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Favor Exchange with Private Costs: An Experiment*

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Abstract/Résumé

We conduct an experiment on a two-player infinitely repeated favor exchange game. In the stage game, each player must decide whether to provide a favor to the other player. A favor generates a fixed benefit for the recipient and a cost for the provider, which can be either low or high. We study the situation where this cost is private information, and it is efficient to provide a favor only when the cost is low. We address two general questions: To which extent subjects exchange favors in ways that are payoff enhancing, given that private information hinders exchanging favors efficiently? Which strategies do subjects choose and what are the driving forces behind their choices? We focus on Stationary Strongly Symmetric (SSS) strategies, where players play the same strategy after any history, and Equality Matching (EM) strategies, where subjects keep track of the net tallies of favors. We find that overall subjects in the experiment exchange favors to a relatively large extent and achieve an average payoff-efficiency index exceeding 60%. Although simpler strategies, as SSS, are played with the highest frequency, more complex strategies, as EM strategies, explain an important proportion of the data. Subjects' behaviors are not always consistent with incentive compatibility or driven by the attainment of the highest payoffs. The results also suggest that rewarding subjects for trusting and reciprocating when it is efficient might be more acceptable than requiring them to take very costly actions on equilibrium path, even when it is overall payoff enhancing.

Nous menons une expérience sur un jeu d'échange de faveurs à deux joueurs répété à l'infini. Dans le jeu de base, chaque joueur doit décider s'il doit rendre une faveur à l'autre joueur. Une faveur génère un bénéfice fixe pour le bénéficiaire et un coût pour le prestataire, ce coût pouvant être faible ou élevé. Nous étudions la situation où ce coût est une information privée, et il est efficient de rendre une faveur uniquement lorsque le coût est faible. Nous abordons deux questions générales : dans quelle mesure les sujets échangent-ils des faveurs de manière à améliorer leur utilité, étant donné que l'information privée empêche un échange de faveurs efficient ? Quelles stratégies choisissent les sujets et quels sont les facteurs qui influencent leurs

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choix ? Nous nous concentrons sur les stratégies Stationary Strongly Symmetric (SSS), où les joueurs suivent la même stratégie après chaque historique, et les stratégies d'Equality Matching (EM), où les sujets suivent les comptes nets de faveurs. Nous trouvons qu'en général, les sujets échangent des faveurs dans une large mesure et atteignent un indice d'efficacité des gains moyen supérieur à 60 %. Bien que des stratégies plus simples, comme les SSS, soient jouées avec une plus grande fréquence, des stratégies plus complexes, telles que les stratégies EM expliquent également une part significative des comportements observés. Les comportements des sujets ne sont pas toujours cohérents avec la compatibilité des incitations ou motivés par l'obtention des gains les plus élevés. En outre, les résultats suggèrent que récompenser la confiance et la réciprocité des joueurs lorsqu'il est efficient de le faire peut être plus acceptable que de les contraindre à prendre des actions coûteuses, même si cela conduit à une plus grande efficacité globale.

Keywords/Mots-clés: Favor exchange, Indefinitely repeated games, Incomplete information, Strategy estimation, Strategy fitting / Échange de faveurs, Jeux répétés à l'infini, Information incomplète, Estimation de stratégie, Ajustement de stratégie

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1 Introduction

Providing a favor is a costly action which only improves the well-being of the recipient but yields no direct benefit to the provider. Many social interactions can be thought of as favor exchange situations. For instance, trading partners may offer special pricing, oligopolistic firms may collude, parents can exchange babysitting services, practitioners can refer patients to each other, representatives in Congress may engage in logrolling, and many favors are typically exchanged within the household and between colleagues or friends. The exchange of favors generates mutual gains for self-interested agents and carries out a part of economic activities through long-term cooperation without the need of explicit agreements. In many favor exchange situations, private information is pervasive, especially information regarding the cost of providing a favor. For example, oligopolistic firms might privately observe their production cost. Similarly, in the context of the referral of clients between associate practitioners, a practitioner may have private information about the condition of her patient. She could provide a specialized treatment herself, 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 ability of the specialist in dealing with such a condition. Analogous arguments apply to the associate specialist in referring some of her clients to the general practitioner. In these situations, a firm (or a practitioner) must decide whether to provide a favor before observing whether the other firm (or practitioner) has done a favor. So favors can be exchanged simultaneously.

We propose a very simple model to study the exchange of favors with private costs. We consider an infinitely repeated game of favor exchange with two players. In the stage game, each player has to decide whether to provide a favor to the other player. Each favor generates a fixed benefit to the recipient and a cost to the favor provider that can take two possible values, low or high. We study a situation of repeated adverse selection where this cost is private information and it is efficient to provide a favor only when the cost is low. We assume that the private costs of the two players are drawn from a joint distribution, independently across periods. In our game, efficiently exchanging favors (i.e. providing a favor if and only if given a low cost) in each period cannot be sustained as an equilibrium, since a player with a low cost can always mimic the behavior of a player with a high cost and non-cooperative behavior (not providing a favor given a low cost) is not detectable.

We investigate two general questions in this paper. We want to assess to which extent subjects exchange favors in a way that is payoff enhancing, in a setting where private information of doing a favor hinders the possibility of exchanging favors efficiently. Furthermore, we aim at understanding the strategies that subjects use in exchanging favors and the forces driving subjects' strategy choices.

There are infinitely many equilibria in these types of games. Players may follow very simple strategies that only depend on the current cost but are independent of the public history; or extremely complicated strategies that rely on both the public and private history. A common approach in the theoretical and experimental literature on repeated games with imperfect monitoring is to focus on public strategies (see, e.g. Aoyagi and Fréchette, 2009, Fudenberg et al., 2012, Embrey et al., 2013, Aoyagi et al., 2019). We focus on two classes of public strategies. The first class is Stationary Strongly Symmetric (SSS) strategies that prescribes players to play after any on equilibrium history the same strategy that only depends on the private cost in the current period. Strongly Symmetric public strategies have been considered in favor exchange games (see. e.g. Athey et al., 2004 and Abdulkadiroğlu and Bagwell, 2013) and are often considered in other applications of repeated games with imperfect monitoring (see Mailath et al., 2006, p. 231). The second class consists of Equality-Matching (EM) strategies. As emphasized by Abdulkadiroglu and Bagwell (2012), Jeitschko and Lau (2017) and Leo (2017), Equality Matching is one of the four principles introduced by anthropologist Fiske (1992) governing social relationships. "In Equality Matching relationships people keep track of the balance or difference among participants and know what would be required to restore balance".[1] There is a natural and commonly expected tendency towards wanting to restore an equal balance. Therefore, the Equality Matching principle entails some concept of 'budgeting', 'turn-taking', 'reciprocity', and 'equality' (see also Leo 2017). In the favor exchange environment, the Equality Matching principle implies that people receiving a favor somehow feel obliged to eventually return the favor. Within this class, we focus on what we call Bounded Favors Bank (BFB) strategies, which we examine theoretically in our companion paper Degan et al. (2023) and the Simple Equality Matching (SEM) strategy. BFB are Markov strategies that, as in Möbius (2001), use the net number of favors of a player as a state variable. A BFB imposes a boundary on the net number of favors that each player can receive (and the paired player can provide). A BFB is characterized by its boundary, which determines the dimension of the state space. When none of the players has yet reached such boundary, a BFB strategy prescribes each

[1] https://www.sscnet.ucla.edu/anthro/faculty/fiske/relmodov.htm

player to do a favor when it is efficient to do so. When a boundary is reached, we consider two types of BFB strategies. The first type, referred as BFB with reward (BFBr) requires a form of reward for the player who provided the maximum net number of favors. The second type, referred as BFB with punishment (BFBp) requires a form of punishment for the player who received the maximum net number of favors. By construction, BFB are symmetric, players start in a balanced position and return to this balanced position with positive probability in the long run. The SEM strategy that we propose is a symmetric extension of the Simple EM relationship introduced and studied in Abdulkadiroglu and Bagwell (2012).[2] In short, players start in a balanced position and a player is prescribed to provide a favor when it is efficient. After the first favor has been provided, players take turns in providing favors, conditional on it being efficient. They never go back to a balanced position where they have the same continuation value.

In line with the EM principle, BFB and SEM strategies incorporate certain rules of thumb we observe in real life. The boundary on the net number of favors in BFB can be considered as a bottom line that both players commonly recognize and find acceptable and incentive compatible. Beyond these boundaries, a common saying such as "enough is enough" describes a situation off the equilibrium path of BFB strategies, where cooperation collapses. The common wisdom requiring that individuals take turns in doing favors in order to sustain a long-term cooperative relationship, is embedded to different extents in our EM strategies in a particular way that depends on the distribution and realization of the private costs and the state space. However, EM strategies are more sophisticated than SSS strategies, as they condition on a summary statistics of the entire public history of favor exchange.

We conduct a lab experiment and strategy analysis to answer the following specific questions. First, to which extent players can achieve efficiency when they exchange favors in the presence of private costs? Second, to understand the strategies used by players and their driving forces we address the following questions: (a) do subjects tend to choose simple strategies as SSS strategy or more complex strategies as our EM strategies? (b) is the prevalence of the different strategies affected by the cost of providing favors or incentive compatibility? (c) does increasing the salience of the balance of favors increases the prevalence of EM strategies? (d) is the prevalence of the different strategies related to the strategy's payoff?

[2] See Section 2 for more details.

In order to address the above questions, we vary our experimental environment along two dimensions: the value of the parameters and the visibility of the net number of favors (i.e., the state variable in BFB strategies). In the first dimension, we vary the value of the (high) cost, so as to affect the equilibrium conditions and so as to alter the set of BFB and SSS strategies that are sustained as equilibria. In the other dimension, we explore different visibilities of the net number of favors. Specifically, in addition to showing the history of favors done and received, we choose whether to show the net number of favors received to subjects in each decision round. This does not affect the set of equilibrium strategies but it might nevertheless affect the subjects' behavior due to a framing effect or other behavioral impact. Given the multiplicity of equilibria in infinitely repeated games, showing explicitly the actual balance of favors in the relationship, might provide a nudge for the subjects to coordinate on using EM strategies, or simply provide more confidence in the relationship and increase the willingness to provide favors.[3]

Our experimental results offer new understandings on long-term bilateral favor exchange relationships and, more generally, on behaviors in two-players incomplete information games where achieving high payoff requires some form of trust and intertemporal reciprocity.

We find that, overall, subjects in our experiment exchange favors to a surprisingly large extent, considering that doing favors is a costly action that provides no direct benefit to the provider and that in our setting the cost of doing a favor is private information. We calculate an index of payoff-efficiency similar to Embrey et al. (2019). The payoff-efficiency index in each session exceeds 50%, with an average of 63% across sessions. However, there exists significant efficiency loss compared to the equilibrium strategies we consider.

We employ the Strategy Frequency Estimation Method (see, e.g., Dal Bó and Fréchette 2011, 2019, Jones 2014, Romero and Rosokha 2018), SFEM hereafter, to measure the prevalence of different strategies. We follow a two-step procedure (see Fudenberg et al. 2012), where in addition to the strategies introduced above, in the first step we also include lenient and forgiving strategies considered in the repeated PD literature.[4] We find interesting answers to our research questions. First, in all the treatments, simpler strategies (SSS strategies) have larger empirical support than

[3]Analogously, in the traditional coordination games, "labelling" does not change the formal structure and the equilibrium set of the game. However, it plays an important role in equilibrium selection (Schelling 1960, Mehta et al. 1994).

[4]We thank the anonymous reviewers for the suggestion of including the SEM and strategies with leniency and forgiveness in our analyses.

more complex strategies (EM strategies and strategies with leniency and forgiveness). Among the SSS strategies, the non-cooperative strategy (never do favors) and the efficient strategy (do favors if and only if cost is low) together explain more than 61% of the observed data across all the treatments. Nevertheless, BFBr strategies account for 10%~30% of the observed data across all the treatments. No other strategy finds empirical support. Second, subjects' behavior is not always consistent with the incentive compatibility conditions. In particular, we find that the SSS strategy of always doing favors when on the equilibrium path and the BFBp strategies are not played with statistically significant probabilities, even in the treatments where they are sustained as equilibrium strategies and theoretically lead to a higher ex-ante expected payoff than the BFBr strategies. These results do not support the expected payoff alone as a driving force behind the adoption of the strategy. Instead, our experimental results indicate that subjects' behavior may be influenced not only by the incentives but also by certain rule of thumb or social norms. In a bilateral relationship with private information, players seem reluctant to provide a favor when it is extremely costly, and social norms that reward subjects for trusting and reciprocating in balanced relationships might be more acceptable than social norms that require taking very costly actions in order to reestablish balance in the relationship. Third, explicitly showing subjects the balance of favors increases the prevalence of BFBr strategies by around 10% at the expenses of SSS strategies. Therefore, our result suggests that explicit forms of balance keeping might enhance the probability that individuals choose EM strategies.

As a complementary approach to the SFEM, we also use the strategy-fitting procedure by Camera et al. (2012) for strategy analysis. We find that the results are mostly consistent with the SFEM and the strategy set we consider performs very well in describing the individuals' behavior in the data.

The paper is organized as follows. Section 2 discusses the related literature and the contributions of our paper. Section 3 and Section 4 present the theoretical model, and strategies we focus on. Section 5 presents the experimental design, the theoretical predictions and research questions. The main results are reported in Section 6 and Section 7 concludes. Additional details on the theoretical results and data analysis, as well as the experiment instructions, can be found in Online Appendix.

2 Contributions and Related Literature

Models of favor exchange with private information have been extensively studied in the theoretical literature. Previous papers have considered models where players privately observe the possibility of providing a favor and only one player at a time can have such possibility (e.g., Möbius 2001, Hauser and Hopenhayn 2008, Abdulkadiroglu and Bagwell 2012, Abdulkadiroğlu and Bagwell 2013, Jeitschko and Lau 2017).[5] A simple family of strategies that has been widely studied in settings with indivisible favors, as ours, is called chip strategies (see Möbius 2001, Abdulkadiroglu and Bagwell 2012, Olszewski and Safronov 2018b), in which players behave as if they were endowed with a finite number of chips, and when a player receives a favor, she has to give a chip to the favor provider. If a player has no chip left, she cannot receive any more favors.[6] Different from these papers, we consider a model where each player can provide a favor in each period and the source of private information is the cost of doing a favor to the other player (see Degan et al. 2023). BFBr with boundary n is mathematically equivalent to the chip strategy with an endowment of n chips to each player. However, BFBp are new to the literature, as the traditional setting with indivisible favors does not allow both players to make favors simultaneously. Our SEM is a symmetric extension of the (asymmetric) Simple EM relationship considered by Abdulkadiroglu and Bagwell (2012), where one of the two players is endowed with a chip and only a player with no chip is prescribed to make a favor, provided that it is efficient. It should be pointed out that also BFBp and SEM could be implemented with chips. In these cases, while for BFB strategies an equal number of chips should be assigned to each player at the beginning of the game, for the SEM strategy a chip should be assigned to the first player who does a favor.

