the strategy(s) with the highest score among the set of strategies we considered as the one is used to classify the behavior of subject in the supergame. Note that subject could be classified by more than one strategy in each supergame.Since the unit of observation is all choices of a subject in a session, as a robustness check, we also report the results by using the all choices of a subject in a session as an unit of observation. We calculate the proportion of each fitted strategy by using sum of the number of each fitted strategy divided by the total number of all fitted strategies for each subject in the session. Again, we still select the strategy(s) with the highest proportion as the one(s) to classify the subject's behavior in the session (i.e., one subject is one observation).

To account for the probability that subjects may occasionally depart from the proposed strategy, we introduce a probability p_ε of making an error exists as in Camera et al.

[50]Because in SFEM we assume one subject uses one strategy with certain probability in a session and the subject does not change the strategy between supergame within a session, instead of following Camera et al. (2012) to use one subject's actions in one supergame as an observation, we consider to use the subject's behavior in all supergames of a session as an observation.

(2012). This can accommodate subjects who make some mistakes in implementing a plan (strategy). The probability p_ε (i) identical across subjects, (ii) constant across round and supergame, and (iii) independent of the strategy considered. Under these condition, the number n of a subject's behavior in each supergame of T rounds that are inconsistent with a strategy A is distributed according to a binomial with parameters p_ε and $T-1$. As a statistical test, strategy A does not fit the observation if the observation lays in the 10% right tail of the distribution of errors.

After fixing p_ε, we said that a strategy A is an subject's behavior in a supergame if the following three conditions are satisfied. First, A correctly predicts the initial action of the subject in the supergame, $x_{A,1} = 1$. This is because we only allow the error can occur across the periods after the first round. Second, A must have the largest consistency score among all seven strategies considered in the supergame, $X_A(T) \geqslant X_{A'}(T)$ for all $A^{'} \neq A$. Third, if n actions of the subject are inconsistent with A, then the probability of such a realization must be within chance, given p_ε and T. The strategy A does not fit the observation if the probability of observing n or more inconsistent actions is smaller than 10%.

We report the results of using $p_\varepsilon = 0.05$ in the Table 33 and Table 32 for the unit of an observation is all choices of a subject in a session and in a supergame, respectively.

The results from both Table 32 and Table 33 show that a majority of individuals is classified by the s^{NN} strategy under the incomplete information setting, however, the efficient strategy becomes the one that classifies the most data under the complete information setting. This results is consistent with Finding 2. We can see that BFBr strategies classify more number of individual behavior than BFBp strategies in all the treatments. This result support Finding 5 and confirm that BFBr strategy is more likely to be played by subjects than BFBp strategy. Due to the feature of this estimation procedure that a sequence of data (i.e., a sequence of choice of a subject) can be classified by multiple strategies, we still observe positive numbers of individuals are classified by BFB strategies even under the

7 Strategies	Baseline-15	Baseline-11	K-15	Chip-15	CompleteInfo
All observations	532	466	308	644	272
BFBr	407	316	279	376	165
-BFBr1	199	163	141	238	80
-BFBr2	208	153	138	138	85
BFBp	368	281	244	230	152
-BFBp1	171	131	114	100	69
-BFBp2	197	150	130	130	83
s^{NN}	220	188	152	320	90
Efficient	214	171	140	257	93
s^{FF}	87	70	56	77	42
Unclassified	131	114	112	121	106

Notes: The unit of an observation is all choices of a subject over a supergame.

Table 32: Individual strategy used - $p_\varepsilon = 0.05$

7 Strategies	Baseline-15	Baseline-11	K-15	Chip-15	CompleteInfo
All observations	42	36	28	42	22
BFBr	10	10	9	6	0
-BFBr1	4	7	6	5	0
-BFBr2	6	3	3	1	0
BFBp	3	3	2	1	2
-BFBp1	2	2	1	0	1
-BFBp2	1	1	1	1	1
s^{NN}	15	17	14	18	7
Efficient	10	8	6	8	9
s^{FF}	3	1	1	1	1
Unclassified	3	1	2	8	6

Notes: The unit of an observation is all choices of a subject over a session.

Table 33: Individual strategy used - $p_\varepsilon = 0.05$

complete information.

Figure 11 reports the percentage of classification by varying p_ε and using all choices of a subject in a session as one unit of observation. The results from Figure 11 is similar as the result from Figure 3.

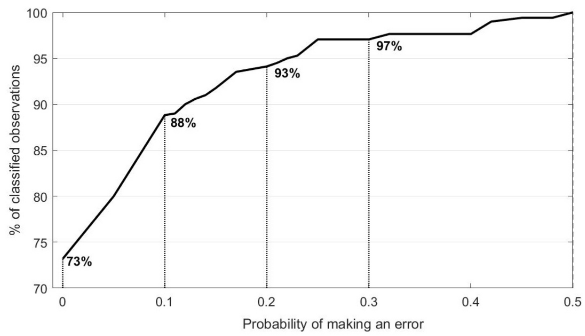


Figure 11: Percentage of classified observations

2.6.8 Frequency of favor provision on four fixed boundaries between groups

We first develop two subgroups (Group Y and Group Z) for all subjects in each treatment with private information according to the results in subsection 2.6.7 (using $p = 0.1$). In each treatment, Group Y contains all subjects who are classified into the BFB strategy. On the other hand, the rest of subjects who use other strategies are included in Group Z. We aim to find more evidence to support the existence of the BFB strategy under the incomplete information setting. Because of the different behavior on the boundaries between subjects who use the BFB strategy and subjects who use the other strategies, we should expect the frequency of "do a favor" should be significantly lower for the subjects in Group Y than in Group Z when conditional on $n = -1$ and $n = -2$. On the other side, we also expect that the subjects of Group Y should choose “do a favor” more frequently than the subjects in Group Z when conditional on $n = 1$ and $n = 2$. Since this analysis is based on the results of individual strategy classification in section 2.6.7 which we only consider BFB strategy with two boundaries $n = 1$ and $n = 2$, we therefore first consider the four fixed boundaries of $n = -2$, $n = -1$, $n = 1$, $n = 2$ for the BFBr and BFBp strategy. The analysis can be easily extend to larger boundaries and the results should not be altered.

Table 34 and Table 35 show the results of comparison between group Y and group Z in each treatment for the frequency of “do a favor” on the four different boundaries.[51] Table 34 shows that the frequency of favor provision in Group Y is significantly lower than in Group Z in the two negative boundaries (i.e. $n = -1$ and $n = -2$) in all the four treatments. In Baseline-15, Baseline-11 and K-15 treatment, the subjects’ frequency of favor provision on boundary $n = -2$ is lower than on boundary of $n = -1$ for Group Y (results are significant in Treatment 1 and 2). On the other hand, in Group Z, we do not find any result to show that the frequency of favor provision on $n = -2$ is significantly smaller than on $n = -1$.

Treatment	Boundary	Frequency		
		Y		Z
1	-1	0.313	$<^{***}$	0.450
		$\vee^{***}$		$\vee$
1	-2	0.131	$<^{***}$	0.440
2	-1	0.232	$<^{***}$	0.345
		$\vee^{*}$		$\wedge$
2	-2	0.164	$<^{***}$	0.482
3	-1	0.173	$<^{*}$	0.300
		$\vee$		$\wedge^{*}$
3	-2	0.166	$<^{**}$	0.514
4	-1	0.201	$<^{***}$	0.478
		$\wedge$		$\wedge$
4	-2	0.300	$<^{***}$	0.544

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

(1) Y refers to group.Y, Z refers to group.Z.

(2) Unconditional on value of cost.

Table 34: Frequency of “do a favor” on two negative boundaries

This result indicate that when the subjects who are classified in the set of BFB strategy arrive to a more negative state (i.e. $n = -2$), they tend to stop doing a favor with higher

[51] Statistical significance is assessed using logit regressions with an indicator variable for one of the two relevant categories. Standard errors are clustered at the level of the session.

probability as they receive more signal about closing to their boundaries. Alternatively speaking, comparing with boundary $n = -1$, the boundary $n = -2$ is more closer to the real boundaries of the subjects in Group Y. Note that the two boundaries we discussed are symmetric and are chose to fulfill the equilibrium condition. One can easily expand the boundary to a larger number by relaxing the value of discount factor. Therefore, the two boundaries are difficult to be observed by the subjects. We suspect there is heterogeneity for the boundaries of subjects and subjects who use BFB strategy could also have asymmetric boundary. We will discuss the heterogeneity of the boundary in next subsection. In the Chip-15 treatment, the frequency of favor provision on $n = -2$ is slightly greater than that on $n = -1$, but the result is not significant.

Treatment	Boundary	Frequency		
		Y		Z
Baseline-15	1	0.406	$>^{***}$	0.246
		$\vee$		$\vee$
Baseline-15	2	0.405	$>^{*}$	0.196
Baseline-11	1	0.343	$>$	0.273
		$\vee$		$\vee$
Baseline-11	2	0.264	$>$	0.259
K-15	1	0.472	$>^{**}$	0.294
		$\vee$		$\vee$
K-15	2	0.453	$>^{***}$	0.202
Chip-15	1	0.248	$<$	0.282
		$\wedge$		$\vee$
Chip-15	2	0.349	$>$	0.278

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

(1) Y refers to group.Y, Z refers to group.Z.

(2) Unconditional on value of cost.

Table 35: Frequency of “do a favor” on two positive boundaries

In Table 35, we observe that the frequency of favor provision in Group Y is significantly higher than in Group Z when conditional on two positive boundaries (i.e. $n = 1$ and $n = 2$) for the Baseline-15 treatment and the K-15 treatment. For the Baseline-11 treatment, the frequency of favor provision in Group Y is higher than that in Group Z but the result is not significant. The results in the Chip-15 treatment is more ambiguous that the frequency of favor provision in Group Y is only slightly higher than that in Group Z on $n = 2$. Note that most of the subjects in Group Y of the four treatments are classified in the BFBr strategy rather than the BFBp strategy.

Overall, the results confirm that for the subjects of group Y who are classified in the BFB strategy, they provide significantly less favor on the two negative boundaries than the other subjects who use other strategies across all the treatments. Because few subjects of group Y are classified in the BFBp strategy (almost all of them are classified in the BFBr strategy), we do not observe significant difference for the frequency of favor provision on two positive boundaries in all the treatments.

2.7 Effect of arriving at negative and positive boundaries on probability of favor provision

Dependent variable: $Decision_t$					
	(1)	(2)	(3)	(4)	(5)
	Baseline-15	Baseline-11	K-15	Chip-15	CompleteInfo
	Logit	Logit	Logit	Logit	Logit
$Net\ Favor\ Positive_t$	-0.075*	-0.084**	-0.126***	-0.064*	-0.069
	(0.040)	(0.040)	(0.049)	(0.037)	(0.043)
$Cost_t$	0.407***	0.350***	0.326***	0.382***	0.307***
	(0.019)	(0.018)	(0.023)	(0.024)	(0.057)
$Net\ Favor\ Positive_t \times Cost_t$	0.116***	0.186***	0.235***	0.188***	0.067
	(0.044)	(0.047)	(0.057)	(0.044)	(0.045)
$Other\ Decision_{t-1}$	0.226***	0.187***	0.228***	0.102***	0.226***
	(0.033)	(0.038)	(0.038)	(0.031)	(0.043)
$Profit_{t-1}$	-0.012***	-0.009***	-0.005*	-0.003	-0.006***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
$Time$	-0.002	-0.004	0.001	-0.004	-0.003**
	(0.002)	(0.003)	(0.001)	(0.003)	(0.001)
Sequence Indicator	√	√	√	√	√
N	2556	2461	1918	2305	1593
$LR\ chi2$	748.700	646.480	475.21	791.520	439.43
$Log\ likelihood$	-840.102	-894.840	-667.176	-708.001	-582.989

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, standard errors in parentheses.

Cluster robust standard errors by session.

$Net\ Favor\ Positive_t$ is dummy binary variable which is 1 when state $k > 0$, otherwise is 0.

Table 36: Panel data analysis of effect of boundaries

3 Peer Recognition and Content Provision Online

3.1 Introduction

In the modern digital economy, the striking development of online platforms has sparked an increasing interest in understanding the underlying motivations of voluntary content provision. Unlike a traditional public goods contribution scenario where more contributors lead to less total output, quite a few online communities, such as Twitter, Facebook, and Instagram, seem to have successfully engaged their users in continuously producing content. Existing literature has explored in detail the impact of monetary incentives on online content contributions,[52], non-commercial users, nevertheless, contribute a significant proportion of the content. The results of Toubia and Stephen (2013) show that the image-related motivation counted for most of the contribution of content providers of Twitter. Correspondingly, literature also suggests that peer recognition, a particular type of image-related utility, plays an important role in motivating potential contributors (e.g., Chen et al. (2017) and Lerner and Tirole (2005)). To further stimulate the productivity of contributors, many online platforms provide information disclosure services (e.g., real-name policy, badge system, etc.) to help contributors build reputation more effectively in online communities and being recognized by more people. However, these policies allow the platforms to abuse the identity information and open the door to mass surveillance (see, Tirole (2019)). As a result, individuals might balance the risk of exposing their private information on the platform with the potential benefit of getting more attention with the credibility that certification brings. On the empirical side, this trade-off will

[52]For instance, Sun and Zhu (2013) studied the incentive effect of advertising revenue on the content creation of Chinese bloggers. Xu et al. (2019) showed how geeks on Stackoverflow signal to the market by answering questions to get better jobs.

substantially affect how contributors are motivated to create content using non-monetary factors (e.g., peer recognition, reciprocity, and self-image), and whether the platform's information disclosure policy stimulates or limits the enthusiasm of creation remain mostly unexplored.

This paper particularly provides pioneering theoretical and empirical studies for the following three questions:[53] first, how would a content provider's contributions on an online platform be motivated by "peer recognition"; second, what factors primarily affect influencers' enthusiasm for online contribution; and third, how does the platform's badge policy (e.g., real-name and honor user certification) affect the contribution of content.

To understand how reputation management and privacy concerns shape the behavior of influencers, we develop a two-period model with an online content platform equipped with both influencers and users. We assume that a Bayesian rational influencer cares about peer recognition by maximizing the sum of votes in both periods. Depending on the range of content that the influencer produces, two classical marketing strategies could be derived: a broad-coverage strategy and a focus strategy. The model predicts that the incentives of reputation management matter a lot for strategy choices of influencers. In particular, influencers with a mediocre reputation prefer the board-coverage strategy, while those with higher reputation prefer the focus strategy. That is, reputable influencers tend to write fewer answers. Furthermore, the influencers who care about their privacy will also contribute less.

We employ a unique data set to test our model predictions. Our data was collected from Zhihu,[54] a leading Question-and-Answer platform in China over a period of two

[53]In this paper, we use both "content provider" and "influencer" interchangeably.