Our paper is also related more broadly to other repeated games with incomplete information, like repeated duopoly games with private cost of production (see, e.g., Athey and Bagwell 2001, Athey et al. 2004, Athey and Bagwell 2008), repeated entry games with private cost of entry (see, .e.g. Kaplan and Ruffle 2012), repeated actions with private evaluations (see, e.g., Aoyagi 2003, 2007), repeated common task game (Leo 2017), and repeated partnership (Radner et al. 1986).

[5] An exception is Olszewski and Safronov (2018a), who consider a much more general setting.

[6] Olszewski and Safronov (2018b) show that chip strategies can approximate the efficient outcomes in these models where players have only two types. Abdulkadiroğlu and Bagwell (2013) allow for divisible favors and, as Hauser and Hopenhayn (2008) and Jeitschko and Lau (2017), consider strategies that allow the balance of favors to appreciate/depreciate over time.

Among these papers, the setting of the seminal duopoly paper by Athey and Bagwell (2001) is close to ours because the firm's cost of production is private information and can take only two values. However, their framework allows for the efficient production to be achieved on equilibrium in each period. Leo (2017) considers a setting where players must accomplish a common task that needs the effort by only one player. He considers a mechanism with communication that allows players to take efficient turns, where the swap between players depend on the cost. As in our setting, it is efficient that only a player with low cost takes the costly action, and some sort of sequentiality in favors emerges naturally from strategies where favors exchange is payoff enhancing.[7]

It is important to point out that our favor-exchange model is related to repeated Prisoner's Dilemma (PD) games with perfect and imperfect public monitoring but there are some important differences between the two. The payoff matrix of repeated PD games can be formulated in a benefit/cost form, where 'cooperation' implies both paying a cost and providing a benefit to the other player (see, for example, Fudenberg et al. 2012 and Aoyagi et al. 2019). However, there is a critical difference in the payoff structure between repeated PD games and our game. An essential feature of PD games is that the action profile that maximizes the sum of (expected, if imperfect monitoring) payoffs of the stage game is that both players cooperate. This is one reason why the literature has focused on the analysis of strategies that support cooperation. Conversely, in our model, conditional on the realization of the cost of making favors, having both players providing a favor never maximizes the sum of the players' payoffs.[8] A second difference is the source of information asymmetry. While in repeated PD with imperfect information each player's move is private information and is observed with error by the other player, in our model players' actions are publicly observed but their types are not. Because of these two differences, strategies supporting the provision of favors unconditional on the cost are not necessarily appealing nor natural in the favor-exchange context.

Compared to theoretical studies on favor exchange, empirical work on this topic remains largely unexplored. 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

[7]In some contexts sequentiality could be an intrinsic feature of the stage game. For example Camera and Gioffré (2022) study an infinitely repeated "helping game" where interactions is one-sided. See Ghidoni and Suetens (2022) for the analysis of the effect of sequentiality in repeated games.

[8]Even in the more general setting where both players can have low costs, there are cost realizations where having both players' doing favors is not efficient.

Möbius (2001) and has focused on comparative static analysis with respect to the parameters of the model. Due to the continuous-time feature of his setting, estimation of individual strategies is beyond the scope of his analysis. A few papers study environments of favor exchange (see Leo 2017 and Hyndman and Müller 2020), but are based on different theoretical models from ours and do not conduct strategy estimation. Our study is the first one that sheds light on the strategies that subjects employ in a favor exchange environment.

Our paper also contributes to the experimental literature on infinitely repeated games, especially the one on repeated PD games that aims at studying the strategies employed by subjects. In experiments on repeated PD games with complete information, using SFEM some papers find that Always Defect (AD) and Tit-for-Tat (TFT) are the most frequently employed strategies across treatments (see, e.g., Dal Bó and Fréchette 2011, Romero and Rosokha 2018, Dal Bó and Fréchette 2019, Romero and Rosokha 2023). Jones (2014) explores an experimental setting where subjects played a series of 3-by-3 versions of the PD game with complete information and finds that subjects are more likely to use a simple selfish strategy of AD 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 well the behavioral patterns in the experiments considered in the literature as long as the discount rate exceeds a particular threshold. Bigoni et al. (2024) present a novel strategy, Payback, which allows players to return to mutual cooperation after a single period of asymmetric punishment in infinitely repeated PD games. Using three meta-datasets from others' experiments, their maximum likelihood estimation results indicate that the fraction of subjects playing Payback is comparable to and higher than that of TFT and Grim in infinitely repeated games with perfect monitoring and imperfect monitoring, respectively. Similar to them, we use SFEM to estimate strategies played by subjects in the repeated game of favor exchange. However, the nature of favors and the incomplete information setting give rise to different types of strategies than in PD games. For the same reasons, we also expect that favor exchange strategies that are payoff enhancing compared to the repetition of Nash equilibrium of the static game are more difficult to achieve than cooperative strategies in PD games. Engle-Warnick and Slonim (2004, 2006), and Camera et al. (2012) use a complementary approach to SFEM to study the strategies used by subjects in infinitely repeated games by selecting the best fitting strategies.

Engle-Warnick and Slonim (2006) find that subjects playGrim strategies that are consistent with equilibrium predictions in the infinitely repeated trust games. In contrast, Camera et al. (2012) find that Grim does not well describe individual behavior in infinitely repeated PD games where players randomly and anonymously meet each other in each period. In addition, Camera et al. (2012) find heterogeneity in individual behavior and suggest that no single strategy can classify the majority of individuals.

Finally, our paper is also related to several other empirical papers that used field data to study the exchange of favors in different scenarios (see, e.g. Flynn and Brockner (2003), Jackson et al. (2012), Szeidl and Szucs (2021)).

3 Model

Our experiment is based on a discrete-time model of exchange of indivisible favors between two infinitely lived players who discount the future according to the discount factor $\delta < 1$. In each period each player has to decide between two actions: "Do a favor", denoted as F, or "Do not do a favor", denoted as N, to the other player. Each player $i \in \{1, 2\}$, 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, $0 < c_l < x < c_h$.

The stage game is represented in the following Table 1.

Table 1: The stage game

player 1	player 2	
	F	N
F	$x - c_1, x - c_2$	$-c_1, x$
N	$x, -c_2$	0, 0

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 realization of the cost at period $t+1$ and hence allows using a recursive formulation of the problem. In each period, a draw of the two players' costs $(c_1, c_2) \in \{(c_l, c_l), (c_l, c_h), (c_h, c_l), (c_h, c_h)\}$ is realized according to the joint probability distribution shown in Table 2. A player has a low cost with marginal probability

$\Pr(c_l) = p$ and a high cost with marginal probability $\Pr(c_h) = 1 - p$. In addition, we assume a particular form of complementarity between players that only one player in each period can have a low cost of providing a favor and hence $p < \frac{1}{2}$. This assumption not only simplifies the analysis but it also keeps the setting closer to models of favors exchange that have studied chip strategies (see, Section 2).

Table 2: Joint distribution of the costs of providing a favor

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

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

We are interested in the situation where the allocations of favors are publicly observed but each player's cost is private information. So a player's cost realization in a period is a player's type. In addition, there is no explicit commitment device available to players. The repeated game we consider is therefore one with imperfect public monitoring where the constituent game is an adverse selection game.[9] We restrict attention to public strategies.

4 Strategies

In infinitely repeated games, the set of equilibrium strategies is infinite. One common approach in the experimental literature on infinitely repeated games is to focus on a subset of simple and intuitive strategies.[10] We therefore restrict our attention to a set of simple and intuitive public pure-strategies for indivisible favor exchange games. In particular, we will consider Stationary Strongly Symmetric (SSS) strategies and two types of Equality Matching strategies, Bounded Favors Bank (BFB) strategies and Simple Equality Matching (SEM) strategy. SSS strategies are strategies where

[9] It is a game with imperfect public monitoring because, although player's moves are publicly observed, since players choose moves conditional on the realization of private types, the link between moves and strategies is not publicly observed (see Mailath et al. (2006)).

[10] See, for example Dal Bó and Fréchette (2011), Dal Bó and Fréchette (2018). An alternative approach is to elicit strategies directly from subjects. See Dal Bó and Fréchette (2019).

after any history on the equilibrium path both players (symmetrically) play the same (stationary) strategy. By contrast, in EM strategies players' actions in each period rely on state variables summarizing the balance of the historical information on the favors exchanged. Therefore, BFB and SEM have a more complex strategy structure than SSS, and may require more sophisticated thinking for players to implement them. Here we concisely present each strategy. Readers can find additional details in Online Appendix A.

Stationary Strongly Symmetric (SSS) strategies

We let s^{qj}, $q, j \in \{F, N\}$, indicate the SSS strategy, where each player takes action q when she has a low cost and action j when she has a high cost, as long as no deviation from this prescription has been detected from the public history, and she reverts to playing the unique stage game pure-strategy equilibrium otherwise.

First, consider SSS strategies that prescribe the same action independent of the cost. Clearly, s^{NN}, where the player does not make favor independent of the cost, is an equilibrium for any discount factor as it prescribes playing the unique stage-game Nash equilibrium in each period. Strategy s^{FF}, prescribing each player to make a favor independent of the cost, constitutes a SSS equilibrium, if and only if $x - c_l p - c_h(1-p) > 0$ (individually rationality) and $\delta \geq \frac{c_h}{x+p(c_h-c_l)}$ (incentive compatibility).

Now consider SSS strategies that prescribe different actions for low and high costs of making favors. It is easy to see that s^{NF}, prescribing a player to make a favor only when she has a high cost induces an average discounted payoff that is not individually rational. As a consequence, s^{NF} can never be an equilibrium strategy. Special attention needs to be given to s^{FN}, which prescribes that in any period each player does a favor if she has a low cost and no deviation has ever been detected, and otherwise she does not provide a favor. This strategy allows achieving the efficient outcome, but when the cost of providing favors is private information, s^{FN} is not an equilibrium strategy for any discount factor.[11]

[11] The outcome induced by s^{FN} maximizes the stage game sum of payoffs and is ex-ante a symmetric Pareto optimum. A deviation from the main prescription can be detected from the public history only when both players do a favor. In fact, given our assumption that at any given time only one of the two players can have a low cost, the outcome where both players provide a favor should never be observed when players follow this strategy. All other outcomes can be observed with a positive probability. As a consequence, a player with a low cost will find it profitable to deviate for any $\delta < 1$. When the costs of providing favors are observable, s^{FN} is an equilibrium for $\delta \geq \frac{c_l}{(x-c_l)p+c_l}$.

Bounded Favors Bank (BFB) strategies

As explained in Degan et al. (2023), BFB are stationary Markov strategies where: on equilibrium path the state variable k, the net number of favors, is defined as the total number of favors received minus the total number of favors provided by player 1; as part of the strategy, players have a finite maximum net number of favors n that they can make or receive; on equilibrium path players play the efficient strategy of the stage-game in any period in which the state variable is not at its boundaries $k < |n|$; once a deviation has been detected, the unique equilibrium of the stage game is played forever on.

Within the class of BFB, we consider two types of pure strategies that differ in the plays at the boundaries: Bounded Favors Bank strategy with Rewards (BFBr) and Bounded Favors Bank strategy with Punishments (BFBp).

A **BFBr strategy with boundary** n, BFBr-n, prescribes that the player who reached her negative boundary of net favors $-n$ (who has provided the maximum net number of favors), is exonerated from providing favors (even if the cost is low) until she receives a favor back.

A **BFBp with boundary** n, BFBp-n, prescribes that the player who reached her positive boundary n (who has received the maximum net number of favors) provides a favor independent of the cost.[12]

Define the value in state k as the average expected discounted payoff induced by a BFB starting from that state. To support a BFB as a (Perfect) Markov Equilibrium, the values must satisfy the individual rationality constraints at any state. In addition, since players' types are not observable, the strategy must be incentive compatible for each type in each possible state. In the companion theory paper Degan et al. (2023), we establish that 1) a BFBr with boundary n is an equilibrium if and only if the discount factor is greater than a threshold δ(n); 2) when c_h is lower than an upper bound, for any $n \geq 1$, BFBp constitutes an equilibrium for δ sufficiently high; 3) fixing δ and other parameters, if a BFBr with boundary n' is an equilibrium strategy, then a BFBr strategy with boundary $n < n'$ is also an equilibrium.[13] While the last result does not always apply to BFBp strategies, in our experiment we will consider parametrization for which it does.

[12] One way to interpret BFB is that they prescribe to provide a favor within m periods (independent of the cost) when (at least) one of the boundaries is reached. BFBr prescribes to provide a favor in the lower boundary within m=∞ and BFBp prescribes to provide a favor at the upper boundary within m=1 periods.

[13] Abdulkadiroglu and Bagwell (2012) have proved this results for chip strategies in a slightly different model. Their proof directly applies to our setting as well.

Simple Equality Matching (SEM) strategy

We consider a modification of the Simple EM relationship that has been studied in the favor exchange model by Abdulkadiroglu and Bagwell (2012). Our SEM strategy is a symmetric Markov strategy with three states: an initial neutral state in which players provide a favor when the cost is low; a state in which player 1 is owned a favor, which happens if he is the last one that provided a favor; a state in which player 1 owns a favor, which happens if he is the last one that received a favor.

Notice that this strategy resembles some features of the BFBr strategy with $n = 1$: it has three states; the player that is owned a favor is exonerated from doing a favor until he receives a favor back; favors are provided only when it is efficient to do so. However, the initial state where players have the same ex-ante payoff is never reached again once the first favor is provided and, hence, symmetry is broken. Players never gets even again, they take turns (conditional on low cost) in providing favors. This difference leads to divergence on the realized state variable and the actions on the equilibrium path between BFBr-1 and SEM.

5 Experimental Design and Research Questions

We first introduce the general experimental setting and provide the theoretical predictions, on the basis of our analysis from Section 4. We then describe the details of the experimental design.

5.1 Parametrization, Treatments, and Research Questions

We fix the payoff of receiving a favor to $x = 10$, the low cost of making a favor to $c_l = 1$, the marginal probability of receiving a low cost to $p = 0.45$, and the discount factor to $\delta = 0.85$. We implement two values for c_h in different treatments, $c_h = 11$ or 15, for which different types of BFB constitute equilibrium strategies.[14] In the following proposition, we provide theoretical predictions for SSS, BFB, and SEM strategies given the parametrization that we use in the experiment.

[14] We choose this parametrization for several reasons. First, we need to ensure that the distinctions between c_l and c_h , c_l and x, and c_h and x are sufficiently pronounced. Second, we need to select a discount factor large enough to satisfy the incentive compatibility conditions as desired, but we also want to avoid fatiguing the subjects. Therefore, we aim to finish each session within two hours, including reading instructions and fee payment, while still allowing a reasonable number of supergames played. In the end, we chose $\delta = 0.85$ based on other experimental studies of indefinitely repeated game (see e.g., Bó (2005), Dal Bó and Fréchette (2011), Fudenberg et al. (2012)).

Proposition 1. *Given our parametrization for $x,\ p,\ c_l,\ c_h,\ \delta$, among the strategies we consider, only the following are perfect equilibrium strategies:*

- s^{NN} *both when* $c_h = 11$ *and* $c_h = 15$;
- s^{FF} *when* $c_h = 11$*;*
- *BFBr-1 and BFBr-2 both when* $c_h = 11$ *and* $c_h = 15$*;*
- *BFBp-1 and BFBp-2 when* $c_h = 11$.

Table 3: Ex-ante Payoffs in BFB, SEM, and SSS strategies

	EM					SSS	
high cost value	BFBr-1	BFBr-2	BFBp-1	BFBp-2	SEM	s^{FN}	s^{FF}
$c_h = 11$	2.856	3.481	3.898	3.980	2.357 (non-eq)	4.050 (non-eq)	3.500
$c_h = 15$	2.856	3.481	3.289 (non-eq)	3.701 (non-eq)	2.357 (non-eq)	4.050 (non-eq)	1.3 (non-eq)

Notes: The payoffs are calculated with $x = 10$, $c_l = 1$, $p = 0.45$, and $\delta = 0.85$.

Table 3 provides the ex-ante payoffs for BFB and SEM strategies, as well as for s^{FN} and s^{FF}. It also indicates, on the basis of Proposition 1, whether each strategy is sustained as an equilibrium, given our parametrization. The table only considers values of n for which, given our parametrization, some BFB-n strategies are an equilibrium.

When we consider BFB strategies, we can see that given n, under our parametrization, players achieve a higher payoff by playing BFBp strategies compared to BFBr strategies. Actually, when $c_h = 11$, the highest payoff achievable with the reward strategies, 3.481 (from BFBr-2), is even lower than the smallest payoff achievable with the punishment strategies, 3.898 (from BFBp-1). Intuitively speaking, the higher payoff for BFBp strategies compared to BFBr strategies is driven by the lower efficiency loss from implementing a punishment $(c_h - x)$ than the efficiency loss from exonerating a reward $(x - c_l)$.[15] However, BFBp strategies are an equilibrium under our parametrization only when $c_h = 11$. When $c_h = 15$, doing a favor is not incentive compatible for

[15] A sufficient condition for BFBp-n to provide a higher ex-ante payoff than BFBr-n is $(x-c_l)p-(c_h-x)(1-p) > 0$, which is the case for our parametrization. See Degan et al. (2023) for a more formal comparison of the payoffs achievable with BFBr and BFBp and SSS strategies.

a high type that is at the positive boundary. Alternating favors in the way prescribed by SEM, not only provides a lower payoff than any BFB strategy but the incentive compatibility condition at the initial neutral state is not satisfied under our parametrization.

When we consider SSS strategies, we notice that, by definition, the ex-ante payoff induced by the efficient strategy (s^{FN}) is independent of the value of c_h and is always the highest. Conversely, the ex-ante payoff for the s^{FF} strategy largely depends on the value of c_h. When $c_h = 11$, the ex-ante payoff achieved by s^{FF} is higher than the BFBr strategies but lower than the BFBp strategies. When c_h is very high ($c_h = 15$), doing a favor independent of the cost, as prescribed by s^{FF} , leads to a significant efficiency loss, which translates into a very low payoff of 1.3. In addition, it does not satisfy the incentive compatibility constraint for the high type.

Treatments — Our experimental design involves two treatment variables. First, as explained above, in line with Proposition 1 and Table 3, we vary the value of the high cost of providing a favor, $c_h = 11$ or $c_h = 15$, across different treatments. Since BFBp and s^{FF} strategies are supported as equilibria only in treatments with $c_h = 11$, comparing treatments with $c_h = 11$ and $c_h = 15$ allows us to examine the extent to which subjects are sensitive to the incentive compatibility conditions imposed by the theoretical model.

The second treatment we introduce is the salience of the state variable k. One of the strategy classes we focus on is EM strategies, where the action played in each period depends on the balance of the favors exchanged between the two players, summarized by the net number of favors received.[16] Theoretically speaking, directly showing the net number of favors received (the value of k) does not provide extra information to subjects since they can always calculate the net number of favors received from the full history of their past actions. However, explicitly showing the value of k might suggest subjects to condition their choices on this variable and may give them a cue to coordinate on implementing the BFB or SEM strategies. Alternatively, being reminded in each round of the achieved balance (imbalance) in the relationship might increase (decrease) the trust towards the matched player and induce subjects to be more (less) willing to reciprocate. Thus, it is interesting to examine whether the probability that the EM strategies are played is influenced by the salience of the net balance of favors.

[16]This is the state variable in BFB strategies and it is related to the state variable in SEM, that also takes into consideration who did the last favor. See Online Appendix A.5.

We summarize this two-by-two design in Table 4 and, on the basis of the theoretical setting and the experimental design we formulate the following research questions.

Table 4: Summary of treatments

Treatment	c_h	Summary information provided on the screen	Equilibrium supported
1 (Baseline-15)	15	baseline	s^{NN} BFBr-1, BFBr-2
2 (Baseline-11)	11	baseline	s^{NN}, s^{FF} BFBr-1, BFBr-2 BFBp-1, BFBp-2
3 (K-15)	15	baseline + k	s^{NN} BFBr-1, BFBr-2
4 (K-11)	11	baseline + k	s^{NN}, s^{FF} BFBr-1, BFBr-2 BFBp-1, BFBp-2

Question 1: To what extents are subjects able to efficiently exchange favors?

Question 2: Which (classes of) strategies are more prevalent, and what are the driving forces behind it?

We will explore Question 2 with the focus from several theoretical or behavioral perspectives and formulate the following specific questions.

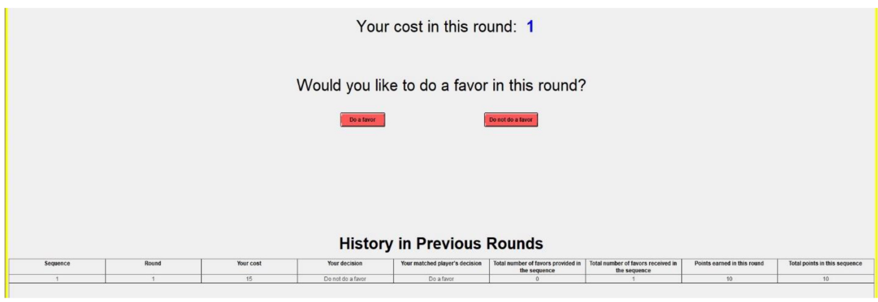
- Q2(a): Do subjects choose more often simple strategies, as SSS, or more complex strategies, as EM?
- Q2(b): Is the prevalence of the different strategies affected by the cost of providing favors and incentive compatibility?
- Q2(c): Does increasing the salience of the balance of favors increase the prevalence of the EM strategies?
- Q2(d): Is the prevalence of the different strategies affected by the ex-ante payoffs generated by the strategies?

5.2 Experimental design: Other details

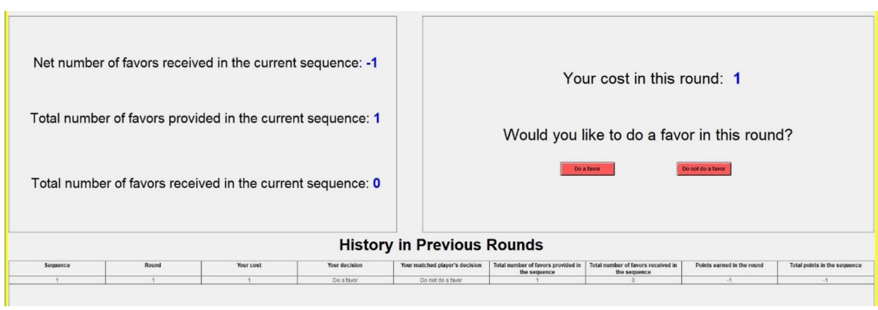
Below we further describe other details of the experimental design, including the constituent stage-game, the information displayed on screen, the supergame, the matching protocol, and the way we pay subjects.

The Stage Game — The stage game is the one that we represented in Table 1.[17] Consistent with our parametrization as in Table 4, we set the low cost $c_l = 1$ and the benefit of receiving a favor from the other player $x = 10$. As in the model, the costs of the two players realized in each period are always private information.

Figure 1: Information displayed in Baseline-15 and K-15



a. Baseline-15 treatment



b. K-15 treatment

Information Displayed — In all treatments, in each supergame, in each round t before making a decision, subjects observe their private costs in round t and the history of play up to round $t-1$,

[17] In the literature of trust games as well as in Roy (2012), subjects have to choose between "Invest" and "No Invest". In our model and experiment, players should not expect an immediate return from doing a favor in the current round. In addition, in our K-15 and K-11 treatments, we show the net number of favors received by subjects, which equals the number of favors received minus the number of favors given. We think that it is easier for subjects to understand the game and avoid confusion by using "Do a favor/Do not do a favor" rather than "Invest/No invest" or a neutral wording such as "Option A/Option B". From the experimental results, the frequency of doing a favor given a high cost is quite low and is much less than the frequency given a low cost, indicating that subjects responded to incentives and using the wording "Do a favor" did not generate an excessive level of social preference.

referred as 'baseline information': their actions, their matched players' actions, their private costs, the number of favors made, the number of favors received, the points earned in a round and in the supergame (see Figure 1.a as an example). Notice that this type of baseline information on the history of play is provided in most of experiments with multiple periods, regardless of whether the experiment is theory-based or not, and usually it is provided in the history table implemented by z-Tree with a small font size. After both players make their choices in each round t, they are reminded of their private costs and their decisions in the round. As well, subjects are shown their matched player's decision and the points earned in the round.

In treatments K-15 and K-11, at the beginning of each round, in addition to the baseline information, subjects are shown on the screen a text box that contains information on the number of net favors received, i.e., the value of the state variable k, with a large and colorful font (see Figure 1.b as an example).

The Supergame — A supergame in the model is the repetition of the stage game for an infinite number of periods. As standard, we implement the supergame in the lab using a random continuation rule proposed by Roth and Murnighan (1978). A supergame consists of multiple rounds, where the stage game is played in each round. The discount factor in our parametrization, $\delta = 0.85$, corresponds to the continuation probability after each round. It implies that after each round the supergame is expected to go on for around 7 ($\frac{1}{1-\delta}$) additional rounds. We did not fix the number of supergames in advance. Instead, when the sessions lasted for 1.5 hours, the ongoing supergame was set to be the last supergame for the session. Further discussion on the random termination methodology can be found in Online Appendix B.1.

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

Payments — We implement the stage game of the theoretical model as it is. Specifically, we use the payoff of the stage game as in Table 1 and pay subjects the average payoffs from all supergames, with a guarantee of a \$15 show-up fee. We chose to do this way in order to capture the model feature that doing a favor results in a loss and only benefits the other player. In the experiment, however, a subject who does not receive a favor in a round would experience a negative payoff from that round and can have an overall negative payoff from playing the game if he does not receive enough favors. Paying subjects a payoff based on the play of all supergames mitigates the potential possibility of negative payoffs from the game.[18]

The experiment was programmed with the z-Tree software (Fischbacher 2007) and conducted at the CIRANO Experimental Economics Laboratory (Canada) between March 2019 and June 2022. 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.[19] 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 in about 2 hours, including reading the instructions and completing the quiz.

6 Experimental Findings

Table 5 reports the details on all the experimental sessions. On average, each session involved 12 supergames and 85 rounds. In total, 194 subjects participated in our experiment, with an average earnings of CAD $28.

We organize the analysis of favor exchange in our sample in three subsections. In subsection 6.1, we provide the descriptive analysis and regression results on the frequency of favor provision, as well as the analysis of the the level of payoff-efficiency achieved by subjects in our experiment. In subsection 6.2, we assess to which extent subjects play the different strategies, using SFEM (Dal Bó and Fréchette 2011, 2019) followed by the strategy fitting-procedure used in Camera et al. (2012). Section 6.3 provides additional analyses on individual behavior.

6.1 Frequency of Favors Provision and Payoff-Efficiency

Table 6 shows the overall frequency of favor provision for each session, both unconditional and conditional on the cost realization. Over all sessions the average unconditional frequency of making favors is 29.9%. As one would expect, the frequency of favor provision is much higher conditional on a low cost (53.8% on average across sessions) than conditional on a high cost (10.9% on average

[18] In a companion experiment, where we study chip strategies using the same underlying model with complete and incomplete information, we take a different approach by providing subjects an endowment in each round and paying them on the basis of the payoffs obtained in four randomly chosen supergames (and a lower show-up fee).

[19] The instructions is available in Online Appendix D.

Table 5: Description of experimental sessions

Treatment	Number of sessions	Number of supergames	Number of rounds	Number of subjects per session	Show-up fee	Average earnings	Dated conducted
Baseline-15	4	10	83	14	C$ 15	C$ 25.44	04/08/19
		15	74	14		C$ 24.31	05/16/19
		13	83	14		C$ 26.48	05/23/19
		14	111	10		C$ 27.51	05/06/22
Baseline-11	4	18	106	10	C$ 15	C$ 25.66	07/26/19
		11	84	12		C$ 28.41	07/29/19
		11	72	14		C$ 26.79	09/26/19
		11	75	14		C$ 27.75	06/23/22
K-15	4	11	79	14	C$ 15	C$ 22.95	10/08/19
		17	86	14		C$ 25.17	10/09/19
		12	93	10		C$ 30.28	03/12/22
		13	85	8		C$ 27.69	04/08/22
K-11	4	9	80	14	C$ 15	C$ 33.53	06/09/22
		10	90	8		C$38.96	06/15/22
		12	85	14		C$ 33.18	06/15/22
		10	82	10		C$ 33.86	06/28/22

across sessions). This difference is statistically significant ($p - value < 0.01$, two-tailed Wilcox signed rank test). These results on aggregate frequencies indicate that subjects can distinguish between the low cost and the high cost and avoid providing a favor when it is too costly. This basic result is complementary to the result of Roy (2012), who finds that a higher benefit of receiving a favor results in a higher rate of favor provision.

Considering the complexity of the environment with incomplete information and the fact that doing a favor implies an instantaneous cost that leads to a negative instantaneous payoff if the favor is not reciprocated or if the cost is high, we think that subjects in our experiment show a high ability to exchange favors.

Panel A and Panel B of Figure 2 report the conditional frequency of favor provision at low cost and high cost, respectively, over time.[20] The comparative analysis between Panel A and Panel B further corroborates that subjects exhibit a higher frequency of providing favors when received the low cost. Remarkably, in the K treatments of Panel A, the frequency of providing favors conditional on the low cost reaches 100% in some supergames. Additionally, for Panel B, which conditions on the high cost, the patterns across all treatments reveal a slight tendency for the frequency of favor

[20]In Online Appendix B.2 Figure B1, we report the unconditional frequency of favor provision over time (all supergames) by treatment and session.

provision to diminish over successive supergames.