[54]The Chinese meaning of "Zhihu" is: "Did you know?" Zhihu (https://www.zhihu.com/) is the Chineses largest online Question-and-Answer platform that is similar to Quora in the U.S. Unlike Quora, there is no multilingual version of Zhihu, and all content on the platform is provided in Chinese. According to Alexa Traffic Rank on August 2018, the website traffic of Zhihu is ranked 112 among all the websites in the world.

years. The data contains all of the activities of the influencers (e.g., answering questions, voting for others, collecting articles). A key feature is that our data also includes all interactions among these influencers (e.g., when does user A vote for the answer of user B), which allows the building of a social network. Social networks play an important role in motivating content provision, in both monetary (e.g., Sun et al. (2017)) and non-monetary aspects (e.g., Zeng and Wei (2013), Susarla et al. (2012) and Goel and Goldstein (2014)). In our research, this additional network information allows us to construct instrumental variables in order to evaluate the true impact of peer recognition. Based on the dynamic network information between influencers, we provide a novel instrumental variable method to tackle the endogeneity issue and properly identify non-monetary incentive effects on "answer creation". Moreover, our data also includes important information about whether a user has submitted personal information for authentication and other characteristics about the quality of the user. Through econometric methods, we develop empirical strategies to identify the content provision incentives associated with "peer recognition" (i.e., vote from other influencers) and how peer effects are influenced by other economic mechanisms and ultimately determine influencers' strategies.

The empirical results reveal the following three findings that are consistent with the predictions of our theoretical model. First, although both OLS and IV estimates indicates that the peers' votes positively and significantly increase the content creation initiatives, we find that the OLS method leads to underestimating the incentive of "peer recognition" for online creation by 40%~50%, which mainly comes from two channels: reputation and privacy concerns. Second, peer incentives affect individual and commercial users differently: commercial users tend to overreact for "marketing purposes." Such results indicate that platform policies may engender externalities on the marketing strategies of commercial content providers (e.g., Goh et al. (2015)), thus changing the distribution of contents: there will be more marketing content and fewer individual opinion based answers/content on the platform. Last, we find that users getting a "best answerer" badge are less likely to be motivated by peers to answer questions by focusing on answering questions about their professional direction. In addition, users who are concerned about their information being exposed are least likely to be motivated to provide content by other influencers' votes. Through a mediation analysis, our results suggest that if the platform could mitigate the negative effects of reputation and privacy concerns from these badge recipients, badge policy would be more effective and spread the incentive effect of recognition to a larger extent.

Our paper contributes to the literature in the following four aspects.

First, it significantly contributes to the literature on the motivations of online content providers. Previous literature (e.g., Lerner and Tirole (2002), Fershtman and Gandal (2011), Xu et al. (2019)) have studied why individuals are willing to contribute and collaborate online free-of-charge. Other articles illustrate the role of money in motivating online creativity (e.g., Sun and Zhu (2013), Kuang et al. (2019) and Wu and Zhu (2019)). Our study is the first to quantify the impact of "peer recognition" on the provision of content for Q&A platform users. Stories about public good contribution have a good explanation power on platforms such as Wikipedia, where the identity of contributors is not highlighted and is less likely to be consistently recognized by the vast majority of platform users. While in social media platforms like Twitter, Facebook and Quora, they are more human-centric and one's contribution is normally listed in a "timeline" style webpage, which is relatively easy to be explored by platform users. Therefore, for the platform, how to stimulate users' creation through peer recognition becomes particularly important. In the paper, we solve an essential, endogenous problem based on our data: an influencer may receive more votes (peer recognition) because she is actively creating answers,[55] or the influencer may be actively creating because she has received (or expects to receive) more votes. In most

[55]We will use "she" to refer a particular influencer in the rest of the paper.

cases, the cost of content creation and content quality are unobserved.[56] As a consequence, it has been difficult to identify the incentives of "peer recognition" for content creation in the previous literature. In this paper, we use the influencers' network information to create instrumental variables and identify the impact of a variable on users' motivation to contribute in ways other than policy shock (e.g., Zhang and Zhu (2011), Wu and Zhu (2019)).[57] Our findings are consistent with empirical results based on recent experiments and suggests that the potential reputation and privacy concerns may lead to understating the effect of peers.[58]

Second, when discussing contribution incentives on social platforms, a large body of current literature (e.g., Marx and Matthews (2000), Chen et al. (2018) and Zhang and Zhu (2011)) build their models based on mechanisms of public good contribution. Since the identification of contributors is more prominent on social platforms like Twitter, Facebook and Quora, and career concerns as described in Holmström (1999) might thus be an important force to shape contributors' behavior and affect the quality and quantity of contribution as well. To the best of our limited knowledge, our model, nevertheless, is one of the first attempts to explicitly address how reputation concerns can affect the contributors' behavior strategically. For instance, as Chen et al. (2018) mentioned, matching accuracy between contributors and content might affect the quality and quantity of contribution. In their model, this matching process is mechanical. However, our model shows that contributors could strategically trade off the matching possibility and the quality in order

[56] Han and Zhao (2019) provides a study where influencers can put a specific price on their content, but on our platform they are all free contributors.

[57] For example, many online platform users may have anticipated the policy and responded to it in advance. To the best of our knowledge, another recent example of using instrumental variables to identify peer effects under the platform is Bailey et al. (2019). Compared with our paper, the authors use machine learning methods to analyze what each user has posted on the platform and to determine whether a user changes the phone due to a malfunctioning device or simply to a peer effect. The instrumental variables that we introduce in the paper are more intuitive and easier to apply.

[58] For example, Chen et al. (2018) demonstrated through an experiment on Wikipedia that the online contributions of domain experts are largely motivated by peers' citations.

to either achieve a higher or maintain their current reputation level. And our empirical evidence also shows that this strategic behavior helps to explain the common declining trends of contribution on social platforms.

Third, our paper also contributes to the literature of information asymmetry under the presence of a two-sided market. There is an extensive and growing literature that discusses the impact of platform policies on eliminating information asymmetry (e.g., Jin and Kato (2006), Roberts (2011), Hui et al. (2016), Saeedi (2019), Hui et al. (2018)). A large body of empirical evidence shows that for e-commerce platforms, badges (certification) issued by platforms to outstanding sellers will not only reduce information asymmetry but will allow sellers to monitor the product quality better in order to maintain "reputation and public praise" after being certified by the platform. More recently, Farronato et al. (2020) use the data from online job search platforms and find that platform authentication did not significantly increase the likelihood of experts being hired compared to user reviews. However, the empirical study about the platform based on content remains largely unexplored. Using the data, we are the first to study such problems empirically. Cagé et al. (2020) collected 2.5 million news stories from newspapers, television, and online sites across all major media outlets in France in 2013. Their study indicates that large companies, constrained by "reputation," are relatively more protective of original content than small companies, and that content with a smaller spread may be better protected. However, compared with e-commerce platforms, little is about the impact of content platform's policy (badge) on content creation. In our paper, we observe multiple types of badge: self-authenticated professionals, best answerers, business users (merchants who promote their products by answering questions), and uncertified users. Each user can be one or more of these types. This wide variety helps to deepen our understanding of the conflicting effects of badge policies on influencers. While badges make it easier for users to identify the quality of an influencer, those badges that include a strong connotation may also limit the content contribution since influencers are responsible for creating content.

Finally, our paper also makes policy suggestions from the perspective of the growing concerns about the "chilling effect" caused by the excessive supervision of privacy by platforms (e.g., Penney, 2016 and Tirole (2019)). Most of the economics literature shows the existence of privacy concerns and the price individuals are willing to pay (e.g., Goldfarb and Tucker (2012), Goh et al., 2015, Athey et al., 2017, Tang, 2019), however, research on the contribution of content to this remains limited. As one of the pioneering studies in economics (e.g., Chiou and Tucker (2017), Han and Zhao (2019)), our paper confirms that platforms' policies may cause the "chilling effect" due to the potential privacy concerns. As the reputation and privacy costs of public expression of personal opinion rise, users with a low cost of speech and fewer privacy concerns may speak more frequently, thus making opinions on the platform polarized. This phenomenon may be particularly true in countries with highly regulated governments. Our conclusion is also consistent with the conjecture of Lambrecht et al. (2018)'s conjecture based on their experiment on Twitter: users dislike external pressures on their communication agenda and, more so than others, prefer to make their own unguided choices by engaging with messages that are explicitly un-artificial and un-commercial. In particular, Twitter stopped their real-name authentication policy since 2020. In contrast, Zhihu begins requiring influencers to authenticate their real names. Our findings suggest that platforms' attitudes towards real-name policies may depend on the trade-off between incentives for content creation and content regulation. Policies based on reputation and privacy may have a backlash against policies that encourage traffic.

The rest of the paper is organized as follows. Section 3.2 presents the theoretical model, which further provides two testable corollaries. Section 3.3 describe the data set that we employ. Section 3.4 identifies and quantifies the impact of peer recognition on content provision. Section 3.5 empirically verifies the model predictions and section 3.6 concludes.

3.2 Theoretical model

In this section, we build a two-period model with an online content platform equipped with both influencers and users, which we describe as follows.

Influencers There is a unit continuum of influencers who write answers on the content platform. The platform randomly pushes a unit mass of potential questions to each influencer. There are two types of questions: "specialized" and "general", with v and $1 - v$ as the proportion in the question pool respectively. Depending on the range of questions that the influencer responds to, two strategies of the influencer could be derived: a broad-coverage strategy (Strategy b) where the influencer is willing to answer both types of questions, and a focus strategy (Strategy f) where she only answers specialized questions.[59] Each influencer needs to allocate a fixed amount of time, as an indicator of effort level, to questions that they want to answer. We normalized each influencer's time that is available for allocation to 1.[60] In particular, influencers can make use of the time more efficiently when answering specialized questions. We use 1 and κ to denote the answer quality of general and specialized questions respectively.

With slightly abuse of the term "quality", we can define the quality of influencers' outcome q_s as a sum of quality when different strategies are employed:

$$q_s = \begin{cases} \kappa & s = f, \\ v\kappa + (1 - v) & s = b. \end{cases}$$

To introduce career concern, we assume that each influencer has a private type θ, where $\theta \in \{h, l\}$. A type-h influencer have a higher capability ϑ_h to favor her readers, and a type-l influencer only have a capability which equals ϑ_l. How ϑ_θ affects the votes of users

[59] We provide in Appendix 3.8.2 a simple and real example illustrating these two strategies.
[60] Here the time can be regaded as an indicator of effort level.

will be discussed in the following subsection.

Users There is a continuum of platform users, with a total measure of 1. Every user is endowed with a continuum of votes. Influencers care about votes from users, while the relationship between answer quality and votes are not deterministic since the user might have a subjective evaluation of the influencer's answers (that is, like or dislike). If users dislike the content, the subjective evaluation will be downgraded by a parameter β_e for specialized answers and β_g for general answers. We assume $0 < \beta_g < \beta_e < 1$, which implies that specialized answers are downgraded less than general answers since the hardcore field knowledge is relatively harder to be ignored and devalued. Therefore, depending on the strategy and whether or not the quality is devalued by the users, there are four levels of subjective evaluation, denoted as q_s^+ and q_s^-,$s \in \{f, b\}$.

$$q_s = \begin{cases} q_f^+ = \kappa & s = f, \\ q_b^+ = \nu\kappa + (1-\nu) & s = b, \\ q_f^- = \beta_e\kappa & s = f, devalued \\ q_b^- = \beta_e\nu\kappa + (1-\nu)\beta_g & s = b, devalued \end{cases}$$

Obviously, $q_f^+ > q_b^+$ and $q_f^- > q_b^-$. To avoid the trivial case, we also assume that no strategy produces a dominant evaluation, i.e. $q_b^+ > q_f^-$. Without loss of generality, the subjective evaluation could be regarded as the numbers of votes the user gives to the influencer.

A user matches an influencer through a random matching market and then the user will decide whether or not to follow this influencer. If yes, the influencer and the user will quit the market and influencers' content will be available to this user. Otherwise, if the user decides not to follow, she will enter the matching market again. We use π_I and π_0 to denote the user's expected gross utility from the matched influencer (I) and a hypothetical average influencer (0) respectively, and d to represent the user's choice about whether to follow, for $d \in \{0, 1\}$. By definition, we have $\pi_I \equiv q_s$ and the objective function of a user is to choose d_t to maximize her expected utility $max_{d_t} d_t \pi_I + (1 - d_t)\pi_0$.

For any successfully paired influencer and user, the probability that the user likes answers written by the influencer is determined by two factors: the range of readers that the influencer answers, and the capability ϑ_θ by which the influencer could favor the users. If we standardize the range of readers when the influencer adopting a broad-coverage strategy is 1, the influencer is likely to have a narrower range when choosing a focus strategy. Therefore, the probability that the user is favored becomes a function of $s$and ϑ_θ, with $p_{\theta,b} > p_{\theta,f}$ and $p_{h,s} > p_{l,s}$. The function form $p_{\theta,s} = \vartheta_\theta v^{1_{\{s=f\}}}$ satisfies these two constraints.

Timing and Career Concerns The model has two periods, $t = 1, 2$. The timing is organized as follows.

Period 1 In the beginning of $t = 1$, the platform randomly matches influencers with users. Recognizing the reputation of the influencer, users decide whether or not to follow. We use π_1 to denote the user's gross utility at $t = 1$. That is, if a user follows, the expected utility that the user gets from viewing the influencer's answer is π_1; otherwise if the user does not follow, $\pi_1 = q_r$, where q_r is the expected quality of content when the user randomly browses.

Period 2 In the beginning of $t = 2$, a group of new influencers arrive at the market, drawn from the same distribution as the $t = 1$. So, the pool of available influencers includes both those with track records from 1 and the new arrivals. Then the user will again decide whether to follow the same influencer for the next period, or exit the following relationship and enter the matching market.

Reputation Concerns As the influencer cares about peer recognition, thus she would like to maximize the sum of votes in both periods. Since votes are perfectly aligned with the quality of answers, therefore a seasoned influencer therefore has incentives to strategically choose her answering strategies to maximize her expected votes:

$$max_{s_1,s_2}\ E_\theta\left[\left(q_{s_1} + d_1 q_{s_2}\right)\right], s_1, s_2 \in \{f, b\};$$

while a newly arrived influencer only maximizes the votes only in the second period.

$$max_{s_2}\ E_\theta\left[q_{s_2}\right], s_2 \in \{f, b\}.$$

Career concerns rise from the first period, when the seasoned influencer chooses her strategy based on two considerations: first, the number of votes in the first period; and second, the possibility of acquiring votes in the second period. The answer quality in the first period not only affects the number of votes but also affects users' decision to follow in the second period through reputation effects. An influencer's reputation is defined as the likelihood that the influencer is of type-h. When an influencer enters the matching market, her type is drawn independently from a distribution with probability ρ_0 of being type h. Therefore, the initial reputation is ρ_0. After an influencer's performance q_i is realized at $t = 1$, her reputations updated following the Bayes' rule: $\rho = \frac{Pr(q_i|h)\times\rho_0}{Pr(q_i|h)\times\rho_0 + Pr(q_i|l)\times(1-\rho_0)}$.