Table 6: Average frequency of "do a favor" - session level

Treatment	Session	Frequency	Frequency$\vert c_l$	Frequency$\vert c_h$
Baseline-15	1	0.2679	0.5617	0.0749
	2	0.3267	0.5692	0.1146
	3	0.3046	0.4602	0.1768
	4	0.2526	0.4548	0.0612
Baseline-11	5	0.2913	0.4703	0.1313
	6	0.2438	0.4440	0.0976
	7	0.2711	0.5123	0.0753
	8	0.2522	0.4967	0.0671
K-15	9	0.2495	0.3679	0.1698
	10	0.3113	0.6070	0.0692
	11	0.3991	0.6422	0.2305
	12	0.2632	0.5319	0.0806
K-11	13	0.3242	0.5722	0.1124
	14	0.3127	0.6781	0.0270
	15	0.3965	0.7111	0.1470
	16	0.3185	0.5304	0.1140

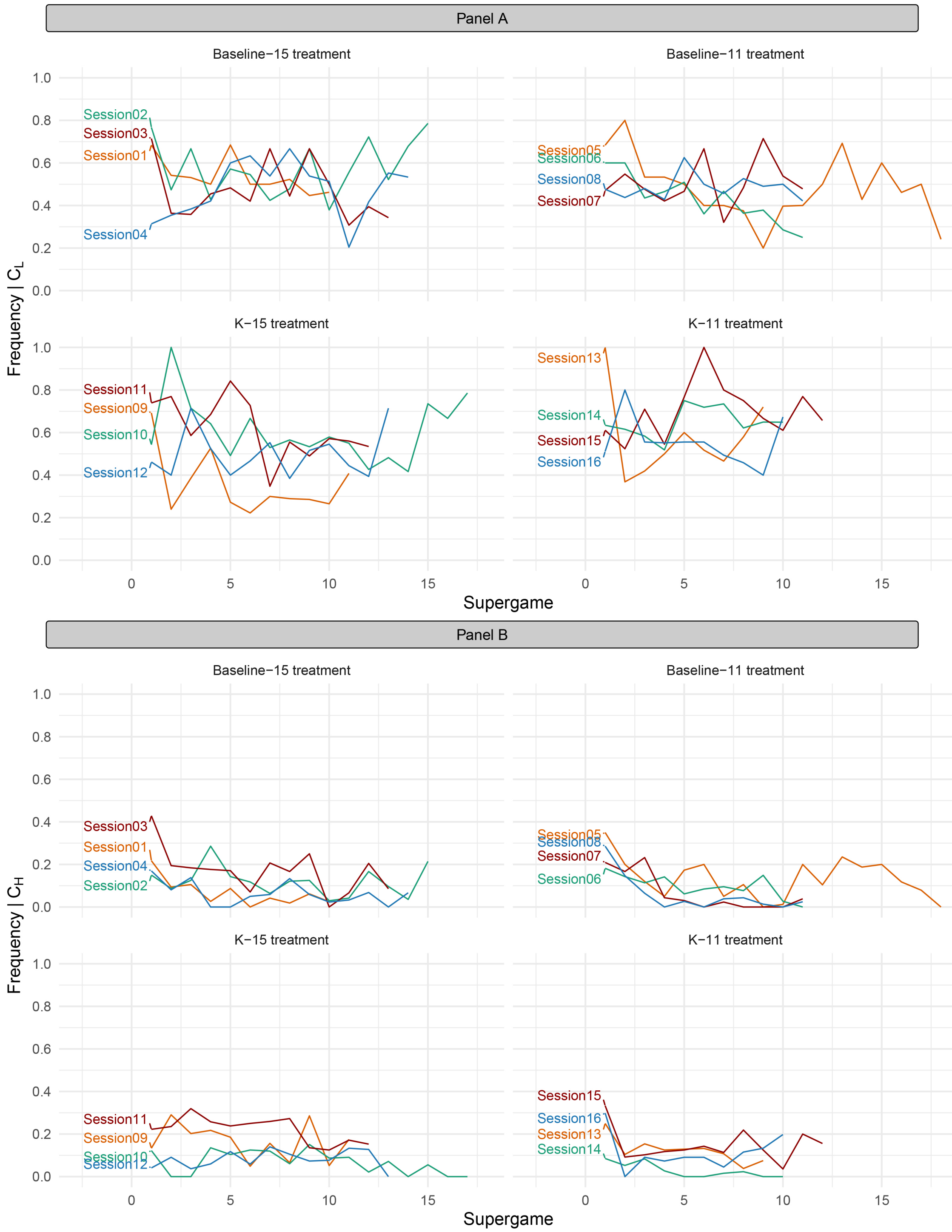
Notes: Frequency is the average frequency of favor provision in the session, pooled across subjects. Frequency$|c_l$ and Frequency$|c_h$ are frequency of favor provision conditional on the low cost and the high cost, respectively.

We further conduct parametric test to assess whether there is a statistically significant difference in the frequency of favor provision between pairs of treatment. As in 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 and we estimate the following regression model using treatments in pairs:

$$Frequency_i^S = \beta_0 + \beta_{T_g} D_{T_g,i}^S + \epsilon_i^S, \tag{1}$$

where $Frequency_i^S$ is the average frequency of favor provided by individual i in supergame S, $D_{T_g,i}^S$ is a dummy variable that indicates the treatment group g in any pair of treatments $(1\, vs.\, 2, 1\, vs.\, 3, 2\, vs.\, 4, 3\, vs.\, 4)$ and ϵ_i^S is an error term. Following Mengel et al. (2022), we control for the supergame length of the previous supergame and the average supergame length of all the previous supergrams, as well as whether the sessions took place before or after the Covid-19 outbreak. The results of these regressions for the parameter of interest, β_{T_g}, are reported in Table 7. The complete results with the impact of the supergame length and Covid-19 are reported in Table B2 in Online Appendix B.3. The p-values are calculated using wild cluster bootstrap inference at

Figure 2: Frequency of favor provision over supergame: conditional on low and high costs



Notes: Frequency | c_L is the average frequency of providing favors at the low cost for each supergame. Frequency | c_H is the average frequency of providing favors at the high cost for each supergame.

the session level (Roodman et al. (2019), StataCorp (2023)).[21]

Our findings indicate that there is no notable treatment effect with regard to the individual frequency of favor provision. In addition, the previous supergame length does not affect the individual frequency of favor provision in 11 out of 12 regressions. The estimated coefficient on the Covid-19 (β_{covid}) indicator is found to be insignificant across comparisons between any two treatments, indicating that the impact of the pandemic on the results of the experiment is not statistically significant.

Table 7: Panel data analysis of individual frequency of favor provision

Reference	Treatment T_g	β_{T_g}	β_{T_g} if c_l	β_{T_g} if c_h
Baseline-15	Baseline-11	-0.028	-0.024	-0.025
		(0.146)	(0.508)	(0.419)
Baseline-15	K-15	0.013	0.015	0.026
		(0.742)	(0.914)	(0.634)
Baseline-11	K-11	0.098	0.140	0.060
		(0.441)	(0.392)	(0.394)
K-15	K-11	-0.001	0.053	-0.073
		(0.987)	(0.517)	(0.482)

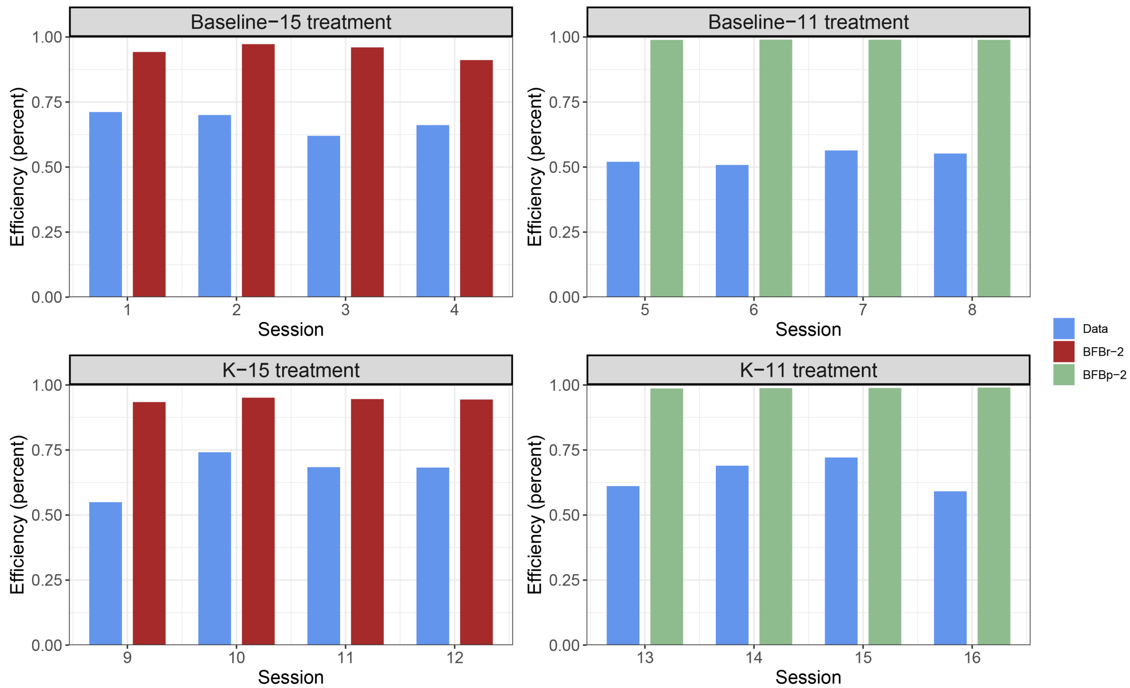
Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, p-values in parentheses. We perform wild cluster bootstrap inference for linear hypotheses about parameters of independent variables at the session level.

To address **Question** Q1, similar to Embrey et al. (2013), we define a payoff-efficiency index that takes into account the realized private costs to evaluate the degree to which subjects exchange favors efficiently. Our payoff-efficiency index is calculated for each pair of players within a supergame (match) based on a min-max normalization: $\frac{Payoff_{actual} - Payoff_{minimum}}{Payoff_{maximum} - Payoff_{minimum}}$, where $Payoff_{actual}$ represents the realized joint payoff based on the subjects' choices. $Payoff_{minimum}$ simulates the minimum joint payoff assuming subjects provide a favor only when the cost is high, while $Payoff_{maximum}$ simulates the maximum joint payoff assuming subjects provide a favor only when the cost is low. Figure 3 presents the average payoff-efficiency index for each session. As a comparison, we also simulate the payoff-efficiency index from the BFBp-2 strategy in treatments with $c_h = 11$ and the BFBr-2 strategy in treatments with $c_h = 15$, which theoretically generate the highest ex-ante payoffs among the set of equilibrium strategies we considered. We find that the

[21] Following Dal Bó and Fréchette (2011); Fudenberg et al. (2012), we also use a pooled regression model with a dummy as the independent variable indicating one of two comparison treatment groups (see Table B3 in Online Appendix B.3).

average payoff-efficiency index in each session exceeds 50%. Explicitly showing the net number of favors k significantly enhances efficiency, but only in treatments where $c_h = 11$.[22] We summarize the analysis on efficiency in the following Finding 1.

Figure 3: Efficiency level across treatments



Notes: Each blue bar represents the average efficiency in a session calculated from the experimental data. Each red bar represents the average efficiency in a session simulated from BFBr-2 strategy. Each green bar represents the average efficiency in a session simulated from BFBp-2 strategy.

Finding 1: The payoff-efficiency index in each session exceeds 50%, with an average of 63% across sessions. However, there exists significant efficiency loss compared to the highest equilibrium payoff generated by BFB strategies.

6.2 The Individual Strategy Estimation

6.2.1 Strategy Frequency Estimation

In this subsection, we employ the SFEM as in Dal Bó and Fréchette (2019) (see also Dal Bó and Fréchette 2011 and Fudenberg et al. 2012) to assess the proportions of the data that can

[22]Table B4 in Online Appendix B.4 reports regression results that assess the difference in the efficiency index between the baseline and the K-treatments.

be accounted by different strategies. Following the experimental literature on infinitely repeated games, we restrict our attention to a subset of strategies. We begin with the SSS and EM strategies that we introduced in section 4, which, as we discuss in the introduction, are relatively simple, intuitive, and relevant to the literature on favor exchange. Since in our data subjects' minimum net number of favors is between -3 and 0 in more than 95% of all the supergames across treatments (see Figure B2 in Online Appendix B.5), and that only BFB strategies with $n \leq 2$ are incentive compatible in at least one treatment, we include the BFB strategies up to boundary $n = 3$ in the estimation.[23] Among the SSS strategies, we include the s^{FN} strategy, which, though not incentive compatible, is the efficient strategy in this game; the s^{NN} strategy that is always an equilibrium, and the s^{FF} strategy that is an equilibrium when c_h=11.

We extend further our strategy set by considering also some lenient and forgiving strategies that have received particular attention in the experimental literature on the infinitely repeated PD game with public and private monitoring (see, e.g. Dal Bó and Fréchette (2011), Dal Bó and Fréchette (2019), Aoyagi et al. (2019), Fudenberg et al. (2012)). In particular, we include the following forgiving strategies: Tit-for-Tat (TFT), Suspicious Tit-for-Tat (STFT), Win-Stay Lose-Shift (WSLS), 2-Tits-for-1-Tat (2TFT). In addition, we include the lenient strategies s_2^{FF} and s_3^{FF}, which are similar to s^{FF} but with players waiting for 2 or 3 rounds of deviations, respectively, before reverting to playing the stage-game Nash equilibrium. Finally, we consider the following strategies that are both forgiving and lenient: Tit-for-2-Tats (TF2T), Tit-for-3-Tats (TF3T) and 2-Tits-for-2-Tats (2TF2T). Each of these additional strategies are summarized in Online Appendix A.6. We include this set of lenient and forgiving strategies for completeness. However, given the differences of our setting from the repeated PD games, in particular that having both players making favors never maximizes the player's joint payoff there are no priori reasons why subjects would play these strategies that aims at supporting playing (FF) with positive probability.[24]

We apply SFEM using our set of strategies and restricting to the last five supergames, when the subjects' behavior is more likely to have stabilized (see, also Aoyagi et al. (2019), Embrey et al. (2013) and Fudenberg et al. (2012)). While the details of SFEM are explained in Online Appendix C.1, it is useful to mention that the estimation procedure assumes that subjects can choose each

[23] BFB with $n = 3$ are not incentive compatible but provide higher payoffs than BFB with smaller n. Including them in the estimation allows to partially address Questions Q2(b) and Q2(d).

[24] This does not exclude that subjects could play some more complex lenient and forgiving strategies.

candidate strategy with a given probability, which remains fixed across supergames. They can however make mistakes in each round with probability $1-\beta$, where $\beta \in (1/2, 1)$. Each entry within the same column represents the estimated probability that subjects chose a given strategy, or in other words the proportion of the observed data accounted for by a given strategy.

Table 8: Strategy frequency estimation

	(1) Baseline-15	(2) Baseline-11	(3) K-15	(4) K-11
EQM	BFBr1,r2; s^{NN}	BFBr1,r2; s^{NN} BFBp1,p2	BFBr1,r2; s^{NN}	BFBr1,r2; s^{NN} BFBp1,p2
BFBr-1	0.000	0.153**	0.245**	0.191***
	(0.039)	(0.065)	(0.099)	(0.069)
BFBr-2	0.124**	0.132**	0.000	0.200**
	(0.059)	(0.062)	(0.024)	(0.082)
s^{NN}	0.463***	0.519***	0.438***	0.189***
	(0.076)	(0.075)	(0.074)	(0.062)
s^{FN}	0.265***	0.148**	0.237***	0.419***
	(0.073)**	(0.060)	(0.081)	(0.089)
SEM	0.148	0.048	0.079	0.000
	(0.073)	(0.047)	(0.073)	(0.025)
Beta	0.883***	0.908***	0.825***	0.826***
	(0.017)	(0.013)	(0.033)	(0.024)

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Boostrapped standard errors in parentheses. The row of EQM lists the equilibrium strategies. We use the data of last 5 supergames in each session.