Matching Market The matching market for influencers and users is organized as follows. At time t, for $t \in \{1, 2\}$, the influencer with the highest reputation first randomly matches with a user. If the matched user decides to follow the influencer, the pair leaves the market and the next round of matching starts for the influencer with the second highest reputation. If the user decides not to follow the influencer, the user will then initiate a random browsing with with an expected quality of content q_r and the influencer is randomly matched with another user. This process is iterated until all users have made their decisions, or until all influencers get a follower. If multiple influencers have the same reputational level, seasoned influencers (who arrived at $t = 0$) match first. If multiple influencers have the same reputational level and starting time, they match in random order. When all the users are matched, the influencers that are left in the market will automatically obtain a random number of votes, the mean of which is normalized to zero. The timing and actions of influencers and users are summarized in Figure 12:

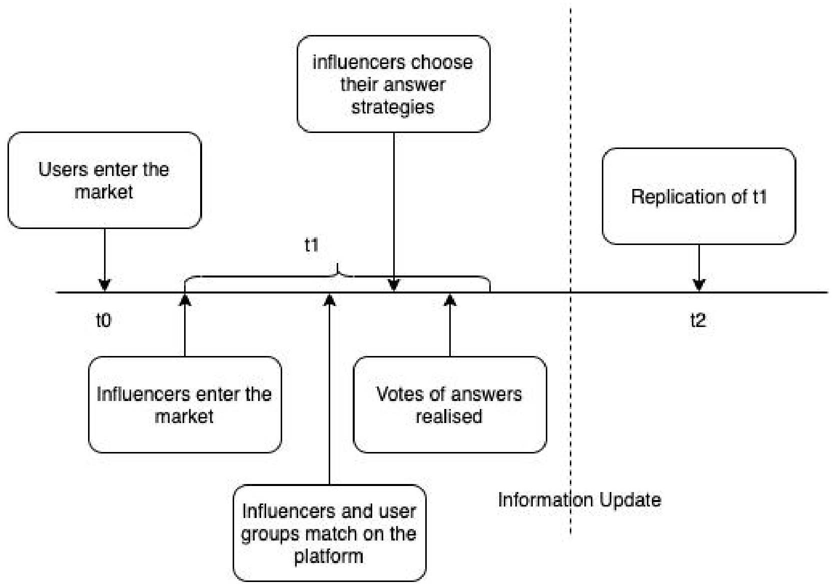


Figure 12: Timing of the model

3.2.1 Equilibrium

We define the equilibrium strategy profile as $(d_t(\rho), s_{\theta,t}(\rho))$, for $\theta \in \{h, l\}$, $t = 1, 2$, where $d_t(\rho)$ is the users' decision to follow an influence with reputation level ρ at time t and

$s_{\theta,t}(\rho)$ refers to the strategy adopted by the type-θ influencer in time t.

To rule out the trivial case when all the influencers are followed or not followed, we assume that if all the information is public, the users are only willing to follow type-h influencers, that is, the average quality $\bar{q}_{\theta,i} = p_{\theta,i}q_i^+ + (1 - p_{\theta,i})q_i^-$ satisfies $\bar{q}_{h,i} > q_r > \bar{q}_{l,i}$. We make the following technical assumption:

Assumption 1. $\beta_e = \frac{\vartheta_l}{\kappa} + \frac{1-\vartheta_l}{\kappa}\beta_g$.

A user will choose to follow an average influencer with reputation ρ_0, i.e. $\rho_0\bar{q}_{h,s} + (1 - \rho_0)\bar{q}_l > q_r, s \in \{f, b\}$, *where q_r is the expected answer quality of randomly browsing.*

Assumption 1 guarantees that answering strategies have no effect on the expected value of answer qualities for type-l influencers and broad-coverage strategy generate higher expected votes, i.e. $\bar{q}_{l,f} = \bar{q}_{l,b} = \bar{q}_l$ and $\bar{q}_{h,f} < \bar{q}_{h,b}$.[61]

Given the above model settings, the strategy of users is simple: since the initial level ρ_0 is preferred than randomly browsing, any influencer whose reputation is equal or higher than ρ_0 will be followed; moreover, in the beginning of period 2, there is plenty of influencers without any record in the market, so any influencer with a reputation lower than ρ_0 will not have any chance of being followed. Since users can always match an influencer with reputation ρ_0, the decision variable of users thus is $d = 1_{\{\rho \geq \rho_0\}}$. We use proposition 1 to conclude the optimal strategy of influencers.[62]

Proposition 1. *The broad-coverage strategy is preferred by average influencers.*

Presence of high reputation influencers Platforms sometimes issue visible badges to make some influencers more prominent. This can be modelled by assuming that a small

[61] If type-h and type-l influencers have different vote-maximizing strategies, the influencers' types will be immediately revealed. Strategic behavior only takes place when the type-l influencer has the incentive to conceal her true type and pretend to behave as a type-h influencer. This assumption assumes out the tension between type-l's own optimal strategy and the benefit of mimicking type-h, which divert our attention to the strategic aspect of reputational concerns.

[62] We provide proofs in Appendix 3.7.

proportion of influencers in the beginning of period 1 have a reputation $\rho^* > \rho_0$. Obviously, if ρ_h is high enough to accommodate any possible reputational loss in period 1 (i.e. after any possible outcome in period 1, the reputation is constantly higher than ρ_0), reputation concerns will not lead to any behavioral distortion. We define $\left[\underline{\rho}, \bar{\rho}\right]$ as the range in which reputation concerns can really alter influencer's strategy choice. and we assume that $\rho^* \in [\rho_0, \bar{\rho}]$ to avoid trivial cases. The following proposition describes the strategic behavior of influencers.

Proposition 2. *Define* $\hat{\rho} = \frac{(1-v\vartheta_l)\rho_0,}{(1-v\vartheta_l)\rho_0,+(1-v\vartheta_h)(1-\rho_0)}$, *influencers with reputation* $\rho^* \in [\hat{\rho}, \bar{\rho}]$ *will choose the focus strategy if and only if* $\bar{q}_{h,b} - \bar{q}_{h,f} < (1-\vartheta_h)\bar{q}_{h,b}$ *and the broad-coverage strategy otherwise.*

Proposition 2 generates striking and counter-intuitive implications, as most of the high-reputation influencers have impressive track records for the past outcomes, and no obvious reasons stop them from continuing to be productive. However, our theoretical model predicts that, despite the incentives of peer recognition, these influencers are more likely to produce fewer answers compared with those with an average reputation. We use corollary 1 to conclude for the further empirical test.

Corollary 1. *The presence of reputation concerns has different impact on influencers with different reputational levels. Other things equal, influencers with a mediocre level of reputation tends to write more answers than those with a high level.*

Privacy concern Answering questions might reveal some private information of the influencer, which could potentially be abused or exploited by other malicious users or platforms. Under the focus strategy, influencers only answer specialized questions that are more professionally oriented, therefore the information disclosure is more likely to take place when adopting the broad-coverage strategy and answering a variety of questions. In our model, this can be reflected by adding a privacy cost C, $C \geq 0$ on the profit function of influencers when $s = b$. This cost has nothing to do with the user-side, so the bayesian updating process will not be affected.

Proposition 3 concludes the impact of privacy concerns on influencers' behavior under this new assumption.

Proposition 3. *With privacy concern, the adopted strategy of an type-h influencer with reputation level $\rho^* \in [\rho_0, \bar{\rho}]$ can be defined by:*

$$s(\rho^*) = \begin{cases} f & \bar{q_{h,f}} - \bar{q}_{h,b} > R(\rho^*) - C, \\ b & \bar{q}_{h,f} - \bar{q}_{h,b} \leq R(\rho^*) - C, \end{cases}$$

where the reputation premia $R(\rho^*)$ is defined as:

$$R(\rho^*) = \begin{cases} (\vartheta_h - \vartheta_l) max\{\bar{q}_{h,b} - C, \bar{q}_{h,f}\}, & \rho^* \in [\rho_0, \hat{\rho}], \\ -(1 - \vartheta_h) max\{\bar{q}_{h,b} - C, \bar{q}_{h,f}\}, & \rho^* \in [\hat{\rho}, \bar{\rho}]. \end{cases}$$

Compared with the basic model, Privacy leaking significantly diminishes the advantage of the broad-coverage strategy. Adding a positive privacy cost C has dual effects. First, it might directly change the optimal strategic choice without career concern; second, it decreases the reputation premium when the reputation level is mediocre, and increases the reputation premium when the reputation is high. In both regimes, it favors the adoption of the focus strategy. As the type-h influencers are more inclined to the focus strategy, the type-l influencers are motivated to do so as well since they need to mimic the type-h influencers. We propose the following corollary for empirical analysis in section 3.5.

Corollary 2. *Other things equal, the influencers who care about their privacy are more likely to adopt a focus strategy rather than a broad-coverage strategy, that is, they will write fewer answers.*

3.3 Data description

Question-and-answer (Q&A) platforms have been rapidly increasing in number in recent years and have attracted a considerable number of users. Differing from web search engines, users on Q&A platforms can ask specific questions. Among all of the online Q&A platforms, Quora and Zhihu are the two leading Q&A websites.[63] Launched in January 2011, Zhihu is the biggest Question-and-Answer community platform in China, and has quickly became one of the most frequently visited websites by Chinese internet users. Users on Zhihu can ask and answer questions, write articles, make comments and vote on the answers and articles. Up to 2019, Zhihu had more than 200 million registered users, of whom 30 million were daily active users, asking hundreds of thousands of new questions or generating other content every day. Figure 13 shows an example of the homepage of a given influencer. By visiting an influencer's homepage, a user observes the influencer's personal information such as nicknames, place of residence, industry, and related personal profiles on the top of the homepage. These items of information are voluntarily disclosed by influencers and have not been verified by the platform.[64]

On the right of the home page, the user can check the "badge" status as to whether she/she has a blue star (self-authenticated), yellow star (best-answerer) or no star. The

[63]Compared with traditional Q&A websites (e.g., Yahoo Answers, WikiAnswers), these platforms offer several improvements. For example, platforms allow users to build social connections such that users can vote for each other's content, collect each other's content, and follow each other; based on the votes that each answer received, platforms use algorithms to analyze the quality of answers and rank them under each question; after creating a user account, a corresponding personal homepage of the user will be generated. Each user's daily activities (e.g., writing answers, voting answers, collecting articles, etc.) will be displayed on the timeline of the homepage and sorted by the time published. Followers of each user will be notified when the user makes a new action.

In Appendix 3.8.1, we provide a simple comparison of the design of user interface between Zhihu and Quora.

[64]Most of the Chinese web pages in this paper are translated by Google, so some of the expressions may not be the most accurate.

Figure 13: An example of a Zhihu user's homepage

real-name verification and "best answerer" reward are two important features. Users who would like to own a blue star must submit relevant authentication document to the platform, including but not limited to: personal information, id card, work certificate, etc. It is worth noting that users with less than a Ph.D. degree and without a position in a science-related industry cannot obtain blue stars. The allocation of yellow stars is based on the platform algorithm, and the platform will only award yellow stars to a very small number of users who are considered as the best answerers in their field. Most of the time, the user does not know when she or she is going to receive a yellow star: the algorithm is so complicated that even if she or she answers several questions in the relevant field and receives a high number of votes, it does not necessarily imply that a yellow star will be awarded immediately. Below the authentication information, it shows how many votes the influencer has received, how many other users she follows, and how many followers she has. In the center of the home page, we see the timeline data that includes the user's historical answers, historical questions, and the total number of articles. We can also find in detail what questions the influencer responded to, what articles she did created, what answers/articles she/she did voted for, and when she completed these activities, etc. Relevant information includes the influencer's historical answers, historical questions, as well as the total number of articles.

We collect the raw data provided by Zhihu.com, which contains timeline information of all influencers (users with more than 10,000 followers) from January 2016 to August 2017.[65] At that time, the platform had around 17 million registered users and most of the network traffics still come from its high-quality textual answers and questions, without being intervened by audio, video and e-book content that were developed later. Therefore, the data sampling period is tentatively chosen by balancing the numbers of influencers that we could study and the identification of sources of incentives.

Our initial data contains 3686 users where some of them do not have complete information, have been "kicked out" (because they have violated the platform's regulations), or are no longer active. In addition to these users' daily activity information, we also captured their follower changes twice in early 2017 and around August 2017, and obtained some additional variables as the total number of received votes during these six months, as well as relevant information on some other variables. Figure 14 illustrates the structure of our data set. Therefore, we select the sample data based on the following criteria, our sample data include: available information of badge received or not (3437 remaining users); available information on users' activities from January 2016 to August 2017 (3003

[65]The timeline mainly includes who did what to whom and when. For example: A voted for The answer To B at 12:02 on January 1, 2018.

remaining users); available information on the number of followers on March and August 2017 (1888 remaining users); total number of followers (78,404,520) of all selected users represent more than 80% of the raw sample (1500 remaining users); and frequency of answer creation $\geqslant 1$ per month (1500 remaining users).

After matching variable information and removing users who had been banded by the platform, we are left with 1888 influencers in our sample. We further select with the number of followers and frequency of activities and finally get a sample with 1500 header influencers: they have answered questions at least once a month on average, and we could see their full profile on the platform, as well as the changing status of their followers over the last six months.[66]

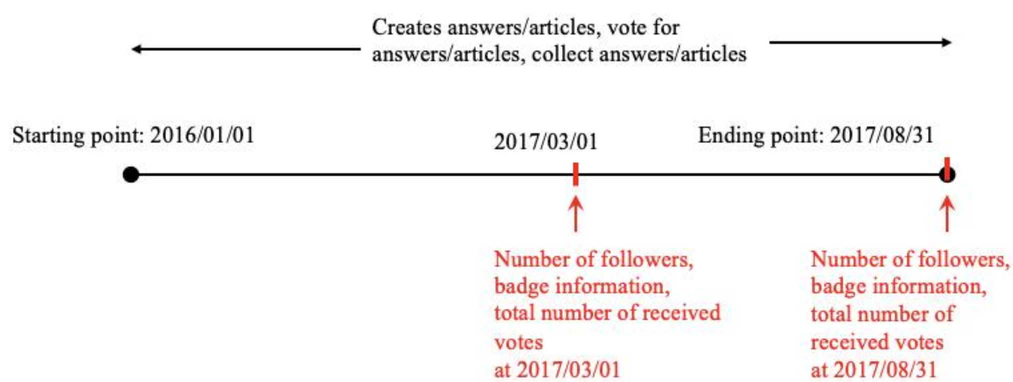


Figure 14: An illustration of the data structure

An important feature of the data is that the platform assigns different types to the users. In the data, the platform provides three kinds of tags to distinguish an ordinary user from "a certified user": self-authenticated professionals (blue star users), best answerers (yellow star users), business users (merchants who promote their products by answering questions),

[66]In Appendix 3.8.3, we provide a more detailed discussion about the representativeness of the selected sample and compare the statistics based on the six-month sample with the full sample.

Type	Type.1	Type.2	Type.3	Type.4	Type.5
Self-authenticated (Blue Star)	√		√		
Best-answerer (Yellow Star)		√	√		
Commercial				√	
Number of users	49	301	61	55	1034
Proportion	3.267%	20.067%	4.067%	3.667%	68.933%
Increasing rate of followers	0.377	0.217	0.320	0.488	0.239
(min, max)	(0.003, 2.223)	(-0.001, 1.447)	(0.006, 1.805)	(0.019, 2.268)	(-0.009, 2.057)
Avg. # of answers created	2.591	1.691	1.967	2.370	2.525
(min, max)	(0, 44)	(0, 83)	(0, 24)	(0, 32)	(0, 268)
Avg. # of votes received	5.606	3.167	4.805	3.076	3.167
(min, max)	(0, 119)	(0, 138)	(0, 100)	(0, 76)	(0, 200)
Avg. # of articles created	0.829	0.290	0.536	2.292	0.425
(min, max)	(0, 14)	(0, 11)	(0, 27)	(1, 22)	(0, 31)
Avg. # of answers collected	0.346	0.696	0.622	0	0.758
(min, max)	(0, 153)	(0, 156)	(0, 73)	(0, 0)	(0, 239)
Avg. # of articles collected	0.059	0.183	0.216	0	0.152
(min, max)	(0, 17)	(0, 23)	(0, 11)	(0, 0)	(0, 30)

Note: 1. Commercial users in Type. 4 can be either self-reported or best-answerer or both.