Following Fudenberg et al. (2012), we apply a two-stage analysis to SFEM. In the first stage, we consider the full set of 19 strategies. Table C.1 in Online Appendix C.1 reports estimates and bootstrapped standard errors for this full set of strategies. We find that only 5 strategies of these 19 strategies are present at frequencies significantly greater than 0 in at least one treatment: the EM strategies BFBr-1, BFBr-2, SEM, and the SSS strategies s^{NN} and s^{FN}. In particular, the two BFBr strategies that are statistically significant can explain between 10%-30% of the behavior of subjects across all the treatments in the first-stage estimation. Among the SSS strategies, both s^{NN} and s^{FN} account for a significant proportion of the data across all the treatments.[25] The SEM strategy explains some of the data only in the Baseline15 and K-15 treatment, and its proportion is statistically significant at the 10% level. The BFBp strategies and s^{FF}, while theoretically predicted to constitute an equilibrium and generate a higher expected payoff than BFBr when $c_h = 11$, do not account for a statistically significant frequency in any treatment. Not surprisingly, none of

[25]With the exception for s^{FN} in the Baseline-11 treatment.

the lenient and forgiving strategies that are typically considered in repeated PD games have an estimated frequency significantly greater than zero.

Table 8 reports the estimation results of the second stage for each treatment. From columns 1 to 4, we see that consistently throughout all treatments the SSS strategies, s^{NN} and s^{FN}, account for more than 61% of the data, all at a 1% significance level. Specifically, s^{NN} is the most prevalent strategy in the Baseline-15, Baseline-11, and K-15 treatments, accounting for between 44% and 52% of the data, and the fourth most popular strategy in the K-11 treatment, accounting for about 19% of the data. This result is also in line with most of the experimental studies on infinitely repeated PD game, where repeatedly playing the unique Nash equilibrium of the stage game is the strategy most likely to be played.[26] In addition, an important and statistically significant proportion of the observations on favors exchange is explained by the efficient strategy s^{FN}, which is not incentive compatible despite providing the highest payoff. It accounts for between 14% and 42% of the data at the 5% or 1% significance level across treatments.[27] BFBr strategies remain statistically significant in the second-stage estimation, accounting for 12%–39% of the data across all treatments. The SEM strategy, however, cannot explain a statistically significant proportion greater than 0 in any treatment in the second stage.

Built on the results from the two-stage analysis of SFEM, the following findings allow us addressing some of our research questions.

Finding 2: The most prevalent strategies in all treatments are two SSS strategies, s^{NN} and s^{FN}. Nevertheless, BFBr-1 and BFBr-2 also explain an important and statistically significant proportion of the favor exchange behavior.

This finding answers to **Question** Q2(a). Although SSS strategies are more prevalent than EM strategies, the latter class, in particular BFBr strategies, also account for a significant proportion of the data. We can extrapolate that in the complex context of favor exchange with private costs, subjects play not only simple strategies but also more complex strategies that follow the Equality

[26]Dal Bó and Fréchette (2011) find that in 4 out of 6 treatments, 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 for more than 20 percent of all the data in each treatment (Table 3 of Fudenberg et al. 2012).

[27]In our companion theory paper (Degan et al. 2023), we show that when the boundary "n" goes to infinity, the BFB-n strategies converge to the efficient strategy. If a player employs a BFB strategy with a large n and the boundary n is not realized in the experimental data,, the SFEM will attribute it to the efficient strategy, as identification of BFB is driven by behavior at the boundaries. The estimated frequency of BFB strategies can therefore be interpreted as a lower bound.

Matching principle of social interactions. This result is in line with existing studies of repeated PD with imperfect monitoring, where simple strategies are played the most but as environment becomes more complex players also use more complex strategies (for example, see Fudenberg et al. (2012) and Aoyagi et al. (2019)).

Finding 3: The BFBp, s^{FF}, SEM, and the additional lenient and forgiving strategies are not chosen with a probability statistically significantly different from zero in any of the treatments.

Finding 3 together with Finding 2 also address **Questions** Q2(b) and Q2(d), on the role played by incentive compatibility and expected payoffs associated with the strategies. Among the EM strategies, only BFBr-1 and BFBr-2 are chosen with a positive probability. These are the only strategies, in addition to s^{NN}, that are incentive compatible across treatments. However when $c_h = 11$, BFBp are not only incentive compatible but also provide a higher expected payoff than BFBr and yet, subjects do not play them with a positive probability. This raises an interesting question on whether, when choosing how to achieve equilibrium in EM relationships, some ways might be considered more acceptable than others. Specifically, rewarding a subject for trusting his matched player might be more acceptable than punishing a subject that owns favors. In other words, giving a break from helping others may be a more common norm than taking very costly action in order to reestablish balance. This is also consistent with the fact that the s^{FF} strategy does not pass the first stage of SFEM despite the fact that, when $c_h = 11$, it is incentive compatible and provides a higher payoff than BFB strategies. One possible explanation for the above patterns is that subjects find a resistance to reciprocate and trust their matched player when this action is highly costly, even if it can lead to higher future rewards. Finally, it is not surprising that subjects never play the SEM strategy, as it is not incentive compatible under our parametrization and, although it is as complex as BFBr-1, it always leads to a lower payoff than other EM strategies. It might also be that the asymmetry after the first favor is provided makes it less attractive.

In summary, Findings 2 and 3 suggest clear evidence that while both simple strategies and more complex strategies that follow the EM principle find empirical support, incentive compatibility and expected payoffs are not as strong predictors of the strategies being chosen by subjects. It is useful to point out that while our model allows both players to make favors simultaneously, our results from SFEM show that strategies that lead players to make favors simultaneously (as in s^{FF} or in BFBp) are not chosen by subjects. Sequentiality in favor provisions emerges in our setting because subjects seem reluctant to follow strategies that prescribe to provide favors when the cost is high, indicating that subjects take short-term efficiency considerations into account. Consistently, an important proportion of subjects play the efficient strategy, which by definition provides the highest payoff, even if it is not incentive compatible in our context with private costs.

Finding 4: Increasing the salience of the net balance of favors increases the prevalence of BFBr strategies by 11-12%.

Finding 4 directly addresses **Question** Q2(c). Explicitly showing subjects the net number of favors "k" does increase the popularity of EM strategies. Specifically, it increases only the popularity of BFBr, at the expenses of SSS strategies. As we have already mentioned, showing "k" does not impact the payoff structure or the set of equilibria of the games. However, it could provide subjects a hint that they should condition their actions on such information, suggest that they should restore a balance in the relationship, and as long as the balance does not become too asymmetric subject might experience more trust. An explicit balance keeping device could also increase trust in the relationship and, as such, enhance the propensity to provide favors at the expenses of the non-cooperative strategy s^{NN}, as it is the case in the K-11 treatment.[28]

Finally, it should be noticed that the estimated β indicates the probability that subjects behave according to the chosen strategy set in the SFEM. It ranges between 82% and 90% in our estimation, showing the strategy set used in the SFEM well explains the behavior. As a reference, the estimation of β is 94-98% in Dal Bó and Fréchette (2019) on the repeated PD game with complete information, and 85-89% in Aoyagi et al. (2019) on the repeated PD game with different monitoring.

6.2.2 Percentage of Classified Observations

In this subsection, we utilize a strategy-fitting procedure, as proposed by Engle-Warnick and Slonim (2006) and Camera et al. (2012), to complement SFEM and assess the extent to which the strategies we propose can explain subjects' behavior in our experimental data. This procedure involves categorizing subjects in a supergame based on the strategies they employ, and we specifically adopt the approach presented by Camera et al. (2012).

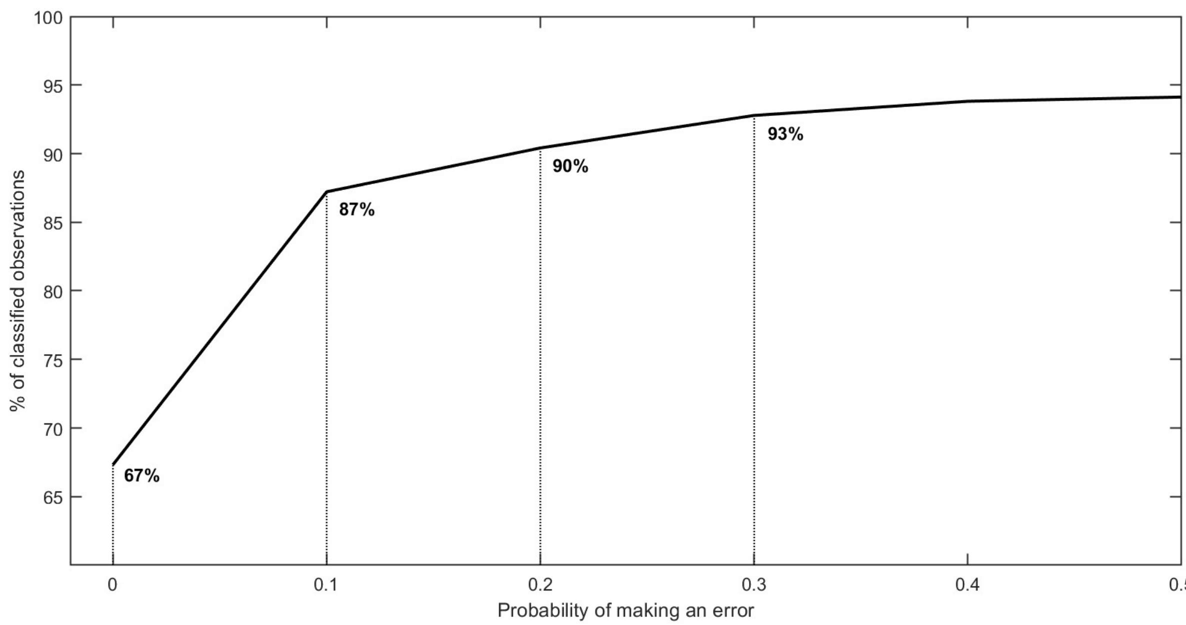
For a detailed description of the strategy-fitting procedure we used and its application to our

[28]This effect is not present in the K-15 treatment maybe because the overall propensity to provide favors is affected by the costs and benefits of providing favors in all situations and not only when it is efficient. This partially addresses Q2(b).

data, please refer to Online Appendix C.2. In summary, this procedure involves categorizing a subject in a supergame with a strategy if three conditions are met: first, the subject followed that strategy in the first round; second, their subsequent behavior is more consistent with that strategy than with any other strategy; and third, the number of deviations from the proposed strategy falls within chance. Unlike SFEM, this procedure imposes a maximum probability of making errors, denoted by p_ε, when following a particular strategy.

An observation, defined as all choices of a subject in a supergame, may be classified by one or more strategies or may remain unclassified. For any fixed probability of making errors, we can calculate the total 'fit' of the set of proposed strategies, which refers to the proportion of observations that are classified by at least one strategy. Figure 4 shows the marginal gain in the total fit as the probability of making errors, p_ε, varies.

Figure 4: Percentage of classified observations



Notes: We use the data of last 5 supergames in each session.

We consider strategies BFBr-1, BFBr-2, SEM, s^{NN}, s^{FN} and let the probability p_ε vary from 0 to 50%. The total fit is 67% when we do not allow subjects to make any mistakes (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 87%. The fit then gradually tapers out. With $p_\varepsilon = 0.3$, we classify 93%

of observations.[29]

The number of classified observations depend on the selected error tolerance level. To provide insight into the number of observations classified by each of the considered strategies, we present the results in Table 9 for $p_\varepsilon = 0.1$.[30]

Table 9: Number of classified observations by strategies

5 Strategies	Baseline-15	Baseline-11	K-15	K-11
All observations	260	250	230	230
BFBr	144	136	110	121
-BFBr1	122	112	96	90
-BFBr2	123	109	88	101
SEM	118	108	89	72
s^{NN}	126	125	103	62
s^{FN}	124	108	86	109
Unclassified	23	19	39	43

Notes: The unit of an observation is all choices of a subject in a supergame. We use the data of last 5 supergames in each session.

We infer from Table 9 that the same observation can be classified by multiple strategies. All the chosen strategies classify more than a quarter of the observations and about 8% to 19% of the observations remains unclassified. BFBr are the strategies that classify the most observations in all treatments. If we rank each strategy according to the number of observations that it classifies, we find that, consistent with the results of SFEM, s^{NN} ranks first in the Baseline-15, Baseline-11, K-15 treatments and s^{FN} ranks first in the K-11 treatment. Different from our results from SFEM, SEM explains more observed data than s^{NN} in the K-11 treatment. In Table C3 in Online Appendix, we provide results from robustness check with the same strategy set and $p_\varepsilon = 0.05$. In Table C4, we also provide strategy fitting analysis with $p_\varepsilon = 0.1$ by including BFBr-n, BFBp-n, n=1, 2, 3, s^{NN}, s^{NF}, s^{FF}, and SEM.

[29] Figure 3 in Camera et al. (2012) shows that when mistakes are not allowed, the total fit of the individual's behavior is 53%. If they increase the probability of mistakes to 0.05, then the total fit of the entire strategy set reaches 81%.

[30] As a comparison, the estimated probability of making a mistake in a round from the SFEM procedure, given the estimated β, is about 0.1.

6.3 Probit Regressions on Individual Behavior

As an additional complementary exercise to understand if subjects' behavior is consistent with BFBr strategies, we run a probit regression for each treatment, controlling for a number of variables. Table 10 reports the regression results.

Table 10: Panel data analysis of effect of boundaries

Dependent variable: $Decision_t$				
	(1)	(2)	(3)	(4)
	Baseline-15	Baseline-11	K-15	K-11
	Probit	Probit	Probit	Probit
$Net\,Favor\,Negative_t$	-0.012	-0.015	0.031	-0.063***
	(0.022)	(0.022)	(0.024)	(0.024)
$Cost_t$	0.345***	0.3349***	0.371***	0.447***
	(0.031)	(0.024)	(0.025)	(0.015)
$Net\,Favor\,Negative_t \times Cost_t$	-0.047*	-0.054**	-0.085***	-0.083***
	(0.026)	(0.027)	(0.030)	(0.028)
$Other\,Decision_{s,1}$	0.053***	0.051***	0.096***	0.084***
	(0.016)	(0.016)	(0.017)	(0.016)
$Supergame_t$	-0.006***	-0.015***	-0.008***	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
$Round_t$	-0.003***	-0.005***	-0.006***	-0.0022*
	(0.001)	(0.002)	(0.002)	(0.001)
N	3798	3506	3304	3376

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, standard errors in parentheses. We report the estimated results of the marginal effects. $Decision_t$ is a binary dummy variable which is equal to 1 when "Do a Favor". $Net\,Favor\,Negative_t$ is a binary dummy variable which is 1 when state $k < 0$, otherwise is 0. $Cost$ is a binary dummy variable which is 1 when it is a low cost, otherwise is 0. $Other\,Decision_{s,1}$ is a binary dummy variable which is equal to 1 when the matched player chooses "Do a Favor" in the first round of the supergame. $Supergame$ is the number of the current supergame at round t, $Round$ is the current number of the round. Round 1 observations are not included. $Sequence\,Length_{s-1}$is the sequence length of the previous supergame. $Avg\,Sequence\,length_{[1,s-1]}$is the average sequence length of all previous supergames.