2. Increasing rate of followers is measured in last six months data. It is calculated approximately by $\Delta log(follower) = log(follower_{t+1}) - log(follower_t)$;

3. Avg. # of answers created is measured by week, Avg. # of votes received only contains the votes from other influencers.

Table 37: Descriptive Statistics (based on six-month selected sample)

and uncertified users.[67] According to the badge information provided by the platform, we divide the users into five types and report the relevant description statistics of each type of user in Table 37. We find that platform authenticated users and business users account for a smaller share of influencers, but have a higher follower growth rate than other types of users and tend to attract more votes. On average, yellow star influencers answer fewer questions than other types of users.

3.4 Identifying the impact of "peer recognition"

3.4.1 Basic regression model

Our first objective is to identify the impact of being recognized as an incentive to share content. We use the number of votes an influencer receives from other influential users as a proxy of "the incentive of recognition." Since one user's answer is endorsed by another means that the answer appears on the vote-up person's timeline and will be seen by all of her followers, voting by other influencers helps the content provider spread the content and increases her influence on the voter's network.[68] We constructed the output variable from the number of questions each influencer answered per week and used the number of

[67]Blue star users are experts in their field, for example, lawyers, engineers, and accountants. Users need to provide licenses to the platform in order to authenticate themselves and get the blue star. The minimum requirement for users in academia is to be at least a Ph.D. student in progress; a student ID is accepted for the real-name system, while professors need to provide certification of employment. The platform only requires that the professional level and employment status online should be truthful, but authenticated users can show either their real names or net names on the site.

Yellow star users are labelled as "best answerer" by the platform. They are set up by the platform in order to enable readers to find valuable answers more quickly and accurately and to motivate content providers to output professional answers continuously. The platform automatically identifies the best respondents in each field according to the algorithm, and the algorithm calculates the topic weight of the reference user in a specific field. Excellent answerers can only be provided by the system and do not support applications or self-recommendation.

[68]e.g., Sun et al. (2019) also discussed the impact of users' choices in online communities on their followers. More recently, Bailey et al. (2019) used data from facebook to explore the impact of peer effects on phone purchase decisions in the U.S. market.

votes received by other influencers in the previous week as the key explanatory variable to construct the regression model:

$$\log\left(Answers_{i,t}+1\right)=\beta_0+\log\left(Votes_{i,t-1}+1\right)\beta_v+x'_{i,t}\beta_x+\delta_i+\delta_t+\eta_{i,t}, \tag{20}$$

where $x_{i,t}$ is a vector of control variables; δ_i and δ_t are two fixed components that captures individual and time fixed effects on the answer creation and $\eta_{i,t}$ is an unobserved error term, where δ_i captures the effect of personal specific unobserved characteristics on the number of questions answered, and δ_t captures the presence of underlying specific time effects (for example, during national holidays, where most people choose to travel, the frequency of answering questions may decrease. The emergence of current social topics in a certain period will also increase the frequency of responses to the overall questions). β_v captures the effect of "peer recognition". If there is no concern about endogeneity β_v is simply the statistical linear correlation between the number of created new answers and received votes that an influencer i receives during the week t. We use the lagged variable of received votes at t to avoid the potential endogeneity problem: the higher number of received votes during the period t may be due to the higher number of questions answered.

Table 38 reports Ordinary Least Square (OLS) regression results using through using weekly panel data from March 2017 to August 2017.[69] The direct estimation results from the first four columns show that an additional 10% of votes received in the given week correspond to an increase in around 1% more created answer in the following week even after controlling for the fixed effects. Receiving votes from other influencers (the act of approving the answer) has a statistically significant positive effect on the content creation. In the last five columns, we gradually add time trends, number of followers and badge

[69]The regression model estimation is based on the selected sample over six months because for six months we know exactly users' badge information. However, some of our subsequent robustness checks are based on two years of data.

Dependent variable: $\log(Answers_t + 1)$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
$\log(Votes_{t-1} + 1)$	0.109***	0.112***	0.083***	0.088***	0.113***	0.088***	0.088***	0.088***	0.088***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$Week$					-0.201***	-0.203***	-0.203***	-0.203***	-0.203***
					(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
$Week^2$					0.008***	0.008***	0.008***	0.008***	0.008***
					(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\log(Follower_0)$						-1.111***	-1.111***	-1.111***	-1.111***
						(0.007)	(0.007)	(0.007)	(0.007)
$Self\ Authenticated$							-0.263		-0.263
							(0.176)		(0.176)
$Best\ Answerer$								-1.514***	-1.514***
								(0.551)	(0.551)
Individual Fixed Effects			√	√	√	√	√	√	√
Time Fixed Effects		√		√	√	√	√	√	√
N	34500	34500	34500	34500	34500	34500	34500	34500	34500
R^2	0.169	0.181	0.602	0.612	0.612	0.612	0.612	0.612	0.612

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, standard errors in parentheses. $\log(Follower_0)$ represents the log number of follower on March 2017. R^2 is adjusted-R^2.

Table 38: OLS regression results of the impact of "peer recognition"

information as control variables. We note that since the number of initial followers is time invariant, we cannot control both individual fixed effects and the number of followers simultaneously. The results indicate that our regression result is in line with the intuition. The amount of influencers' content contribution gradually decreases as time passes. We suspect that this is due to the exhaustion of the knowledge reserve (every user's knowledge is limited, so it is very challenging to provide content continuously), or due to multi-homing (some influencers may provide content on several platforms at once after they become famous, thus reducing their content contributions on the original platform). The number of content contributions by best answerers is generally smaller than that of other influencers.[70]

3.4.2 From the correlation to the causality

Although we use lag variables in the above formula to avoid possible endogeneity problems, the above regression results are still limited to showing the statistical correlation between "the number of received votes" and "the number of created answers," rather than its incentive effect on "answer creation." The endogeneity problem resists because of the omission of important variables. For example, we do not see the effort level of providing answers, and as the model shows, influencers may strategically choose different level of effort to produce answers. At the same time, a topic in a particular field may be unusually topical at a particular point in time, so that different influencers in this field provide more answers than others. To address these underlying considerations, we develop strategies to identify the causal relationship between "the number of received votes" and "the number of creations."

[70] In Appendix 3.7 we check and compare the impact from both "all votes" and "votes from influencers", the results indicate that the votes from other influencers are good enough to capture the "peer recognition" effect.

We provide an instrumental variable method to tackle the endogeneity issue. The construction of the instrumental variable is based on user interactions on social networks to identify such causal relationships. Figure 15 illustrates the construction and validation of instrumental variables.

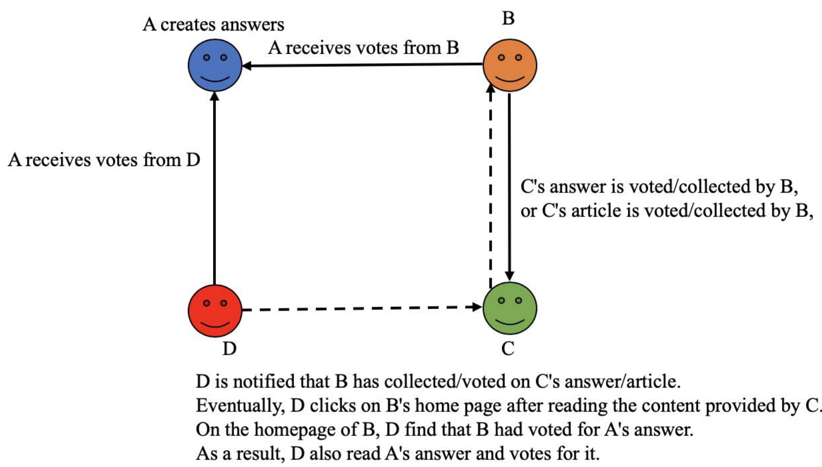


Figure 15: Illustration of instrumental variables

We assume that there are four influencers A, B, C, and D. A creates an answer. B has read and voted for this answer. Meanwhile, B also reads an answer from C and choses to vote for it. Therefore, both the answers of A and C appear on B's homepage sequentially. Now imaging the fourth influencer D views the answer of C because of B's vote. With some probability, D will visit B's homepage and thus have the chance to view B's previous vote for A's answer as well. In this vein, A's answer obtains an additional exposure opportunity when one of its voters, B, votes for C's answer; and this opportunity has nothing to do with the quality of A's answer itself.

In general, our instrumental variables assume that in a social network, votes from one user to other influencers have a positive spill over effect on content sharing (see, Fershtman and Gandal (2011)) due to increased traffic from content exposure. We use the number of votes/collections from B to other users (e.g., C) as a potential instrumental variable.

Since A's content creation quantity is only motivated by the number of votes it obtains, B's behaviors toward C can be used as valid instruments. On the one hand, they do not directly affect the creation enthusiasm of A, nor are they correlated with the quality or effort level chosen by A (exclusion restriction); on the other hand, B's behavior toward C will bring additional votes to A's content through D (reveal condition). In data, one influencer may have four actions on another: answer voting, answer collection, article voting, and article collection. Each of these four actions may cause additional votes by other influencers on the answer for a given influencer, we use them as potential instrumental variables to identify the effect of "peer recognition." Our identification strategy comes from the unique nature of the online content platform, where users' communication with each other allows us to correctly identify the impact of a variable on users' motivations to contribute in ways other than policy shock (e.g., Zhang and Zhu (2011), Wu and Zhu (2019)). We consider a system of equations below:

$$\log\left(Answers_{i,t}+1\right) = \beta_0 + \log\left(Votes_{i,t-1}+1\right)\beta_v + x'_{i,t}\beta_x + \delta_i + \delta_t + \eta_{i,t},$$
$$\log\left(Votes_{i,t-1}+1\right) = \gamma_0 + z_{i,t-1}\gamma_z + x'_{i,t}\gamma_x + \delta_i + \delta_t + v_{i,t},$$

where $z_{i,t-1} = \left(z_{i,t-1}^{answer\ vote}, z_{i,t-1}^{answer\ collect}, z_{i,t-1}^{article\ vote}, z_{i,t-1}^{article\ collect}\right)'$ is a set of potential instrumental variables that we have discussed above, that is:

$$z_{i,t-1}^{answer\ vote} = \log\left[\left(\sum_{j\ votes\ for\ i's\ answer\ during\ t-1} Votes\ for\ Answsers\ Other\ than\ i_{j,t-1}\right)+1\right],$$

$$z_{i,t-1}^{answer\ collect} = \log\left[\left(\sum_{j\ votes\ for\ i's\ answer\ during\ t-1} Collects\ Answser\ Other\ than\ i_{j,t-1}\right) + 1\right],$$

$$z_{i,t-1}^{article\ vote} = \log\left[\left(\sum_{j\ votes\ for\ i's\ answer\ during\ t-1} Votes\ for\ Articles\ Other\ than\ i_{j,t-1}\right) + 1\right],$$

$$z_{i,t-1}^{article\ collect} = \log\left[\left(\sum_{j\ votes\ for\ i's\ answer\ during\ t-1} Collects\ Articles\ Other\ than\ i_{j,t-1}\right) + 1\right].$$

Table 39 reports the first-stage results of IV estimation by controlling potential instrumental variables and fixed components. The four potential instrumental variables are the total number of votes/collections for other influencers by influencers who voted for the influencer i in period t (i.e., the sum of the actions of B to C in Figure 15). The results show that none of the instrumental variables are weak instruments (they all satisfy the reveal condition), and confirm our previous hypothesis that voting for someone else had a positive spillover effect. However, in verifying the exclusion restriction, the Hansen J (or Sargan–Hansen J) statistic shows that only the voting and collection of other influencer's articles are the valid variables. This finding suggests that voting up or collecting other influencers' answer may be related to some other unobserved factors. For example, in Figure 15, B votes for both C and A at the same time, most likely because C and A are under the same question that is highly topical at that a given period. During the same period, A may have answered many questions related to hot topics. Therefore, we end up choosing only the collection and voting of articles as the instrumental variables.

Dependent var: $\log(Votes_{t-1}+1)$			
Instrumental var	(1)	(2)	(3)
$\log(Article\ votes_{t-1}+1)$	0.042***	0.206***	
	(0.013)	(0.016)	
$\log(Article\ collections_{t-1}+1)$	-0.116***	0.599***	
	(0.012)	(0.011)	
$\log(Answer\ votes_{t-1})$	0.311***		0.310***
	(0.002)		(0.003)
$\log(Answer\ collections_{t-1})$	0.033***		0.001
	(0.006)		(0.007)
Individual Fixed Effects	√	√	√
Time Fixed Effects	√	√	√
N	34500	34500	34500
F stat	7341.123	1612.798	14582.19
Hansen J statistic	17.070	2.125	11.630
(p-value)	(0.001)	(0.145)	(0.001)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. The explanatory variables are the total number of votes/collections for other users by people who voted for the influencer i in period t.

Table 39: First-stage results and IV diagnostics

Discussion We also notice that in some recent studies, scholars are using similar ideas to construct instrumental variables. For example, Farronato et al. (2020) use the average rating given by a reviewer as an instrumental variable to evaluate the impact of online rating/review. We point out that one should be very careful when using this kind of instrumental variables because many of the platform-related variables, such as whether the platform has a special promotion, are unobservable. These factors are likely to be ignored and these violate the exclusion restriction. One significant advantage of our data is that we observe four different types of activities that are related to each other but have different meanings. This has allowed us to build the Hansen J test to verify the validity of the instrumental variables: it is extremely important because our verification shows that only two of the four variables are valid instruments. The other two may be invalidated because they are related to some current hot topics (e.g., the U.S. presidential election, the COVID-19 pandemic) that affect the influencers' enthusiasm to provide contributions and the probability of receiving more votes. On the contrary, the publication of articles has little relevance with hot topics. Most of the time, articles are published based on the author's personal interests, which is more like a notepad. Therefore, the article based instrument variables are easier to satisfy the exclusion restriction.

Dependent variable: $\log(Answers_t + 1)$						
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	IV	IV	IV
$\log(Votes_{t-1} + 1)$	0.109***	0.083***	0.088***	0.158***	0.126***	0.124***
	(0.004)	(0.004)	(0.004)	(0.013)	(0.013)	(0.014)
Intercept	0.624***	0.644***	0.817***	0.587***	0.611***	0.470***
	(0.014)	(0.004)	(0.014)	(0.017)	(0.011)	(0.017)
Individual Fixed Effects		√	√		√	√
Time Fixed Effects			√			√
N	34500	34500	34500	34500	34500	34500
R^2	0.169	0.602	0.612	0.169	0.600	0.611

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, standard errors in parentheses.
Instrumental variables are $\log(Article\ collections_{t-1} + 1)$ and $\log(Article\ votes_{t-1} + 1)$.
R^2 is adjusted-R^2.

Table 40: Instrumental Variable regression results

Table 40 shows the results based on the IV estimates. We find that OLS estimates have seriously underestimated the actual effect of "peer recognition" on encouraging content creation. The true estimated effect based on the instrumental variables is 40%-50% higher than the OLS estimates. This fact shows that there are some underlying factors that prevent the "peer recognition" effect from playing out, which ultimately leads OLS to underestimate the effect.[71] We also consider that the IV estimate increases the variance, which may cause

[71]In Appendix 3.8.6, we provide an evidence of the existence of heterogenous effects that prevent the

the underestimation from OLS estimates to become statistically insignificant. We further test the difference between OLS and IV estimates by using both Hausman and Durbin-Wu-Hausman test. The results are highly consistent, with both tests showing a p-value of less than 0.001.[72]

According to our model in section 3.2, possible underlying factors include switching answering strategies and the privacy concern. In the next section, we will identify whether these two are valid channels through which the effect of peers are attenuated.

3.5 What attenuates the effect of peers?

3.5.1 Differences between commercial and non commercial users

On the Zhihu platform, there are two types of influencers: commercial and non-commercial (personal) users. Excellent personal content providers are also responsible for producing products (answers to questions), which may make them less motivated by privacy concerns (e.g., reputational or privacy concerns). For commercial users, their purpose on the platform is mainly to promote their products by answering questions, essentially to achieve the purpose of advertising by providing free content. Therefore this additional incentive might counterbalance privacy concerns, which makes the privacy cost C much smaller compared with that of non-commercial users. According to corollary 2, when the privacy cost C is smaller, influencers are more likely to adopt a broad-coverage strategy, and write more answers. Therefore, if the privacy concern is an issue for non-commercial users,

efficiency of "peer recognition." When we extend the timeline to two years, we find that the instrumental estimate was still higher than the OLS estimate, but the overall effect increased over the longer timeline, which suggests that some factors may reduce this peer effect over time: for example, multihoming, knowledge drying, reputation accumulation, changes in platform competition environment, etc. Thus, in the following study, we fixe the timeline at six months, so as to use the additional variables we have observed to confirm which channels were primarily reducing peer motivation.

[72]More precisely, for Hausman test, we get 10.880 as value of test statistics and 0.001 as p-value. And for Durbin-Wu-Hausman test, we get 10.91847 as value of test statistics and 0.000 as p-value.

commercial users should be more motivated by others' recognition.

Dependent variable: $\log(Answers_t + 1)$				
	(1)	(2)	(3)	(4)
	OLS	OLS	IV	IV
$\log(Votes_{t-1} + 1)$	0.088***	0.085***	0.124***	0.107***
	(0.004)	(0.004)	(0.013)	(0.014)
$Week$	-0.203***	-0.202***	-0.202***	-0.201***
	(0.023)	(0.023)	(0.023)	(0.023)
$Week^2$	0.008***	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
$\log(Follower_0)$	-1.111***	-1.477*	-0.885**	-1.541*
	(0.007)	(0.804)	(0.410)	(0.791)
$Commercial$		0.124		0.146
		(0.409)		(0.405)
$Commercial \times \log(Votes_{t-1} + 1)$		0.058***		0.342***
		(0.022)		(0.063)
Individual Fixed Effects	√	√	√	√
Time Fixed Effects	√	√	√	√
N	34500	34500	34500	34500
R^2	0.612	0.612	0.611	0.609

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; standard errors in parentheses.
$Commercial$ is a binary dummy variable, $Commercial = 1$ when it is a commercial user.
R^2 is adjusted, it is derived from LSDV (Least Square Dummy Variable) regression with Stata.

Table 41: Impact on creating new answers - commercial and non commercial influencers

Table 41 reports the regression results by using $Commercial$, a binary variable indicating whether an influencer is a commercial user. The regression results are in line with our expectations, and the reduction in the incentive effect is due to "non-commercial users" (i.e., individual users). In this paper, we compare the OLS coefficient with the cross-term (column 2) and the IV coefficient without cross-term (column 3) to infer how the cross-term corrects the deviation caused by OLS. At the same time, we also provide IV results with the cross-term regression (column 4), which allows us to correct further the possible bias of the conditional coefficient due to the use of OLS estimation. After taking into account the cross term between the commercial user and the "peer recognition," the incentive effect received by the commercial user under OLS estimation is almost the same as the result of using instrumental variables. At the same time, both OSL and IV estimation clearly indicate that commercial users are more motivated by others' recognition. [73]

3.5.2 Reputational and privacy concerns

The above results provide some preliminary evidence of the privacy concern. However, one might argue that the stronger motivation of commercial users are because of inherent heterogeneity between commercial and non-commercial users. In this subsection, we restrict our attention to non-commercial users and further explore whether reputational and privacy concerns are also reasons for influencers to write fewer answers. Corollary 1 predicts that influencers with a significantly high reputation (i.e., best answerer) will write fewer answers to avoid a reputational clash on the platform. In the sense of social responsibility, they may seek to provide more rigorous and high-quality answers rather than a higher number of answers. Privacy concerns are addressed in Corollary 2, influencers may be less likely to answer questions, or less motivated by peers, for fear of overexposure of personal information.

We divided all non-commercial influencers into two categories: users who get "best answerer" and users who get "self authenticated." Table 42 reports the regression results.

[73] We also find the same results when looking at the spillover effect on content providing. Corresponding results are reported in Appendix 3.8.5. Therefore, we will focus on non-commercial influencers in our subsequent studies. In Appendix 3.8.8, we study the impact of getting a badge without specifying the type of badge. This can be either a badge indicating if an influencer has self-authenticated, or a badge showing if an influencer is a best answer of her/her field, or a badge indicates if an influencer is simply a commercial user. Results in Table 54 show that the fact of holding a badge negatively affects the frequency of providing new answers. We know that commercial users are more likely to be motivated than other influencers, which indicates that the other two types of influencers are far more conservative in their responses to other people's votes. Further empirical evidences are provided in the following subsections.

Dependent variable: $\log(Anwers_t + 1)$						
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	IV	IV	IV
$\log(Votes_{t-1} + 1)$	0.085***	0.086***	0.094***	0.107***	0.112***	0.113***
	(0.004)	(0.004)	(0.004)	(0.014)	(0.014)	(0.016)
$Week$	-0.208***	-0.208***	-0.209***	-0.208***	-0.208***	-0.208***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
$Week^2$	0.008***	0.008***	0.009***	0.009***	0.009***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\log(Follower_0)$	0.329***	0.329***	0.322***	0.313***	0.310***	0.309***
	(0.112)	(0.112)	(0.112)	(0.110)	(0.110)	(0.110)
$Self\ Authenticated$		-0.935***			-0.854***	
		(0.188)			(0.188)	
$Self\ Authenticated \times \log(Votes_{t-1} + 1)$		-0.004			-0.057	
		(0.015)			(0.049)	
$Best\ Answerer$			0.105			0.129
			(0.143)			(0.143)
$Best\ Answerer \times \log(Votes_{t-1} + 1)$			-0.033***			-0.032
			(0.009)			(0.025)
Individual Fixed Effects	√	√	√	√	√	√
Time Fixed Effects	√	√	√	√	√	√
N	33235	33235	33235	33235	33235	33235
R^2	0.615	0.615	0.615	0.613	0.613	0.613

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

R^2 is adjusted, it is derived from LSDV (Least Square Dummy Variable) regression with Stata.

Table 42: Effects of reputational and/or privacy concerns (non-commercial users)

The regression results show that, on average, users who are motivated by other influencers are not affected by submitting personal information to the platform. The OLS results show that the main factor that affects motivation depends on whether the user is a "best answerer" awarded by the platform. But the results are not significant under the IV estimation, since the cross-term directly affects the significance. The results indicate that content providers may trade-off between quantity and quality of the answers due to the potential "reputation concerns" and choose their content more carefully.[74]

However, we find that there is no significant effect on self-authenticated users based on the regression results of Table 42. Does the disclosure of information really not affect content incentives? Based on the results of Table 42, we have the following three concerns: first of all, some users have both badges (i.e., they are self authenticated best answerers). While yellow stars are more obviously associated with a reputation, some users may consider blue stars to be a reputation as well. Secondly, by disclosing their information on the website and obtaining a blue star badge, there are certain restrictions: for example, the user should be at least a doctoral student, and the disclosure is limited to work and education. Both of these concerns may affect our regression results.

We further launch regressions for all self-authenticated influencers and all the best answerers separately, and evaluate the conditional impact of gaining the "best answer" on those who are self-authenticated influencers. And for those best answerers, the impact of self-authenticated on them. Results are reported in Table 43. The results confirmed the existence of "reputational concerns". Whether or not an influencer actively discloses information to the platform and obtains the authentication, getting "best answerer" will affect the incentive she/she receives from others. However, when we restrict our sample to all the best answerers, while the IV estimation shows that getting a "blue star" (self-authentication) significantly and negatively reduce the effect of peer recognition, the OLS result remains insignificant.

[74]We provide in Appendix 3.8.7 an additional check of the potential multi-homing concern. The best candidates may also receive less incentive from others' votes because other competing platforms may poach them after they are awarded as "best answerer" in their field. Under the assumption that the multi-homing probability is positively correlated with the number of followers, our estimation result shows that the multi-homing concern only exists in the "non-best answerer" group. After controlling both the number of followers and the "best answerer," the increase of followers has a positive and significant impact on peer incentives of best answerers. Such finding shows that the multihoming concern is significantly reduced among "best answerers". However, the reputational concerns related to the yellow badge still exists and even dominates the potential multihoming effect.

Dependent variable: $\log(Answers_t + 1)$								
	Conditional on self-authenticated influencers				Conditional on best answerers			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
$\log(Votes_{t-1} + 1)$	0.083***	0.117***	0.053	0.136	0.059***	0.060***	0.102***	0.122***
	(0.014)	(0.022)	(0.049)	(0.085)	(0.007)	(0.008)	(0.024)	(0.027)
$Week$	-0.264***	-0.266***	-0.267***	-0.276***	-0.231***	-0.230***	-0.226***	-0.228***
	(0.086)	(0.086)	(0.084)	(0.084)	(0.044)	(0.044)	(0.044)	(0.043)
$Week^2$	0.011***	0.011***	0.011***	0.011***	0.009***	0.009***	0.009***	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
$\log(Follower_0)$	-0.345***	-0.384***	-0.355***	-0.384***	1.707	1.706	1.590	1.533
	(0.086)	(0.075)	(0.085)	(0.074)	(1.159)	(1.160)	(1.137)	(1.139)
$Self\ Authenticated$						0.167		0.221
						(0.176)		(0.180)
$Self\ Authenticated \times \log(Votes_{t-1} + 1)$						-0.003		-0.123**
						(0.019)		(0.060)
$Best\ Answerer$		-0.047		0.038				
		(0.150)		(0.152)				
$Best\ Answerer \times \log(Votes_{t-1} + 1)$		-0.055*		-0.169*				
		(0.029)		(0.094)				
Individual Fixed Effects	√	√	√	√	√	√	√	√
Time Fixed Effects	√	√	√	√	√	√	√	√
N	2530	2530	2530	2530	8326	8326	8326	8326
R^2	0.599	0.599	0.595	0.595	0.568	0.588	0.561	0.573

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

R^2 is adjusted, it is derived from LSDV (Least Square Dummy Variable) regression with Stata.

Table 43: Heterogenous effects of reputation and/or privacy concerns (non-commercial users)

Summarily, our results show that getting a "blue star" does not show too much privacy concern for the overall user. However, for those who receive a "yellow star", the extra blue star reduces the incentive from peers. We suspect that this reflects two possible selectivity effects in the sample: first, it is possible that the users on our platform themselves do not care about personal privacy. For example, if in real life, many users' personal information has been leaked through other channels, this may make them not care too much about their privacy on the platform. Second, for those who already provide detailed personal data to the platform (i.e., self-authenticated), they are particularly vulnerable to information leakage through answer questions since they are easier to be identified by potential malicious users.

3.5.3 Impact of secondary information disclosure

We consider influencers who wish to disclose a portion of their information voluntarily but cannot be verified by the platform. For these users, there is absolutely no reputational concern when they disclose their information. And we evaluate the impact of "information disclosure" on these influencers. On the platform, influencers are also allowed to disclose their work units, living places and other personal information. This information can be very informal and is voluntarily disclosed by users. Since they cannot be truly verified by the platform, we regard them as "secondary information disclosure."

We categorize these influencers without any badge information into three types based on their level of information disclosure.

1. No badge influencers who have reported both their place of residence and their work address;

2. No badge influencers who have either reported their place of residence or their work address; and

3. No badge influencers who do not report any information.

Dependent variable: $\log(Answers_t + 1)$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	Type 1	Type 2	Type 3	All-IV	Type 1-IV	Type 2-IV	Type 3-IV
$\log(Votes_{t-1} + 1)$	0.093***	0.122***	0.071***	0.080***	0.107***	0.135***	0.049*	0.145***
	(0.005)	(0.008)	(0.008)	(0.010)	(0.017)	(0.028)	(0.029)	(0.025)
$Week$	-0.200***	-0.195***	-0.215***	-0.185***	-0.200***	-0.196***	-0.214***	-0.178***
	(0.028)	(0.045)	(0.045)	(0.058)	(0.027)	(0.044)	(0.044)	(0.058)
$Week^2$	0.008***	0.007***	0.008***	0.007***	0.008***	0.008***	0.009***	0.007***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
$\log(Follower_0)$	0.322**	0.609*	-0.027	-0.440	0.313**	0.604***	-0.023	-0.537
	(0.113)	(0.134)	(0.156)	(0.355)	(0.111)	(0.131)	(0.153)	(0.351)
Individual Fixed Effects	√	√	√	√	√	√	√	√
Time Fixed Effects	√	√	√	√	√	√	√	√
N	23782	9499	8694	5589	23782	9499	8694	5589
R^2	0.626	0.609	0.648	0.621	0.623	0.606	0.646	0.619

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.
R^2 is adjusted, it is derived from LSDV (Least Square Dummy Variable) regression with Stata.

Table 44: Effect of information disclosure on no badge influencers

Table 44 report the regression results. For the first type of influencers, who have disclosed both their place of residence and their work address, the incentive effect estimated by OLS estimation is very similar to the IV estimation (column 2,5 and 6). Such empirical results confirm the potential "selection effect": Those influencers who are concerned about their information will not choose to disclose their information and get the platform authentication. As a result, they will be less motivated when receiving other influencers' votes.

Overall, our results show that reputation concerns plays a significant role for non-commercial influencers. The platform badge policies not only encourage commercial influencers to speak more frequently but also limit the incentive for best answerers to contribute content. In the long term, the platform may be flooded with "low-quality" content and lose its attraction. In addition, if the "selection effect" makes some users unwilling to disclose their information on the platform and more cautious about providing content, the platform may only be left with only users who do not care about information disclosure and lose the diversified content. Such findings partly explains the rising concerns about the "chilling effect": the improvement of the platform's supervisory power may have a blocking effect on users' speech, which makes some users refuse to answer questions or express their opinions. As the space available for public opinion is reduced, users with a low cost of speech may speak more frequently, thus making the platform appear as "single polarization". This phenomenon may be particularly true in countries with highly regulated governments.[75]

3.5.4 Causal mediation analysis

As we have shown in Section 3.4.2, the IV estimate indicates the total causal effect of receiving peers' votes on content provision. In the previous subsection, it is shown that the badge given by the platform prevent influencers from contributing more because of the potential reputational and privacy concerns. Would the badge motivate content provision if there is no reputational and privacy concern? We conclude this section with a study of the badge's mediating effect.