The results of columns 1 to 4 show that in all treatments, reaching negative states ($k < 0$) significantly decreases the probability of favor provision when the cost received is low.[31] It means that subjects have significantly less incentive to provide a favor in negative states even conditional on having a low cost. This is consistent with BFBr, which prescribes subjects to stop providing a favor in the negative boundary states even if the cost is low. The effect of reaching negative states is insignificant conditional on the cost being high. This is coherent with the frequencies of providing favors that are shown in Table 6, unconditional on the net number of favors. These

[31]The effect of the cross-term is significantly negative and large, while the effect of $Net\,Favor\,Negative_t$ is small and insignificant.

results corroborate the idea that subjects use BFBr in a favor exchange game under incomplete information.

7 Conclusion

While favor exchange models with private information have received attention from the theoretical literature, experimental work on the subject is still limited. The experiment presented in this paper studies the behavior and strategy choices in our favor exchange game with private costs. By conducting the experiment, we are able to assess (i) to which extent subjects exchange favors in a way that is payoff enhancing; (ii) the strategies that subjects use in exchanging favors and the forces driving subjects' strategy choices.

We find that subjects exhibit a significant propensity towards providing favors, considering that in our environment the cost of providing a favor is private information. SSS strategies, specifically, never providing favors and the efficient strategy (which is not an equilibrium strategy under private information), are the most prevalent ones. However, strategy frequency estimation, strategy-fitting analysis, and reduced-form approaches based on panel data analysis indicate that a proportion of subjects' behavior is explained by, or at least consistent with, BFBr strategies. On the other hand, neither BFBp nor the SSS strategy of always providing a favor explain a significant proportion of the data, despite the fact that they are equilibrium strategies with higher expected payoffs in some treatments. Finally, showing subjects explicitly the tallies of net favors increases the prevalence of BFBr strategies.

The results from our experiment provide some general insights about behaviors and strategy choices in more general settings of repeated bilateral interactions with private information where the Equality Matching principle might be at play. Subjects are more inclined to use simple rather than complex strategies, but they also use more complex strategies that follow the Equality Matching principle. In addition, incentive compatibility conditions or ex-ante payoffs may not always be a good predictor for the strategy choices. The fact that, BFBp and s^{FF} strategies are not chosen by subjects suggests that subjects are reluctant to provide favors when it is highly costly and that social norms that reward subjects for trusting and reciprocating in balanced relationships might be more acceptable than social norms that require taking very costly actions to reestablish balance in the relationship. Finally, our experiment provides some evidence that explicit forms of balance keeping might enhance the probability that individuals choose EM strategies or simply increase trust in the relationship and, as such, enhance the propensity to provide favors.

Several possible directions for future research could be profitably expanded. In a companion paper, Degan et al (2023) compare the exchange of favors in a complete versus private information setting and consider treatments where exchanging favors imply trading chips. It would be also of interest to consider a setting where subjects are allowed to communicate with each other. In fact, while communication could improve efficiency, when the cost of providing favors is private information, it could also possibly induce subjects to lie to get more favors. We leave such extensions to future research.

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Online Appendix

A Appendix A: Details of Theoretical Results

A.1 Stationary Strongly Symmetric (SSS) Pure Strategies

We consider SSS pure strategies : s^{FN}, s^{FF},s^{NN}, and s^{NF}. What we call the efficient strategy, s^{FN}, leads to the highest symmetric average discounted payoff, $v^{FN} = (x - c_l)p$. s^{FF} and s^{NN} lead to the average discounted payoff $v^{FF} = [x - c_l p - c_h(1-p)] > 0$ and $v^{NN} = 0$, respectively. Finally, the average discounted payoff of s^{NF} is $v^{NF} = (x - c_h)(1-p) < 0$.

Lemma 1. *When the cost of providing a favor is private information, two SSS pure-strategies can constitute a Stationary Strongly Symmetric Equilibrium:*
(i) s^{NN}*, for any* c_l, c_h, x, δ*; and*
(ii) s^{FF} *if and only if the following two assumptions are satisfied:*

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

Proof. A strategy is an equilibrium if and only if it satisfies individual rationality (IR) and incentive compatibility (IC) constraints. Neither s^{FN}nor s^{NF}can be SSS equilibria.
s^{FN} satisfies the (IR) constraint but it does not satisfy the (IC) constraint of the low type for any value of the discount factor. The recursive formulation of the incentive constraint for the low type is $-c_l(1-\delta) + \delta(x - c_l)p \geq \delta(x - c_l)p$, which is never satisfied $\forall c_l > 0$.
s^{NF} cannot be an equilibrium because it is not individually rational (IR).
(i) s^{NN} consists of the repetition of the unique static Nash Equilibrium, so the result follows.
(ii) s^{FF} is an equilibrium if and only if it satisfies individual rationality (IR) and incentive compatibility (IC) constraints. (IR) is satisfied if and only if $v^{FF} > 0$, which is condition A1. Condition A2 represents the (IC) constraint for the low type. The (IC) constraint for the high type, $(1-\delta)(x - c_h) + \delta\left[x - c_l p - c_h(1-p)\right] \geq x(1-\delta)$, is always trivially satisfied.

■

A.2 BFBr

Let $\widetilde{K} = K \cup \{\emptyset\}$ be the state space, where K=$\{-n, ..-1, 0, 1, ...n\}$, $|K| = 2n+1$. On equilibrium path $k \in K$, while once a deviation has been detected $k = \emptyset$. The state space is the same for BFBr and BFBp.

The BFBr strategy with boundary n for player 1 at each t is described in (2):[32]

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

Table A1 presents the transition matrix of the state variable k for BFBr. The first column contains the observed action profile y=(y_1, y_2) in a period, where $y_i = F(N)$ if player i did (did not do) a favor. The other columns represent the possible values of the state variables at the beginning of a period. Each entrance in the table then corresponds to the state variable at the beginning of the next period, given the action profile and the state variable at the beginning of the period.

Table A1: Transition to state k' from state k in BFBr

$y = (y_1, y_2)$	$k \neq \{-n, n\}$	$k = n$	$k = -n$	$k = \emptyset$
(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)	$\emptyset$	$\emptyset$	$\emptyset$	$\emptyset$

Once a deviation from the prescription of BFBr is detected in the public history, the state variable moves to the deviation regime $k = \emptyset$ and stays there ever after. This happens when a player who should be rewarded does not abstain from providing a favor, or when both players provide a favor in the same period.[33]

A.2.1 Values of BFBr

From the description of the strategy and the law of motion of the state variable, we can calculate the "value" (the average expected discounted payoff for player 1) at each state k, v_k.[34] We provide

[32]BFBr for player 2 is analogous.

[33]Due to the correlation structure of the costs, on the equilibrium path at most one player should provide a favor in any period.

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

these values, separately for the interior and boundary states, in the following formulas when $k \in K$. Given the symmetry of our environment, the average discounted payoff for player 2 in state k is, v_{-k}.[35] When $k \in (-n, n)$,

$$v_k = (1-\delta)[px - pc_l + (1-2p)0] + \delta[pv_{k-1} + pv_{k+1} + (1-2p)v_k], \tag{3}$$

where the first term on the RHS is the normalized expected payoff from the current period and the second term is the normalized expected continuation payoff. When the state variable is at the boundaries, $k = n$ or $k = -n$,

$$v_n = (1-\delta)[p(-c_l) + (1-p)0] + \delta[pv_{n-1} + (1-p)v_n], \tag{4}$$

and

$$v_{-n} = (1-\delta)[px + (1-p)0] + \delta[pv_{-n+1} + (1-p)v_{-n}]. \tag{5}$$

Equation (3) for v_k is a second-order difference equation, with boundary conditions (4) and (5). See Degan et al. (2023) for the analytical solution.

A.2.2 Individual Rationality Constraints of BFBr

We impose that players are free to walk away from their bilateral relationship, and if they do so, they obtain a zero payoff. Therefore, the individual rationality (IR) constraints are that $v_k \geq 0$, for all $k \in \widetilde{K}$. Degan et al. (2023) show that v_k is decreasing in k, so that (IR) constraints are satisfied if and only if $v_n \geq 0$.

A.2.3 Incentive Constraints of BFBr

In order for the proposed BFBr to be an equilibrium, it must be incentive compatible. When player 1 has low cost, $\Pr(c_j = c_h | c_i = c_l) = 1$. The incentive constraints for the low type (ICL) are shown in Table A2:

Given $\Pr(c_j = c_l | c_i = c_h) = \frac{p}{1-p}$ 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 A3.

[35] The value when $k = \emptyset$ is $v_\emptyset$=0 for both players.

Table A2: Incentive constraints for the low type in BFBr

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

Table A3: Incentive constraints for the high type in BFBr

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

A direct application of the analysis of Abdulkadiroglu and Bagwell (2012) for the Chip Strategies, implies that a necessary and sufficient condition for a BFBr to be an equilibrium strategy is that the (ICL) constraint in state $-n+1$ holds (see Degan et al. (2023)).

A.3 BFBp

A BFBp strategy with boundary n for player 1 at each period t is represented in equation (6):

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

The transition Matrix of the State Variable for the Punishment strategy is illustrated in the following Table A4. The explanation of the elements in the table is analogous to that in Table A1.

Table A4: Transition to state k' from state k in BFBp

$y = (y_1, y_2)$	$k \neq \{-n, n\}$	$k = n$	$k = -n$	$k = \emptyset$
(F, N)	$k-1$	$n-1$	$\emptyset$	$\emptyset$
(N, F)	$k+1$	$\emptyset$	$-n+1$	$\emptyset$
(N, N)	k	n	$-n$	$\emptyset$
(F, F)	$\emptyset$	$\emptyset$	$\emptyset$	$\emptyset$

A.3.1 Values of BFBp Strategy

From the description of BFBp and the law of motion of the state variable, the value at each state k, $\bar{v}_k$, is as follow. When $k \in (-n, n)$

$$\bar{v}_k = (1-\delta)p(x-c_l) + \delta p(\bar{v}_{k-1} + \bar{v}_{k+1}) + \delta(1-2p)\bar{v}_k, \tag{7}$$

When the state variable is at the boundaries, n and $-n$:

$$\bar{v}_n = (1-\delta)[p(x-c_l) - (1-p)c_h] + \delta(1-p)\bar{v}_{n-1} + \delta p \bar{v}_n, \tag{8}$$

$$\bar{v}_{-n} = (1-\delta)(x - pc_l) + \delta((1-p)\bar{v}_{-n+1} + p\bar{v}_{-n}), \tag{9}$$

Equation (7) is a second-order difference equation, with boundary conditions (8) and (9). See Degan et al. (2023) for the analytical solution.

A.3.2 Individual Rationality Constraints of BFBp

Analogous to BFBr, (IR) constraints for BFBp are that $\overline{v}_k \geq 0$, for all $k \in K$. Degan et al. (2023) show that $\overline{v}_k$ is decreasing in k, so that (IR) constraints are satisfied if and only if $\overline{v}_n \geq 0$.

A.3.3 Incentive Constraints of BFBp

The (IC) under BFBp are presented in Table A5 and Table A6 for low and high types, respectively.

Table A5: Incentive constraints for the low type in BFBp

[1]	$-c_l(1-\delta) + \delta(\bar{v}_{k-1} - \bar{v}_k) \geq 0$	$k \in \{-n+1, ...n-1\}$
[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 A6: Incentive constraints for the high type BFBp

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

We describe and discuss (IR) and (IC) constraints in the accompanying theoretical paper. In a nutshell, a BFBp constitutes an equilibrium if the following constraints are satisfied: (1) the (IR) constraint in state $k = n$; (2) the (IC) constraint for the low type in state $k = j \leq 0$, where $(\bar{v}_{k-1} - \bar{v}_k)$ is minimized; and (3) the (IC) constraint for the high type in state $k = n$.

Compared to the conditions for BFBr, the (IR) constraints are no longer implied by the (ICL) constraints and incentives must be given to the high type to make a favor when he has reached n, the maximum net number of favors received.

A.4 Simple Equality Matching (SEM) Strategies

A SEM strategy is a Markovian strategy with state $k^s \in K^s = \{-1, 0, 1\} \cup \{\emptyset\}$. State 0 is the initial neutral state where players are even; state 1 is one where player 1 owes (player 2 is owned) a favor and state -1 is one where player 1 is owned (player 2 owes) a favor. For player 1 a SEM strategy at each period t is represented in equation (10):

$$s_1^{SEM}(k, c_1) = \begin{cases} \text{F} & \text{if} \quad c_1 = c_l \text{ and } (k^s = 0 \text{ or } k^s = 1) \\ \text{N} & \text{if} \quad \text{otherwise} \end{cases} . \tag{10}$$

The transition Matrix of the State Variable for the SEM is illustrated in the following Table A7.

Table A7: Transition to state k' from state k in SEM

y	$k^s = 0$	$k^s = 1$	$k^s = -1$	$k^s = \emptyset$
(F, N)	-1	-1	$\emptyset$	$\emptyset$
(N, F)	1	$\emptyset$	1	$\emptyset$
(N, N)	0	1	-1	$\emptyset$
(F, F)	$\emptyset$	$\emptyset$	$\emptyset$	$\emptyset$

A.4.1 Values of SEM

From the description of SEM and the law of motion of the state variable, the value at state -1 and 1 are, respectively:

$$v_{-1}^s = p[(1-\delta)x + \delta v_1^s] + (1-p)\delta v_{-1}^s, \tag{11}$$

$$v_1^s = p[-(1-\delta)c_l + \delta v_{-1}^s] + (1-p)\delta v_1^s, \tag{12}$$

From the, the value at state 0 is :

$$v_0 = p[-(1-\delta)c_l + \delta v_{-1}^s) + p[(1-\delta)x + \delta v_1^s)] + (1-2p)\delta v_0^s, \tag{13}$$

Solving for $v_1$and v_{-1} from equations (11) and (12) we obtain:

$$v^s_{-1} = \frac{p[p\delta(x-c_l)+(1-\delta)x]}{1-\delta(1-2p)}, \tag{14}$$

$$v^s_1 = \frac{p[p\delta(x-c_l)-(1-\delta)c_l]}{1-\delta(1-2p)}, \tag{15}$$

The value v^s_0 can be obtained by substituting these into (13).

A.4.2 Individual Rationality Constraints of SEM

It is easy to see that $v^s_{-1} \geq v^s_0 \geq v^s_1$. So (IR) constraints of SEM are satisfied if and only if $v^s_1 \geq 0$, that is for $\delta \geq \frac{c_l}{c_l+(x-c_l)p}$.

A.4.3 Incentive Constraints of SEM

The (IC) for SEM are presented in Table A8 and Table A9 for low and high types, respectively.

Table A8: Incentive constraints for the low type for SEM

[1]	$-c_l(1-\delta)+\delta v^s_{-1} \geq \delta v^s_0$	$k^s = 0$
[2]	$-c_l(1-\delta)+\delta v^s_{-1} \geq \delta v^s_1$	$k^s = 1$
[3]	$\delta v^s_{-1} \geq -c_l(1-\delta)$	$k^s = -1$

As long as all IR constraints are satisfied, the ICL in state 1 is trivially satisfied. Since $v^s_{-1} \geq v^s_0 \geq v^s_1$, the more stringent ICL constraint is the one in state 0.

Table A9: Incentive constraints for the high type for SEM

[1]	$\frac{1-2p}{1-p}\delta v^s_0 + \frac{p}{1-p}[(1-\delta)x+\delta v^s_1] \geq -(1-\delta)c_h + \frac{1-2p}{1-p}\delta v^s_{-1} + \frac{p}{1-p}(1-\delta)x$	$k^s = 0$
[2]	$\frac{1-2p}{1-p}\delta v^s_{-1} + \frac{p}{1-p}[(1-\delta)x+\delta v^s_1] \geq -(1-\delta)c_h + \frac{p}{1-p}(1-\delta)x$	$k^s = -1$
[3]	$\delta v^s_1 \geq -(1-\delta)c_h + \delta v^s_{-1}$	$k^s = 1$

As long as all IR constraints are satisfied, it is easy to see that the ICH in 1 is satisfied.

A.5 Examples of BFB and SEM Strategies

We provide a numerical example that illustrates the differences in the strategy profiles prescribes by BFB and SEM. For simplicity we consider BFB with n=1.

Consider the following table. The first column represents a possible realization of the costs in the first nine periods of a supergame. Column (1) indicates the state variable for player 1 at the beginning of a period, column (2) the prescribed action profile and columns (3) the state variable at the end of the period, for BFBp-1. Columns (1')-(2')-(3') and columns (1")-(2")-(3") represent the analogous for BFBr-1 and SEM, respectively.

The elements of BFBp-1 outlined in blue represent the situations where the action profile and/or the state variables of BFBp-1 are different from BFBr-1. Similarly the elements of SEM outlined in red represent the situations where action profile and/or the state variables of SEM are different from BFBr-1.

Table A10: BFBp, BFBr-1 and SEM

		BFBp-1			BFBr-1			SEM	
costs	(1)	(2)	(3)	(1')	(2')	(3')	(1")	(2")	(3")
(c1,c2)	k	(y_1, y_2)	k'	k	(y_1, y_2)	k'	k^s	(y_1, y_2)	$k^{s\prime}$
(ch,ch)	0	(N,N)	0	0	(N,N)	0	0	(N,N)	0
(cl,ch)	0	(F,N)	-1	0	(F,N)	-1	0	(F,N)	-1
(cl,ch)	-1	(F,F)	-1	-1	(N,N)	-1	-1	(N,N)	-1
(ch,cl)	-1	(N,F)	0	-1	(N,F)	0	-1	(N,F)	1
(ch,cl)	0	(N,F)	1	0	(N,F)	1	1	(N,N)	1
(ch,ch)	1	(F,N)	0	1	(N,N)	1	1	(N,N)	1
(cl,ch)	0	(F,N)	-1	1	(F,N)	0	1	(F,N)	-1
(cl,ch)	-1	(F,F)	-1	0	(F,N)	-1	-1	(N,N)	-1

Notice that there is a link between k and k^S. In particular, $k = k^S$ when $k \in \{-1, 1\}$ and $k^S = -1$ when $k = 0$ and player 1 did the last favor, while $k^S = 1$ when $k = 0$ and player 2 did the last favor.

A.6 Lenient and Forgiving Strategies

We describe the various lenient and forgiving strategies that we include in the strategy analysis in the following Table 11.

Table 11: Description of additional strategies

Strategy	
s_2^{FF}	Play "F" until 2 consecutive rounds occur in which either player played "N", then play "N" forever
s_3^{FF}	Play "F" until 3 consecutive rounds occur in which either player played "N", then play "N" forever
TFT	Play "F" unless the matched player played "N" last round
STFT	Play "N" in the first round, then play TFT
WSLS	Play "F" if both players played the same last round, otherwise play "N"
2TFT	Play "F" unless the matched player played "N" in either of the last 2 rounds
	(play 2 rounds of "N" if the matched player played "N")
TF2T	Play "F" unless the matched player played "N" in both of the last 2 rounds
TF3T	Play "F" unless the matched player played "N" in all of the last 3 rounds
2TF2T	Play "F" unless the matched player played 2 consecutive "N" in the last 3 rounds
	(play 2 rounds of "N" if the matched player played "N" twice in a row)

B Appendix B: Additional Experimental Results

B.1 Size of Datasets and Random Termination Methodology in Related Works

Table B1 reports an overview of datasets and experimental approaches in some related experimental works on infinitely repeated game. All of these related papers consist of no more than 4 sessions per treatment, with the number of subjects per session ranging from 8 to 22. The size of our sessions per treatment and the number of subjects per session are not much different from the existing relative works.

In the experimental literature on repeated games that use random terminations to implement an indefinite horizon, researchers have employed several different approaches. Each approach has its own cons and pros. The most common approach is to draw random variables spontaneously during the experimental session, for instance, as in Engle-Warnick and Slonim (2004), Dal Bó and Fréchette (2011). Our paper follows this approach. This approach unavoidably produces imbalanced data sets since experimenters do not have full control over the number of supergames and number of rounds in each supergame. However, this approach is the most natural way to implement random terminations and closest to true randomness. The second approach is to use pre-drawn random sequences. For instance, in Lugovskyy et al. (2017), all indefinite-horizon sessions consist of 15 sequences. There are three sessions for each treatment, each session using one of the three pre-

Table B1: Overview of datasets and random termination methodology

Game	Total subjects	Sessions per treatment	Subjects per session	Methodology	Pre-drawn random sequences	Pre-determine number of sequences	Number of subjects across treatments
Engle-Warnick and Slonim (2004)							
Trust game	146	4	16–20	Random termination	No	Yes	Different
Dal Bó and Fréchette (2011)							
PD game	266	3	12–20	Random termination	No	No	Different
Fréchette and Yuksel (2017)							
PD game	192	3	12–20	Random termination	No	Yes	Different
Leo (2017)							
Turn-taking game	129	2	15–18	Random termination	No	No	Different
Lugovskyy, Puzzello, Sorensen, Walker and Williams (2017)							
VCM game	348	3	8–16	Random termination	Yes	Yes	Different
Aoyagi, Bhaskar and Fréchette (2019)							
PD game	372	4	14–20	Random termination	No	No	Different
Dal Bó and Fréchette (2019)							
PD game	372	2–3	12–22	Random termination	No	No	Different
Kloosterman and Mago (2023)							
Volunteers Dilemma game	120	4	10	Block random termination	Yes	Yes	Same
Smyth and Rodet (2023)							
PD and Red Queen games	192	3	8	Random termination	Yes	Yes	Same
Our papers							
Favor Exchange game	194	4	8–14	Random termination	No	No	Different

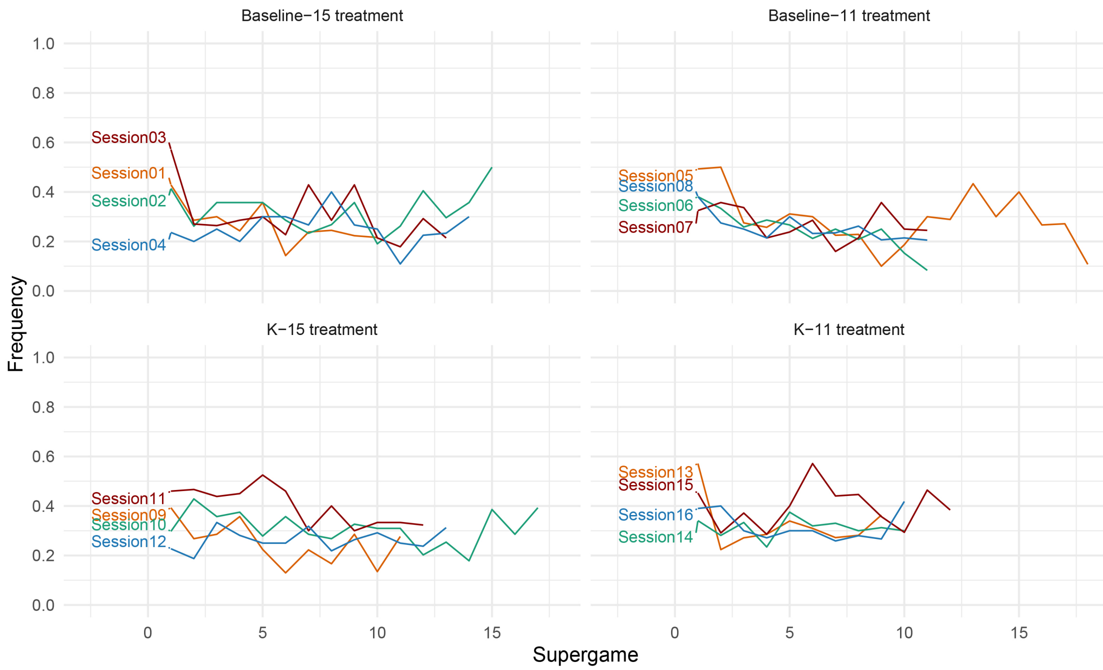
drawn random sequences, so the data is balanced across treatments while it allows some variations on the length of the supergames across sessions within each treatment. In addition, experimenters have better control in terms of the total duration of the experimental sessions. However, on the other hand, this approach sacrifices a bit “true randomness.” In some studies, researchers pre-determine the number of supergames but still use spontaneous random draws to determine the length of the supergame, such as in Bó (2005). A fixed number of supergames can be a very useful design feature, especially in studies that compare treatment with finite horizon and indefinite horizon, as in Bó (2005) and Lugovskyy et al. (2017).

Fréchette and Yuksel (2017) compares behavior under four different implementations of infinitely repeated games in the laboratory: the standard random termination method, two methods involving a fixed number of repetitions with payoff discounting, followed by random termination or a coordination game, and a new method—block random termination—in which subjects receive feedback about termination at the end of each block rather than each round. The method of block random termination has gained more popularity in recent years, for instance, employed by Kloosterman and Mago (2023) on infinitely repeated volunteer's dilemma, Duffy et al. (2024) in indefinite-horizon asset markets, and Jiang et al. (2023) in an experiment on monetary policy. Although the method can guarantee observing the data in at least one block, which reduces the variance of the supergame length especially when the number of supergames or markets is fewer, we did not opt for this design since we are concerned that it will add more complications to our environment with private costs.

B.2 Frequency of Favor Provision over Time

Figure B1 displays the unconditional frequency of favor provision over time (all supergames) by treatment and session. The results depicted in Figure B1 indicate an initial decline in favor provision, followed by a rebound across nearly all treatments.

Figure B1: Frequency of favor provision over supergame



Notes: Frequency is the average frequency of favor provision for each supergame.

B.3 Level of Favor Provision: Robustness Check

The results of the treatment effect (β_{T_g}) remain consistent. Table B2 reports the full results of the regression model (1) in the paper. For each pairwise comparison in Table B3, we report the results of a pooled Probit regression over all subjects' decisions, with a dummy as the independent variable indicating the treatment group in each treatment pair. We also perform wild cluster bootstrap inference for linear hypotheses about the parameter of the dummy variable at the session level.

Table B2: Panel data analysis of individual frequency of favor provision: Full results

Reference	Treatment T_g	β_{T_g}	$\beta_{Seq,Length_{s-1}}$	$\beta_{Avg\,Seq\,length_{[1,s-1]}}$	β_{covid}
Panel A: No conditioning					
Baseline-15	Baseline-11	-0.028	–0.000	0.004	-0.033
		(0.146)	(0.909)	(0.486)	(0.182)
Baseline-15	K-15	0.013	-0.001	-0.004	0.025
		(0.742)	(0.690)	(0.661)	(0.770)
Baseline-11	K-11	0.098	0.000	0.010	-0.012
		(0.441)	(0.949)	(0.257)	(0.622)
K-15	K-11	-0.001	0.000	-0.002	0.055
		(0.987)	(0.844)	(0.865)	(0.614)
Panel B: Conditioning on low cost					
Baseline-15	Baseline-11	-0.024	0.000	-0.001	-0.011
		(0.508)	(0.927)	(0.890)	(0.772)
Baseline-15	K-15	0.015	-0.001	-0.010	0.055
		(0.914)	(0.869)	(0.407)	(0.659)
Baseline-11	K-11	0.140	-0.003	0.025	0.054
		(0.392)	(0.428)	(0.116)	(0.321)
K-15	K-11	0.053	-0.002	0.016	0.063
		(0.517)	(0.703)	(0.473)	(0.784)
Panel C: Conditioning on high cost					
Baseline-15	Baseline-11	-0.025	0.000	0.004	-0.063
		(0.419)	(0.702)	(0.459)	(0.127)
Baseline-15	K-15	0.026	0.001	-0.001	-0.000
		(0.634)	(0.304)	(0.943)	(0.999)
Baseline-11	K-11	0.060	-0.000	-0.002	-0.053
		(0.394)	(0.768)	(0.638)	(0.397)
K-15	K-11	-0.073	0.002	-0.013**	0.075
		(0.482)	(0.362)	(0.034)	(0.557)

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, p-values in parentheses. We perform wild cluster bootstrap inference for linear hypotheses about parameters of independent variables at the session level.

Table B3: Probability of favor provision between treatments

Reference	Treatment T_g	β_{T_g}	$\beta_{Seq,Length_{s-1}}$	$\beta_{Avg\,Seq\,length_{[1,s-1]}}$	β_{covid}
Panel A: No conditioning					
Baseline-15	Baseline-11	-0.014	0.000	0.002	-0.017
		(0.181)	(0.793)	(0.526)	(0.123)
Baseline-15	K-15	0.022	-0.000	-0.007	0.049
		(0.475)	(0.970)	(0.433)	(0.473)
Baseline-11	K-11	0.087	-0.002	0.012	0.009
		(0.174)	(0.517)	(0.174)	(0.368)
K-15	K-11	-0.011	-0.001	0.002	0.078
		(0.859)	(0.756)	(0.903)	(0.436)
Panel B: Conditioning on low cost					
Baseline-15	Baseline-11	-0.016	-0.000	0.001	0.013
		(0.432)	(0.945)	(0.896)	(0.591)
Baseline-15	K-15	0.002	-0.003	-0.009	0.084
		(0.973)	(0.546)	(0.376)	(0.383)
Baseline-11	K-11	0.137	-0.003	0.028*	0.068
		(0.184)	(0.329)	(0.060)	(0.100)
K-15	K-11	0.073	-0.004	0.022	0.074
		(0.108)	(0.344)	(0.382)	(0.661)
Panel C: Conditioning on high cost					
Baseline-15	Baseline-11	-0.013	0.001	0.002	-0.040
		(0.675)	(0.498)	(0.675)	(0.100)
Baseline-15	K-15	0.040	0.001	-0.003	0.019
		(0.297)	(0.388)	(0.702)	(0.778)
Baseline-11	K-11	0.046	-0.000	-0.002	-0.040
		(0.256)	(0.896)	(0.800)	(0.346)
K-15	K-11	-0.078	0.000	-0.011	0.067
		(0.224)	(0.895)	(0.143)	(0.382)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, p-values in parentheses. We perform wild cluster bootstrap inference for linear hypotheses about the parameter of the independent variable at the session level. In the regressions, we also control the supergame length of the previous supergame, the average supergame length of all the previous supergame, and the Covid-19.