The main difficulty is that influencers have selection issue in getting badges, which leads to another endogeneity problem. In our previous empirical studies, we find the number of votes and collections of other influences' articles can be solid instrumental variables for

[75]Just before the completion of this paper, Zhihu has launched a more rigid "real name" authentication policy: the platform requires every registered user to provide a mobile phone number and pass the real-name authentication. Users who refuse to contribute will be subject to certain restrictions on what they can say on the platform. Such a policy worries many users, some of whom even refuse to continue exporting content online. We provide an anecdotal evidence in our Appendix 3.8.9.

the votes. These variables are clearly not related to the unobserved factors that affect the badge selection process. In this section, we try to decompose the total effect of receiving votes as the summation of its direct and indirect effect (c.f., Pearl (2012)). We consider the following models:

$$\begin{aligned}
\log(Votes+1) =& z'\beta^{z}_{Votes} + \varepsilon^{Votes} \\
Badge =& \beta^{0}_{Badge} + \log(Votes+1) \times \beta^{Votes}_{Badge} + \varepsilon^{Badge} \\
\log(Answers+1) =& \beta^{0}_{Answers} + \log(Votes+1) \times \beta^{Votes}_{Answers} + Badge \times \beta^{Badge}_{Answers} + \\
& \log(Votes+1) \times Badge \times \beta^{Votes\times Badge}_{Answers} + \varepsilon^{Answsers}.
\end{aligned}$$

The parameters in the models are theoretically identifiable. Since a set of instrumental variables z is uncorrelated with both ε^{Votes} and ε^{Badge}, we can use z to identify both β^{z}_{Votes} and β^{Votes}_{Badge} and get $\log\widehat{(Votes}+1)$ and $\widehat{Badge}$ as a function of z. In particular, both $\log\widehat{(Votes}+1)$ and $\widehat{Badge}$ are uncorrelated with unobserved factors in the error term $\varepsilon^{Answsers}$. This allows us to further identify $\beta^{Votes}_{Answers}$ and $\beta^{Badge}_{Answers}$.

The main difficulty is that we cannot directly observe in the data when each influencer gets a badge. However, we know that the platform launched since July 2016 the blue and yellow star policy, which means that before 2016, all influencers have no badges. Our estimation procedure is:

1. We know that the platform launched since July 2016 the blue and yellow star policy, which means that before 2016, all influencers have no badges. We regress each user's badge status on the sum of their received votes before July 2016, and identify the second formula with the instrumental variables. We get $\hat{\beta}^{Votes}_{Badge}$ and $\widehat{Badge}$;

2. We run the equation of $Answers$ by:

$$\log\left(Answers+1\right) = \beta^{0}_{Answers} + \log\left(Votes+1\right) \times \beta^{Votes}_{Answers} + \widehat{Badge} \times \beta^{Badge}_{Answers} + \log\left(Votes+1\right) \times \widehat{Badge} \times \beta^{Votes\times Badge}_{Answers} + \varepsilon^{Answsers}.$$

Using the panel data from last 6 months, we use instrumental variables to estimate the above model and get $\hat{\beta}^{Votes}_{Answers}$, $\hat{\beta}^{Badge}_{Answers}$ and $\hat{\beta}^{Votes\times Badge}_{Answers}$.

The above procedure allows us to evaluate a sequence of causal relations where receiving votes cause badge acquisition, and both receiving votes and badge acquisition cause the content creation. We are able to decompose the total effect of receiving peers' votes on content provision into the "*indirect effect*" of receiving votes on content provision that is mediated by badge ($\hat{\beta}^{Votes}_{Badge} \times \hat{\beta}^{Badge}_{Answers}$), and the "*direct effect*" of receiving votes on content provision that is not mediated by badge ($\hat{\beta}^{Votes}_{Answers} + \hat{\beta}^{0}_{Badge} \times \hat{\beta}^{Votes\times Badge}_{Answers}$). Both effects are the effects from removing reputation and privacy concern through our instrumental variables.

Table 45 reports the results of both types of badge. After filtering out the reputation and privacy concerns, the results show that getting someone else's vote increases the probability of getting a "best answerer" badge. However, the number of votes has no significant effect on the probability of getting a "self authenticated" badge. Our finding is consistent with our story: voting does not indirectly affect the number of answers through a "self authenticated" badge, and the two badges themselves significantly affect answering questions. In particular, the "self authenticated" badge has more impact on the answer than the "best answerer" badge. Because a "self authenticated badge" is obtained by application, users who apply for it generally hope to make their answers more credible. In comparison, the "best answerer" badge is algorithmically linked to influencers, who gained more professional recognition and used to answer many questions.

Badge Type	$Self\ Authenticated$	$Best\ Answerer$
	(1)	(3)
$\hat{\beta}^{Votes}_{Answers}$	0.104***	0.104***
	(0.034)	(0.034)
$\hat{\beta}^{0}_{Badge}$	0.053**	0.147***
	(0.023)	(0.038)
$\hat{\beta}^{Votes}_{Badge}$	0.006	0.033***
	(0.006)	(0.009)
$\hat{\beta}^{Badge}_{Answers}$	4.462**	1.288**
	(2.099)	(0.606)
$\hat{\beta}^{Votes \times Badge}_{Answers}$	-0.011	-0.003
	(0.392)	(0.108)
Nature Direct Effect (NDE)	0.103	0.104
Nature Indirect Effect (NIE)	0.026	0.043
Total Effect	0.129	0.147
NIE/TE (%)	20.16%	29.25%

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are reported in brackets. The total effect equals the sum of nature direct effect (NDE), nature indirect effect (NIE) and $\hat{\beta}^{Votes}_{Badge} \times \hat{\beta}^{Votes \times Badge}_{Answers}$. NIE/TE (%) indicates the fraction of output response for which mediation would be sufficient.

Table 45: Would the badge motivate creativity if there is no reputational and privacy concern?

Our results show that the mediating influence of both badges accounts for about one-third of the total impact. The privacy and reputation concerns may affect both the direct and indirect effects: More users would have applied for a blue star without privacy concerns, and harvesting a blue star would motivate them to answer more questions. Without reputation concerns, yellow star users would be more responsive to others' recognition. Such findings indicate that if the platform could mitigate the negative effect caused by reputation and privacy concerns from these badge recipients, badge policy would be effective and spread the incentive effect of recognition to a large extent.

3.6 Conclusion

Online content provision is undoubtedly a dynamic topic in the digital era, and there is an increasing number of related empirical studies over recent years. Our paper provides both the theoretical foundation and solid empirical evidence to show the "peer recognition" effect on online contributions. The theoretical model indicates two search strategies that a influencer may consider: the broad-coverage strategy and a focus strategy; and explains how the strategic decision of an influencer is affected by the changes of peer recognition, reputation and privacy concerns through the analysis of model equilibrium. Our empirical method of constructing instrumental variables has proven to be simple and feasible in practice, which solves the endogenous problems in many platform-based empirical studies of digital economics and widens the research boundary.

This study also has important implications on the gamification design of online platforms. In the past, badges are regarded a crucial component of rewards that provides incentives to badge holders. Our research, however, shows that online content platforms should consider not only the incentive effect of badges, but also the privacy concerns and related content producing strategies. Otherwise, the badge system might not work in the way that the platforms expect.

From an empirical perspective, our results directly provide a quantification of the impact of "peer recognition." It is well known that if influencers are adequately incentivized by platform policies and become more productive, they will bring higher traffic to the platform and higher corresponding advertising revenue. Being able to effectively encourage content provision not only allows content readers to read abundant, higher-quality, and more diverse content but also points the way forward for policymakers to regulate content platforms: an effective policy should be to eliminate information asymmetry in two-sided markets without compromising the motivation of influencers. Our empirical results prove that reputational and privacy concerns occur simultaneously in practical situations. In particular, our results also reveal the considerations that platforms should have when formulating policies related to the "real-name system": while users are more accountable for each answer provided after obtaining real-name authentication, they may also become less active in providing content for fear of overexposing their privacies. The mediation analysis indicate that badge policy would be effective and spread the incentive effect of recognition to a large extent if there is no reputation and privacy concerns.

3.7 Appendix C

3.7.1 Proof of Proposition 1

Proposition. *The board-coverage strategy is preferred by average influencers.*

Proof. Given the equilibrium behavior of users, we can infer that type-h influencers will definitely prefer b over f, if $\bar{q}_{h,f} = \bar{q}_{h,b}$. The reason is quite straightforward: If the expected quality are the same, broad-coverage strategy have a higher possibility to produce a positive outcome, because $p_{h,b} > p_{h,f}$, and a positive outcome will convert the matched group of users into followers and obtain their votes in period 2.

Therefore, there exists a reputation premium R, so that type-h influencers will choose strategy f if and only if the difference of expected answer quality from strategy f and those from strategy b is equal or higher than R. Obviously, type-l influencers will mimic the strategy of type-h influencer at no cost in period 1 and truthfully reveal their types in period 2, when the reputational concerns no more exists. The equilibrium strategy when all the influencers' reputation is ρ_0 thus is:

$$s_{\theta,1}(\rho_0) = \begin{cases} f & \bar{q_{h,f}} - \bar{q}_{h,b} > R, \\ b & \bar{q}_{h,f} - \bar{q}_{h,b} \leq R, \end{cases} \quad s_{\theta,2}(\rho_0) = \begin{cases} f & \bar{q_{h,f}} > \bar{q}_{h,b}, \\ b & \bar{q_{h,f}} \leq \bar{q}_{h,b}. \end{cases} \quad \theta \in \{h, l\}.$$

And R has to be higher enough to cover lost of votes caused by the difference of probability of being unfollowed in period 2. The possible loss of votes in period 2, when there is no longer any reputational concern, would be $max\{\bar{q}_{h,b}, \bar{q}_{h,f}\}$. According to Assumption 1, $\bar{q}_{h,b} > \bar{q}_{h,f}$. Therefore,

$$R = (p_{h,b} - p_{h,f})max\{\bar{q}_{h,b}, \bar{q}_{h,f}\} = (\vartheta_h - \vartheta_l)\bar{q}_{h,b}.$$

By Assumption 1, $\bar{q_{h,f}} - \bar{q}_{h,b} < 0 < R$, the board-coverage strategy is preferred by average influencers. ■

3.7.2 Proof of Lemma 3.7.2

Lemma. *reputational concerns matters in the range* $\left[\underline{\rho}, \bar{\rho}\right]$*, where* $\bar{\rho} = \frac{(1-p_{l,b})\rho_0}{(1-p_{l,b})\rho_0+(1-p_{h,b})(1-\rho_0)}$ *and* $\underline{\rho} = \frac{p_{l,f}\rho_0}{p_{l,f}\rho_0+p_{h,f}(1-\rho_0)}$.

Proof. The lower and upper bounds are defined by the following two equations:

$$\rho_0 = \frac{p_{h,f}\underline{\rho}}{p_{h,f}\underline{\rho} + p_{l,f}(1-\underline{\rho})},$$
$$\rho_0 = \frac{(1-p_{h,b})\bar{\rho}}{(1-p_{h,b})\bar{\rho} + (1-p_{l,b})(1-\bar{\rho})}.$$

That is, the lower bound $\underline{\rho}$ is defined at the reputational level which the influencer can barely improve to ρ_0 if and only if the influencer takes a focus strategy and obtains an success; and the upper bound $\bar{\rho}$ is defined at the reputational level at which the influencer can still achieve ρ_0 after taking a broad-coverage strategy but the answer quality is poor q_b^-. simplifying these two equations yield the results of Lemma 3.7.2. ■

3.7.3 Proof of Proposition 2

Proposition. *Define* $\hat{\rho} = \frac{(1-p_{l,f})\rho_0,}{(1-p_{l,f})\rho_0,+(1-p_{h,f})(1-\rho_0)}$*, the reputation premia of influencers are:*

$$R = \begin{cases} (p_{h,b} - p_{l,b})max\{\bar{q}_{h,b}, \bar{q}_{h,f}\}, & \rho^* \in [\rho_0, \hat{\rho}], \\ -(1-p_{h,b})max\{\bar{q}_{h,b}, \bar{q}_{h,f}\}, & \rho^* \in [\hat{\rho}, \bar{\rho}]. \end{cases}$$

Proof. The reputation premium will remain the same, as long as a presence of a poor quality answer, either q_f^- or q_b^-, will turn down the reputational level lower than ρ_0. In such a case, the broad-coverage strategy has an advantage of being "safer", that is, this strategy induces a lower probability of having a negative outcome. However, at a certain reputational level, the influencer might be able to afford a negative outcome from the focus strategy, but not from the broad-coverage strategy. This threshold is defined by the equation:

$$\rho_0 = \frac{(1 - p_{h,f})\hat{\rho}}{(1 - p_{h,f})(\hat{\rho} + (1 - p_{l,f})(1 - \hat{\rho})}.$$

■ Therefore, if the influencer's reputation in the range $[\hat{\rho}, \bar{\rho}]$, the focus strategy becomes a 100% safe strategy, since adopting the focus strategy, the influencer's posterior reputation will not drop below ρ_0, regardless the outcome of period 1; while adopting the broad-coverage strategy leads to a probability $1 - \vartheta_h$, to produce a negative outcome and consequently drive the posterior reputation lower than ρ_0. As a consequence, the reputation premium of the focus strategy drastically changes from positive to negative for these high-reputation influencers. Unless adopting a broad-cover strategy leads to sufficiently more votes in period 1, high-reputation influencers prefer to adopt the focus strategy. The risk premium can thus be calculated by the expected loss of votes in period 2 when adopting the broad-coverage strategy, that is, $R = -(1 - p_{h,b})\bar{q}_{h,b}$.

3.8 Appendix D

3.8.1 A comparison of Zhihu and Quora's user interface

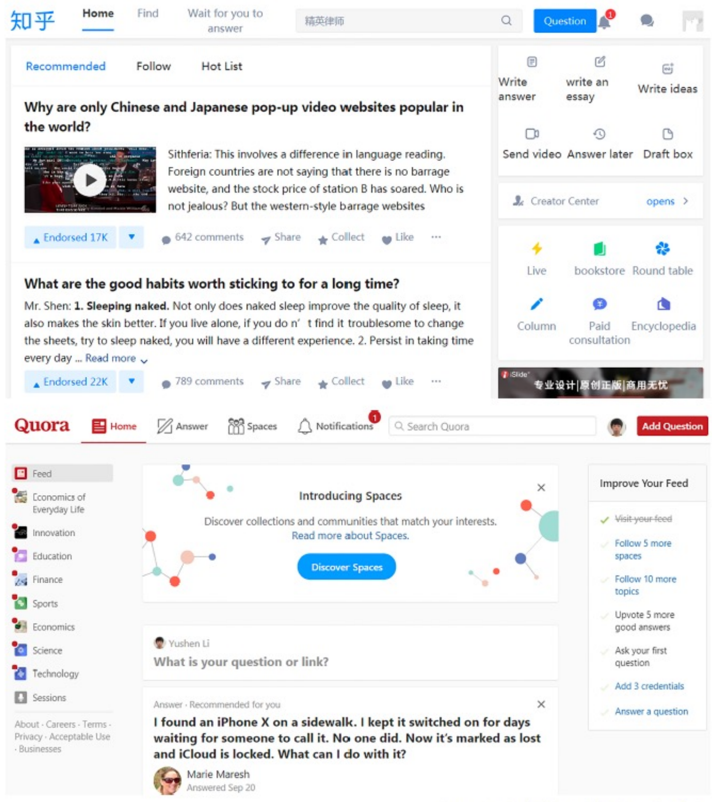


Figure 16: A comparison of Zhihu and Quora's user interface (Chinese web pages is generated directly through Google translate)

3.8.2 Broad-coverage strategy vs Focus strategy strategy

We provide in Figure 17 and 18 an illustration of two types of influencers. The influencer in Figure 17 looks like she is using the broad-coverage strategy. She has a lot of followers and frequently answers many different questions. She has been certified by the platform, confirming that she worked for a well-known Chinese scientific institution. However, many of her answers are not directly related to her own expertise. Meanwhile, the influencer in Figure 18 looks like she is using the focus strategy. She has fewer influencers than the previous one and self-reported on the platform that her real-life job is as a lawyer. She is certified by the platform as a "best answerer" and focuses on answering legal questions. She also provides answers less frequently than the first influencer. In fact, on the platform, we see both types of influencers as being pervasive.

Focus level construction The organization of the question topics of Zhihu is based on a topic tree, which can be described as a DAG (Directed Acyclic Graph), in which all vertices have at least one in-edges except the root. That is, any topic except the "root" has at least one parent topics. The topic tree provides us an opportunity to precisely measure the level of focus in three steps: first, we use machine learning to categorize all the questions that an influencer answered to identify the influencer's favorable topics; second, we detect the lowest common ancestor of all of the favorable topics of this influencer on the topic tree; third, we employ the distance between the lowest common ancestor and the root as the measure of focus. We use an example of a topic tree to illustrate how we measure the focus level of influencers in Figure 19.

As the green lines indicate, if influencer A is good at topics "Nature" and "Philosophy", A's focus level would be 0, since the lowest common ancestor of these two topics is the root node itself. A lower focus level implies that A's favorable topics covers a broader field of knowledge. Alternatively, if an influencer B is good at "Economics" and "Human", there are two paths through which these nodes can connect with each other: 1) Economics <- Social Science <- subject <- root -> Entity -> Human; 2) Economics <- Social Science <- Society <- Entity -> Human. The common ancestor of the first path is "root", while that of the second path is "Entity". Since root is at level 0 and "entity" is at level 1, "entity" is qualified to be the lowest ancestor and the focus level is thus 1, its distance to the root

Figure 17: A user answering questions by adopting Broad-coverage strategy

Figure 18: A user answering questions by adopting Focus strategy

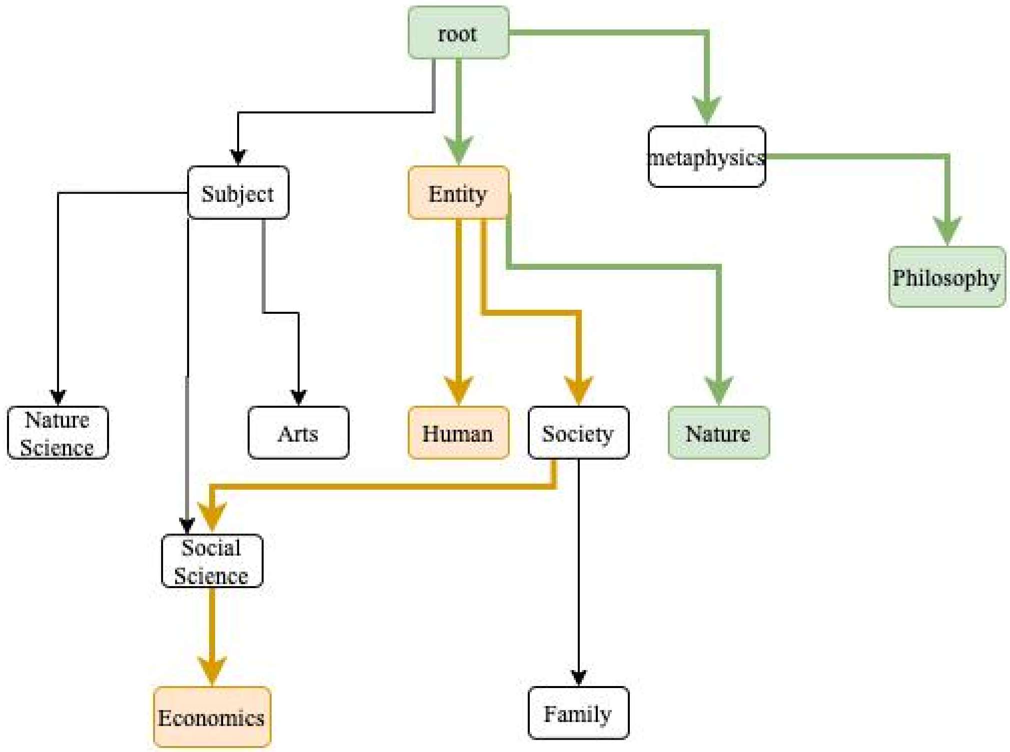


Figure 19: Example of a Topic Tree

node.

Regression evidence Results from Table 46 show that influencers with a "best answerer" badge are more likely to focus on certain specific topics when creating answers. Meanwhile, the number of created answers is negatively associated with the value of focus level. Such results are consistent with what we provide in Figure 17 and 18. An influencer with a potential high reputational concerns (e.g., "best answerer") has a stronger intensity to choose "focus strategy" and answer fewer questions. Figure 20 reports the estimated cumulative distribution function of users with a "best answerer" badge and those without "best answerer" badge. We find that the distribution of "best answerer" scholastically

Dependent variable: $Focus\ Level$			
	(1)	(2)	(3)
$Best\ Answerer$	0.491***	0.621***	0.640***
	(0.084)	(0.074)	(0.075)
$log(Answerers)$		-0.541***	-0.533***
		(0.026)	(0.026)
$log(Follower_0)$			-0.088**
			(0.041)
$Intercept$	0.919***	3.775***	4.650***
	(0.042)	(0.142)	(0.442)
N	1500	1500	1500
R^2	0.022	0.241	0.242

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

(1) A value of $Focus\ Level$ belongs to $\{0, 1, 2, 3, 4, 5, 6, 7\}$. The higher value of $FocusLevel$, the answers of influencer is more focused on certain specific topics.

(2) $Best\ Answerer$ is a binary variable that indicates if influencer has a best-answerer badge.

(3) $\log(Answerers)$ is the total number of answers created during the last 20 months.

Table 46: Regression results based on the focus levels

dominants the distribution of other uses, which further indicates the evidence that these user focus more in answering questions related to their field.

3.8.3 Sample comparisons

Figure 21a) shows the cumulative distribution function of followers, and we sort influencers by their weekly frequency of answering questions. The influencer who is ranking at 1500 creates around one answer per month, and these 1500 most active people probably account for more than 83 percent of followers. We reported both results from the sample based on six months (where we can see more variables) and the sample based on two years. We find a high degree of overlap in the results, and the groups of selected influencers based on our selection criteria did not change over time. The only difference was that the overall

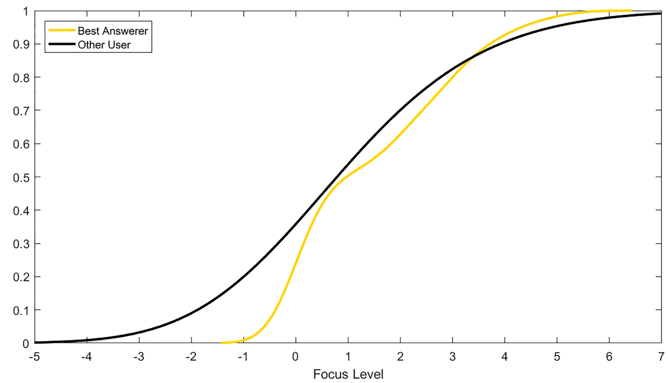
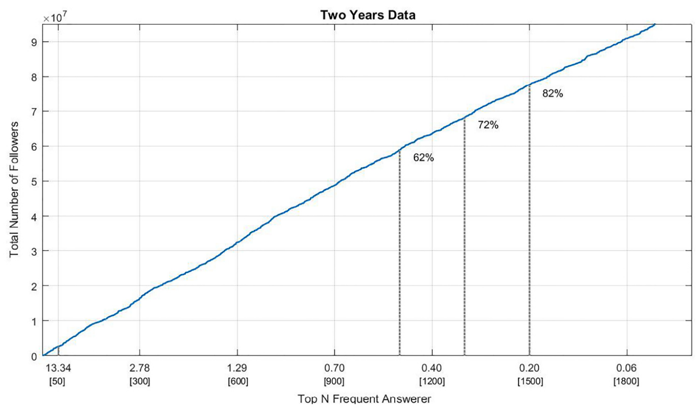


Figure 20: Cummulative distribution function of focus level between "best-answerers" and other users

frequency of answering questions in the last six months of the sample declined compared to the overall sample. We will consider and analyze this factor in the subsequent regression model.

Table 47 reports a comparison of relevant statistical values between the full sample and 6-month samples. We find that the statistical data of the two samples were highly similar, which means that our samples based on the last six months were very representative. Besides, we also check the coincidence of the influencers selected based on our criteria in the two samples. We find that 66.50% of the 388 influencers excluded in the two samples are matched. We also have concerns about whether users who had been active for two years in the original sample might have been excluded in the last six months because they were less active than in the previous 18 months. So we also double-checked user activity frequencies in the original (two-year based) and selected (six-month based) sample. Figure 22 reports the comparison, we find that there is a high degree of overlap in activity frequencies between the two samples and that users who frequently answered questions in the full sample were also positive respondents in the six-month sample.



(a)

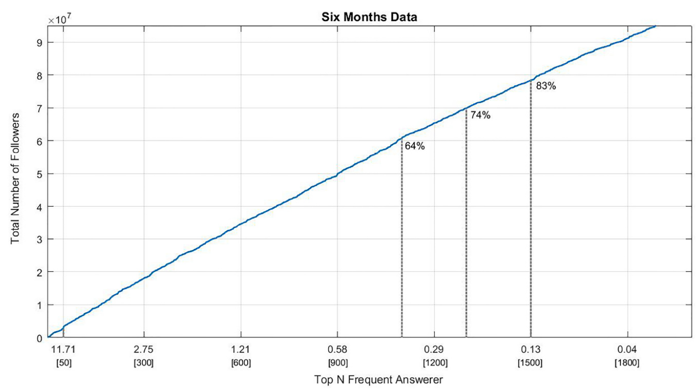


Figure 21: Top N frequent influencers (brackets show the number of remaining influencers) versus accumulated total number of followers

	Two-year full sample (81.77% of total followers)	Six-month sample (82.55% of total followers)
Total number of influencers	1888/1500	1888/1500
Increasing rate of followers	0.224	0.251
(min, max)	(-0.014, 2.268)	(-0.001, 2.268)
Avg. number of answers created	2.392	2.331
(min, max)	(0, 316)	(0, 268)
Avg. number of votes received	3.267	3.310
(min, max)	(0, 200)	(0, 200)

Note: 1. Influencers are the influential users in the platform, each of them has at least 10,000 followers;

2. Increasing rate of followers is measured in last six months data. It is calculated approximately by

$\Delta log(follower) = log(follower_{t+1}) - log(follower_t)$;

3. Avg. # of answers created is measured by week, Avg. # of votes received only contains the votes from other influencers;

4. 66.50% matching rate for unselected users (388) between two years and six months datasets.

Table 47: Summary of statistics

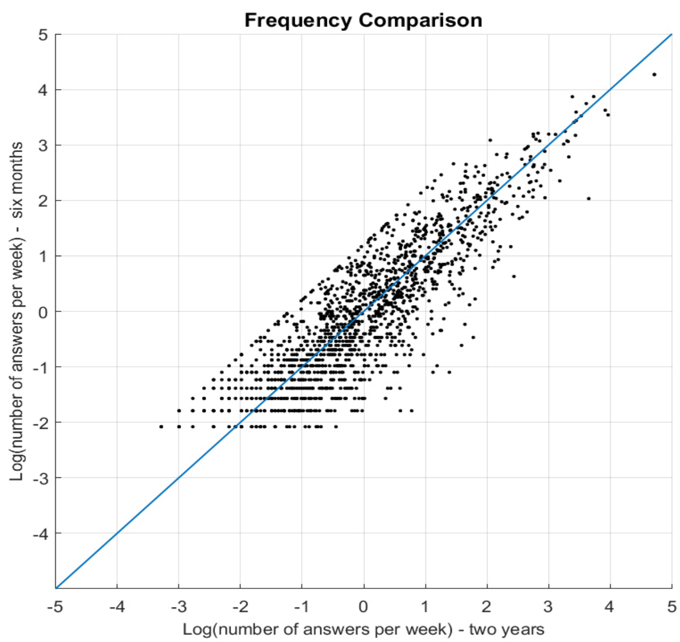


Figure 22: Comparing answer created per week per user between six-month and two-year data

3.8.4 Cross-sectional data checks

In the data, however, we do not directly observe the weekly increase in the number of votes from all followings, nor do we observe the weekly increase in the number of votes. We can observe the changes in the number of all votes before and after six months in the data. Therefore we check the following regression model:

$$\log\left(Answers_i\right) = \beta_0 + \Delta \log\left(Votes_i\right)\beta_v + \eta_i,$$
$$\log\left(Answers_i\right) = \beta_0 + \Delta \log\left(All\ Votes_i\right)\beta_v + \eta_i.$$

Regression results in the Table 48 indicate that there is almost no additional effect on the incentive of creating answers when replacing the votes received from influencers by all users. The correlation coefficients from our two regressions are almost exactly the same, which means that the vote from other influencers is a good proxy for the "peer recognition" effect. We also note that the regression coefficient of the cross-sectional data is much higher than the regression result of the panel data, which well proves that the use of lag variable can help us eliminate many potential endogenous problems.

3.8.5 Impact of knowledge spillover

One explanation of the impact of “peer recognition” is knowledge spillover: the potential number of users who can read the answer because of the other influencers’ votes may bring more votes and followers. As we have mentioned in the theoretical model, peer recognition may amplify the influence of content providers through the dissemination of knowledge and thus motivate the influencers to contribute more actively. In **??** 3.8.5, we revise all the regression results by changing the variable $\log\left(Votes_{i,t-1}+1\right)$ by $\log\left(Readers_{i,t-1}+1\right)$.

Dependent var.: $\log(Answers)$		
	(1)	(2)
	OLS	OLS
$\Delta \log(Votes)$	0.438***	
	(0.050)	
$\Delta \log(All\ Votes)$		0.444***
		(0.049)
Intercept	3.020***	3.012***
	(0.038)	(0.037)
N	1500	1500
R^2	0.047	0.050

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Standard errors in parentheses.

Table 48: The impact of "all votes" and "votes" on the answer creations

All the other variables remain unchanged, we consider the following regressions:

$$\log\left(Answers_{i,t} + 1\right) = \beta_0 + \log\left(Readers_{i,t-1} + 1\right)\beta_r + x'_{i,t}\beta_x + \delta_i + \delta_t + \eta_{i,t}, \tag{21}$$

$$with$$

$$Readers_{i,t-1} = \sum_{influencer\ j\ votes\ i\ during\ t-1} Votes_{j,t-1} \times Follower_{j,0}, \tag{22}$$

where the variable $Readers$ can be also interpreted by the potential traffics brought by the influencers who vote for the answers.

Table 49 report results of estimation from both OLS and IV models. The regression results showed that, although by construction, potential readers show a smaller influence on content creation than "received votes from influencers' votes." A 1% increase in the number of the potential number of readers raises the number of answers by 0.1%. The instrumental variables also pass the test perfectly and prove that OLS greatly underestimated the actual effect of knowledge spillover in the new regression model by almost ten times the OLS coefficient. The instrumental variables also pass the tests perfectly and prove that OLS greatly underestimated the actual effect of knowledge spillover in the new regression model by almost ten times the OLS coefficient. We report the tests related to the first stage of IV method as well as the diagnostic tests in Table 50. Specifically, this time, we construct our instruments variables by the corresponding readers brings to other articles:

$$Readers\ article\ votes_i = \sum_{influencer\ j\ votes\ i\ during\ t-1} Article\ votes_{j,t-1} \times Follower_{j,0},$$

$$Readers\ article\ collections_i = \sum_{influencer\ j\ votes\ i\ during\ t-1} Article\ collections_{j,t-1} \times Follower_{j,0},$$

where $Article\ collections_{j,t-1}$ and $Article\ collections_{j,t-1}$ are the total number of other articles that an influencer j, who votes for i's answers, votes for and collects during the period $t-1$.

Finally, we also report results by controlling if an influencer is a commercial user. Table 51 shows that if we exclude individual users and look at business users separately, the OSL results are exactly the same as the IV results.

Such regression results suggest the following: first, our method of instrumental variables is indeed robust, and we get similar results in two different situations; second, indeed, "peer recognition" can be explained to some extent by the knowledge spill over effects of content sharing via votes among the influencers; and third, we find that content providers are more concerned about whether their content is endorsed by other "experts" (i.e., influencers) than by how many ordinary users read it. One potential explanation is that in our content platform, only answers that are highly ranked under questions get more exposure. On our platform, influencers' votes are usually heavily weighted by the platform's algorithms, which means that in many instances, an ordinary user's vote has negligible weighting over an influencers' vote. Therefore, for the influencers on the platform, the

Dependent variable: $\log(Answers_t + 1)$											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	OLS	OLS	OLS	OLS	OLS	OLS	IV	IV	IV	IV	IV
$\log(Readers_{t-1} + 1)$	0.013^{***}	0.050^{***}	0.010^{***}	0.010^{***}	0.010^{***}	0.010^{***}	0.020^{***}	0.073^{***}	0.016^{***}	0.015^{***}	0.015^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$Week$					-0.204^{***}	-0.204^{***}					-0.204^{***}
					(0.023)	(0.023)					(0.023)
$Week^2$					0.008^{***}	0.008^{***}					0.008^{***}
					(0.001)	(0.001)					(0.001)
$\log(Follower_0)$						-1.333^{***}					-1.300
						(0.411)					(0.806)
Intercept	0.635^{***}	0.421^{***}	0.652^{***}	0.504^{***}	0.879^{***}	15.766^{***}	0.594^{***}	0.289^{***}	0.618^{***}	0.798^{***}	0.850^{***}
	(0.014)	(0.006)	(0.004)	(0.014)	(0.045)	(4.578)	(0.017)	(0.010)	(0.010)	(0.017)	(0.047)
Individual Fixed Effects			√	√	√	√			√	√	√
Time Fixed Effects		√		√	√	√		√		√	√
N	34500	34500	34500	34500	34500	34500	34500	34500	34500	34500	34500
R^2	0.116	0.127	0.593	0.609	0.609	0.609	0.098	0.105	0.571	0.587	0.587

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

R^2 is adjusted-R^2.

Table 49: The impact of potential knowledge spillover

Dependent variable: $\log(Readers_{t-1}+1)$	
Instrument	(1)
$\log(Readers\ article\ votes_i+1)$	1.606***
	(0.204)
$\log(Readers\ article\ collections_i+1)$	4.860***
	(0.084)
Individual Fixed Effects	√
Time Fixed Effects	√
N	34500
R^2	0.030
Kleibergen-Paap Wald stat	1680.40
(p-value)	(0.000)
Hansen J statistic	0.971
(p-value)	(0.325)
F stat	34.80

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Table 50: First stage results and diagnostic Test

increased exposure caused by the direct rise in the ranking of answers by the votes of other influencers is far more motivating than the potential audience inspired by the votes of influencers. Such results are consistent with our model's assumption and support why we choose to focus primarily on all influencers' interactions.

3.8.6 Existence of heterogeneities

We re-estimate all of the results by extending the time period to two years. Table 52 shows the corresponding results based on the two-year-period data. When we extend the timeline to two years, we find that the instrumental estimate was still higher than the OLS estimate, but the overall effect doubled over the longer timeline. This means that some factors may reduce this peer effect over time: for example, multihoming, knowledge drying, reputation accumulation, changes in platform competition environment, etc... Therefore, we fix the

Dependent variable: $\log(Answers_t + 1)$				
	(1)	(2)	(3)	(4)
	OLS	OLS	IV	IV
$\log(Readers_{t-1} + 1)$	0.010***	0.010***	0.020***	0.018***
	(0.001)	(0.001)	(0.002)	(0.002)
$Week$	-0.204***	-0.204***	-0.204***	-0.202***
	(0.023)	(0.023)	(0.023)	(0.023)
$Week^2$	0.008***	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
$\log(Follower_0)$	-1.333***	-1.297	-0.017	-0.017
	(0.411)	(0.807)	(0.017)	(0.017)
$Commercial$		-0.038		-0.087
		(0.410)		(0.086)
$Commercial \times \log(Readers_{t-1} + 1)$		0.012***		0.039***
		(0.003)		(0.008)
Individual Fixed Effects	√	√	√	√
Time Fixed Effects	√	√	√	√
N	34500	34500	34500	34500
R^2	0.609	0.610	0.605	0.607

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

$Commercial$ is a binary dummy variable.

R^2 is adjusted, it is derived from LSDV (Least Square Dummy Variable) regression with Stata.

Table 51: Impact on creating new answers - commercial and non commercial influencers

timeline for six months, in order to use the additional variables we observed to check which channels were primarily reducing peer motivation.

Dependent variable: $\log(Answers_t + 1)$						
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	IV	IV	IV
$\log(Votes_{t-1} + 1)$	0.199***	0.203***	0.198***	0.271***	0.281***	0.277***
	(0.002)	(0.002)	(0.002)	(0.010)	(0.012)	(0.012)
Intercept	0.517***	0.494***	0.498***	0.462***	0.429***	0.433***
	(0.013)	(0.020)	(0.015)	(0.015)	(0.022)	(0.018)
Individual Fixed Effects			√			√
Time Fixed Effects		√	√		√	√
N	118500	118500	118500	118500	118500	118500
R^2	0.157	0.163	0.547	0.145	0.160	0.535

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, standard errors in parentheses.
Instrumental variables are $\log(Article\ collections_{t-1} + 1)$ and $\log(Article\ votes_{t-1} + 1)$.
R^2 is adjusted-R^2.

Table 52: Instrumental Variable regression results

3.8.7 Concern of potential multi-homing

The best candidates may also receive less incentive from others' votes because other competing platforms may poach them after they have been awarded as "best answerer" in their field. Under the assumption that the multi-homing probability is positively correlated with the number of followers, our estimation result in Table 53 shows that the multi-homing concern only exists in the "non-best answerer" group. After controlling both the number of followers and the "best answerer," the increase of followers has a positive and significant impact on peer incentives of "best answerer". Such finding shows that the multihoming concern is significantly reduced among the "best answerer". However, the reputational concerns related to the yellow badge still exist and even dominate the potential multihoming effect. After controlling for all variables, the crossover between the "best answerer" and the votes received is still significantly negative. Even after the followers are taken into account, the majority of influencers are less motivated to vote if they are "best answerer." Based on Figure 23, we find that only about 10% of superstars (with more than 100,000 followers) for whom getting "best answerer" might make them more motivated by peer recognition. For other influencers in general, reputational concerns remains and significantly affects their content contributions.

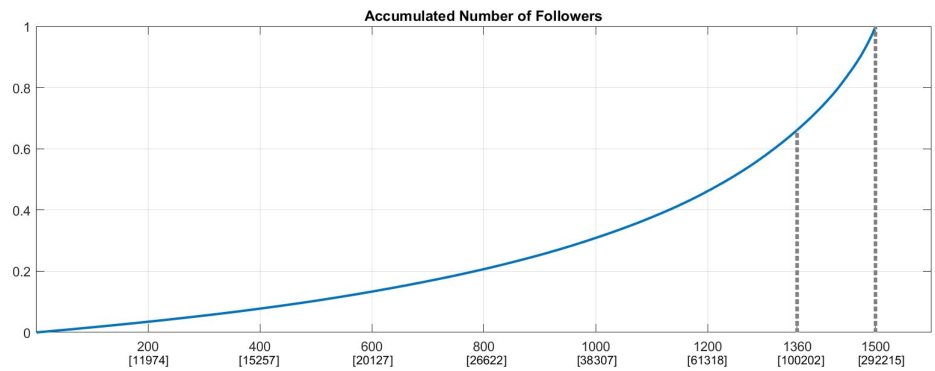


Figure 23: Influencers are ranked by their number of followers

3.8.8 Impact of getting a badge

In this section, we check the effect of the badge issued by the platform on influencers' motivation for providing answers. In particular, we do not specify the types of badge. Holding a badge indicates that an influencer belongs to at least one of the following categories: first, a self-authenticated user; second, a platform awarded "best answerer"; and third, a commercial user. Results in Table 54 show that the fact of holding a badge negatively affects on frequency of providing new answers.

Dependent variable: $\log(Answers_t + 1)$						
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
$\log(Votes_{t-1} + 1)$	0.183***	0.187	0.170***	0.194	0.280***	0.441**
	(0.054)	(0.186)	(0.055)	(0.186)	(0.065)	(0.223)
$Week$	-0.208***	-0.208***	-0.209***	-0.209***	-0.209***	-0.209***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
$Week^2$	0.008***	0.009***	0.009***	0.009***	0.008***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\log(Follower_0)$	0.346***	0.325***	0.337***	0.047*	0.357***	0.372***
	(0.112)	(0.116)	(0.116)	(0.026)	(0.112)	(0.119)
$\log(Follower_0) \times \log(Votes_{t-1} + 1)$	-0.009*	-0.007	-0.007	-0.008	-0.018***	-0.032
	(0.005)	(0.018)	(0.005)	(0.018)	(0.006)	(0.022)
$Best$			-0.892**	-0.894**	-0.550	-0.147
			(0.375)	(0.400)	(0.388)	(0.537)
$\log(Follower_0) \times Best$			-1.174***	-1.170***	-1.204***	-1.242***
			(0.307)	(0.302)	(0.307)	(0.304)
$\log(Votes_{t-1} + 1) \times Best$			-0.031***	-0.013	-0.408***	-0.855**
			(0.009)	(0.030)	(0.122)	(0.411)
$\log(Follower_0) \times \log(Votes_{t-1} + 1) \times Best$					0.036***	0.081**
					(0.011)	(0.039)
Individual Fixed Effects	√	√	√	√	√	√
Time Fixed Effects	√	√	√	√	√	√
N	33235	33235	33235	33235	33235	33235
R^2	0.615	0.611	0.615	0.611	0.615	0.611

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

R^2 is adjusted, it is derived from LSDV (Least Square Dummy Variable) regression with Stata.

Table 53: Impact of number followers on answers created (non-commercial influencers)

Dependent variable: $\log(Answers_t + 1)$						
	(1)	(2)	(3)	(3)	(4)	(4)
	OLS	OLS	OLS	IV	IV	IV
			(non-commercial)			(non-commercial)
$\log(Votes_{t-1} + 1)$	0.088***	0.093***	0.093***	0.124***	0.112***	0.113***
	(0.004)	(0.005)	(0.005)	(0.013)	(0.016)	(0.016)
$Week$	-0.203***	-0.203***	-0.209***	-0.202***	-0.201***	-0.208***
	(0.024)	(0.023)	(0.024)	(0.023)	(0.023)	(0.023)
$Week^2$	0.008***	0.008***	0.007***	0.008***	0.008***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\log(Follower_0)$	-1.111***	-1.500*	0.323***	-0.885**	-1.539*	0.313***
	(0.410)	(0.804)	(0.112)	(0.410)	(0.790)	(0.110)
$Badge$		0.166	0.102		0.197	0.107
		(0.409)	(0.143)		(0.406)	(0.143)
$Badge \times \log(Votes_{t-1} + 1)$		-0.018***	-0.025***		0.047*	-0.008
		(0.008)	(0.009)		(0.028)	(0.029)
Individual Fixed Effects	√	√	√	√	√	√
Time Fixed Effects	√	√	√	√	√	√
N	34500	34500	33235	34500	34500	33235
R^2	0.611	0.611	0.615	0.608	0.607	0.609

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

R^2 is adjusted, it is derived from LSDV (Least Square Dummy Variable) regression with Stata.

Table 54: Impact on creating new answers - badge and no badge influencers

3.8.9 An anecdotal evidence of privacy concern

In the late December 2019, Zhihu has launched a more severe “real name” authentication policy: the platform requires every registered user to provide mobile phone details and pass the real-name authentication. Users who refuse to contribute will be subject to certain restrictions as to what they can say on the platform. Such a policy worries many users, some of whom even refuse to continue exporting content online. Figure 25 shows an article by Mather King, one of the "best answerer" under the math questions. The article received more than 3,000 votes within two days of publication. In the article, the author made clear her potential concerns about personal privacy disclosure after being asked to provide real-name information. She said that she would henceforth stop contributing any academic content to the platform.

按照相关法律法规规定，为了更好的提供服务，保障帐号安全，需要你进行帐号的真实身份核验。我们提供 +86 手机号、身份证号、身份证件等多种核验方式。未核验的帐号，我们可能会限制提问、回答、文章、评论等操作。

点击「实名认证入口」进行核验。知乎也会通过其他方式提醒你去核验。

如果你有任何问题，请联系「知乎小管家」。

感谢你的理解与支持。

According to the relevant laws and regulations, you are required to provide the real identity of your account in order to allow us to provide better service and ensure the security of the account. We offer the following verification methods: 1) by providing your mobile phone; 2) by providing your national identification number; 3) by providing your passport number. Unverified accounts will be blocked from asking questions, answering questions, creating articles, and even making comments.

Please click *real-name authentication* to verify your account. Zhihu will also notify you to verify your personal account in other ways.

If you have any questions, please contact [Zhihu manager].

Thanks for your cooperation and understanding.

Figure 24: An anecdotal evidence of the raising privacy concerns in the platform

Dear friends,

I received an official notice from Zhihu that if I do not perform real-name authentication, I can no longer "speak" in this platform. Frankly speaking, it may be bad for me to do real-name authentication based on what I have done in the past. (It's not difficult to find out who I am, but it is falling into snare if I report my identity information.) If I perform real-name authentication, I will need to speak cautiously and will be very unhappy. If something happens, it will be even more frightening. I do not want these things to happen. Therefore, I choose to do not perform real-name authentication and never speak in this platform. Recently, the contents I have published were often deleted or blocked by the platform. The behaviors of the platform for me are same as asking me to shut up.

In this platform, I published many answers and articles which are mainly used for spreading knowledge of Probability Theory. I have tried my best to write as many answers/articles as I can in this field. Since my current research does not focus on probability theory, it is difficult for me to publish any new creation specific to this field. Hence, I cannot continue to maintain the Random Walk column and share new knowledge related to Random Walk anymore. By the way, this column is also inconsistent with the current entertainment style in Zhihu.

I have to stop sharing other interesting news as well. I just hope that you will try your best to find the opinions of all parties, try to read them even if you do not like them. Please do not be played around and cheated by unitary voice. Tries to check whether it is consistent and to avoid double standard by putting the logic you have accepted to another thing you are looking at.

Zhihu is becoming more and more entertaining now, I can even take this opportunity to stop using it and save my time to do other meaningful things.

Thank you, bye!

Figure 25: An anecdotal evidence of the raising privacy concerns on the platform

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