B.4 Comparison of Payoff-efficiency Index across Treatments

Table B4 report parametric test to assess whether there is a statistically significant difference in the efficiency level between pairs of treatment. In each regression, we include a dummy variable that indicates the treatment group g in any pair of treatments. Notice that, due to the normalization of the payoff-efficiency index, only indexes for treatments with the same value of c_h are directly comparable.

Table B4: Comparison of efficiency across treatments

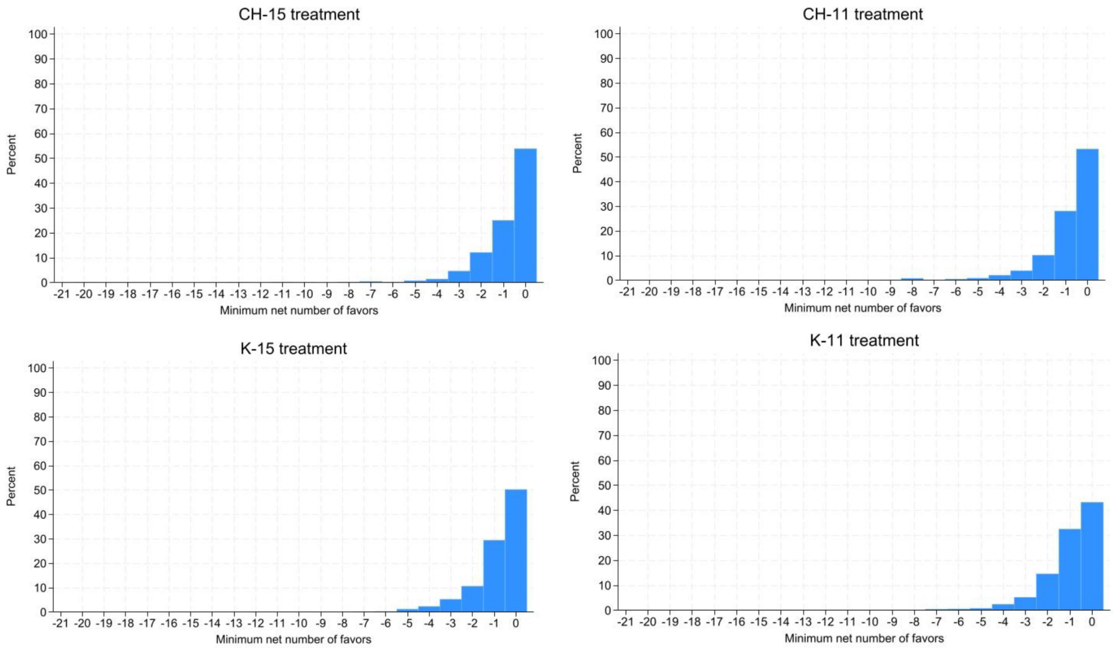
Reference	Treatment T_g	β_{T_g}
Baseline-15	K-15	0.000
		(0.994)
Baseline-11	K-11	0.123***
		(0.002)

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, p-values in parentheses. We perform wild cluster bootstrap inference for linear hypotheses about parameters of independent variables at the session level.

B.5 Percent of Minimum Net Number of Favors

We first calculate the minimum net number of favors (k) for each subject in each supergame. We then report the percents of these minimum ks by treatment in Figure B2. The result of the maximum net number of favors is the mirror image of the minimum net number of favors. Since k is the difference between the number of favors received and the number of favors provided, the minimum k represents subject's tolerance for providing favors to others, given the length of a supergame. The results show that in over 90% of all supergames across treatments, the minimum k for all subjects is between -2 and 0, and over 95% between -3 and 0. The average length of the supergame is 7 period in our experiment.

Figure B2: Percent of minimum k



C Appendix C: Details of Strategy Estimation and Strategy-fitting Procedure

C.1 Strategy Estimation through Maximum Likelihood

Our SFEM estimation procedure and notation follows Dal Bó and Fréchette (2019) as closely as possible. We assume that each subject $i \in I$ (the set of subjects) chooses to play a strategy among a predetermined finite set of strategies Φ. In particular, strategy s^{σ}, $\sigma \in \Phi$, is played by each subject with probability ϕ^{σ} for all supergames in a session. That is, if this strategy is selected to be used, the subject does not change the strategy between supergames within a session. However, in each round subjects are allowed to make mistakes and choose an action that is not recommended by the strategy. More precisely, in each round the chosen strategy is played with probability $\beta \in (\frac{1}{2}, 1)$ and a mistake happens with the complementary probability $1 - \beta$. We let s^{σ}_{imrc} denote the choice prescribed by strategy σ in round r of supergame m, given the realization of the subject's cost c in round r and the public history in the supergame up to round r. When the strategy prescribes "do a favor" s^{σ}_{imrc} is assigned the value 1, and when it prescribes "do not do a favor" it is assigned the value 0. We let c_{imr} denote subject i's actual choice in round r and supergame m. This choice variable takes the value 1 or 0 if the subject chose "do a favor" or "do not do a favor", respectively. The likelihood of the choices made by subject i when she follows strategy σ can be written as equation 16.

$$Pr_i(s^\sigma) = \prod_{M_i} \prod_{R_{im}} (\beta)^{I^\sigma_{imr}} (1-\beta)^{1-I^\sigma_{imr}}, \tag{16}$$

where $I^\sigma_{imr} = 1\{s^\sigma_{imrc} = c_{imr}\}$ is an indicator function that takes the value 1 if the observed choice is consistent with the prescription of strategy σ, M_i is the set of supergames faced by subject i and R_{im} is the set of rounds in supergame m for subject i and the probability of making mistakes $1-\beta$ is constant across strategies. The estimation is based on the following individual log-likelihood function 17,

$$LL(\{c_{imr}\}_{i,m,r}|\beta, \phi^1, ...\phi^\Phi) = \sum_{i \in I} ln\left(\sum_{\sigma \in \Phi} \phi^\sigma Pr_i(s^\sigma)\right) \tag{17}$$

The parameters to be estimated are: ϕ^σ, for $\sigma \in \Phi$, the probability of playing strategy s^σ or, equivalently, the proportion of the data attributed to such strategy, and β.

Since the cost in our model is private information and the BFB strategies we consider rely on the public history, the way s^σ_{imrc} is constructed in our paper for the different strategies on and off equilibrium path is more complicated than Dal Bó and Fréchette (2019). To provide a practical illustration, let's consider strategy BFBr-n in a given supergame m. The public history is summarized by the state variable k. At the beginning, where $k = 0$, or in other interior states if a deviation was never publicly detected, $s^{BFBr}_{imrc_l} = 1$ and $s^{BFBr}_{imrc_h} = 0$, that is, the strategy prescribes "do a favor" if the cost is low and "do not do a favor" if the cost is high. Suppose that subject i has a low cost. If she makes a favor, then $I^{BFBr}_{imr} = 1$ otherwise $I^{BFBr}_{imr} = 0$. Suppose now that the subject has a high cost. If she makes a favor, then $I^{BFBr}_{imr} = 0$ otherwise $I^{BFBr}_{imr} = 1$. To see which action the strategy prescribes in round $r' = r+1$, we need first to see whether a deviation was detected from the public history. If a deviation was detected then $k = \emptyset$ and from then on $s^{BFBr}_{imr'c} = 0$. If a deviation was never detected even if it happened, the state variable in round r' is calculated according to the transition matrix in Table A1 and the players behave as if it is still on the equilibrium path. Similar steps apply when the state variable is at the boundaries.

Notice that if a deviation is publicly detected in round r, the indicator I^{BFBr}_{imr} must be 0 for at least one of the two subjects. However, it is possible that a subject deviates in a round, so that $I_{imr}^{BFBr} = 0$ but that the deviation is not detectable from the public history (for example when somebody with a low cost does not do a favor) so that next round's state variable is not $k = \emptyset$. Similarly, even if subject i followed the prescription of the strategy, it is possible that her matched player made a mistake, so that from the following round the strategy prescribes $s_{imr'c}^{BFBr} = 0$ to both matched subjects, for each round $r' > r$ and cost realization.

Table C1 reports the first-stage results of SFEM, using data only from the last supergames. In this section, we additionally present the results of SFEM using the full data set, which serve as robustness checks.

Table C1: Strategy frequency estimation: first stage with last 5 supergames

	(1) Baseline-15	(2) Baseline-11	(3) K-15	(4) K-11
EQM	BFBr1,r2; s^{NN}	BFBr1,r2; s^{NN} BFBp1,p2	BFBr1,r2; s^{NN}	BFBr1,r2; s^{NN} BFBp1,p2
BFBr-1	0.000	0.131**	0.168**	0.144**
	(0.019)	(0.059)	(0.082)	(0.059)
BFBr-2	0.101*	0.096*	0.000	0.157**
	(0.055)	(0.056)	(0.008)	(0.075)
BFBr-3	0.000	0.047	0.000	0.000
	(0.023)	(0.052)	(0.051)	(0.010)
BFBp-1	0.000	0.000	0.028	0.000
	(0.000)	(0.006)	(0.029)	(0.003)
BFBp-2	0.010	0.000	0.000	0.024
	(0.030)	(0.026)	(0.005)	(0.030)
BFBp-3	0.038	0.033	0.000	0.000
	(0.036)	(0.037)	(0.027)	(0.007)
s^{NN}	0.410***	0.496***	0.392***	0.117**
	(0.077)	(0.077)	(0.074)	(0.051)
s^{FN}	0.200***	0.099	0.151*	0.365***
	(0.066)	(0.065)	(0.085)	(0.084)
s^{FF}	0.027	0.000	0.027	0.042
	(0.025)	(0.001)	(0.029)	(0.031)
s^{FF}-2	0.000	0.000	0.000	0.040
	(0.000)	(0.000)	(0.000)	(0.035)
s^{FF}-3	0.000	0.000	0.025	0.000
	(0.015)	(0.000)	(0.024)	(0.000)
SEM	0.098*	0.042	0.110*	0.000
	(0.057)	(0.043)	(0.066)	(0.002)
TFT	0.069	0.039	0.000	0.042
	(0.043)	(0.033)	(0.003)	(0.033)
STFT	0.000	0.017	0.044	0.017
	(0.002)	(0.019)	(0.031)	(0.021)
WSLS	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
TF2T	0.016	0.000	0.017	0.000
	(0.019)	(0.000)	(0.022)	(0.002)
TF3T	0.040	0.000	0.039	0.000
	(0.032)	(0.000)	(0.033)	(0.000)
2TFT	0.000	0.000	0.000	0.000
	(0.013)	(0.002)	(0.018)	(0.003)
2TF2T	0.000	0.000	0.000	0.052
	(0.001)	(0.001)	(0.004)	(0.035)
Beta	0.900***	0.915***	0.879***	0.874***
	(0.013)	(0.012)	(0.016)	(0.012)

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Boostrapped standard errors in parentheses. The row of EQM lists the equilibrium strategies. We use the data of last 5 supergames in each session.

Table C2: Strategy frequency estimation: first stage with all supergames

	(1) Baseline-15	(2) Baseline-11	(3) K-15	(4) K-11
EQM	BFBr1,r2; s^{NN}	BFBr1,r2; s^{NN} BFBp1,p2	BFBr1,r2; s^{NN}	BFBr1,r2; s^{NN} BFBp1,p2
BFBr-1	0.000	0.170***	0.075*	0.161***
	(0.018)	(0.057)	(0.044)	(0.057)
BFBr-2	0.140***	0.000	0.034	0.107**
	(0.054)	(0.000)	(0.030)	(0.052)
BFBr-3	0.000	0.000	0.029	0.008
	(0.014)	(0.004)	(0.040)	(0.021)
BFBp-1	0.000	0.000	0.026	0.000
	(0.006)	(0.000)	(0.026)	(0.000)
BFBp-2	0.013	0.016	0.000	0.021
	(0.025)	(0.020)	(0.000)	(0.031)
BFBp-3	0.000	0.027	0.000	0.000
	(0.020)	(0.027)	(0.010)	(0.005)
s^{NN}	0.405***	0.458***	0.457***	0.138**
	(0.071)	(0.076)	(0.076)	(0.057)
s^{FN}	0.214***	0.197***	0.103*	0.424***
	(0.061)	(0.062)	(0.057)	(0.081)
s^{FF}	0.026	0.001	0.024	0.077
	(0.025)	(0.009)	(0.025)	(0.020)
s^{FF}-2	0.057	0.000	0.000	0.000
	(0.039)	(0.000)	(0.000)	(0.044)
s^{FF}-3	0.000	0.000	0.000	0.000
	(0.010)	(0.000)	(0.000)	(0.000)
SEM	0.085*	0.024	0.120**	0.000
	(0.044)	(0.029)	(0.053)	(0.020)
TFT	0.032	0.040	0.023	0.077*
	(0.030)	(0.029)	(0.029)	(0.044)
STFT	0.000	0.049	0.000	0.000
	(0.001)	(0.033)	(0.004)	(0.020)
WSLS	0.009	0.000	0.000	0.000
	(0.017)	(0.000)	(0.000)	(0.000)
TF2T	0.000	0.012	0.065	0.000
	(0.003)	(0.018)	(0.036)	(0.009)
TF3T	0.019	0.000	0.022	0.000
	(0.020)	(0.000)	(0.022)	(0.000)
2TFT	0.000	0.007	0.023	0.035
	(0.009)	(0.019)	(0.022)	(0.014)
2TF2T	0.000	0.000	0.000	0.008
	(0.001)	(0.001)	(0.008)	(0.016)
Beta	0.859***	0.853***	0.832***	0.838***
	(0.015)	(0.014)	(0.014)	(0.011)

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Boostrapped standard errors in parentheses. The row of EQM lists the equilibrium strategies. We use all the data in each session.

Table C3: Strategy frequency estimation: second stage with all supergames

	(1) Baseline-15	(2) Baseline-11	(3) K-15	(4) K-11
EQM	BFBr1,r2; s^{NN}	BFBr1,r2; s^{NN} BFBp1,p2	BFBr1,r2; s^{NN}	BFBr1,r2; s^{NN} BFBp1,p2
BFBr-1	0.000	0.165***	0.084*	0.140**
	(0.019)	(0.057)	(0.048)	(0.061)
BFBr-2	0.166***	0.028	0.043	0.141**
	(0.056)	(0.029)	(0.036)	(0.068)
s^{NN}	0.410***	0.486***	0.450***	0.158***
	(0.071)	(0.075)	(0.075)	(0.057)
s^{FN}	0.255***	0.214***	0.152***	0.433***
	(0.063)	(0.063)	(0.058)	(0.083)
SEM	0.082*	0.026	0.142**	0.000
	(0.045)	(0.030)**	(0.058)	(0.027)
TFT	0.087**	0.080	0.130**	0.128**
	(0.041)	(0.040)	(0.053)	(0.054)
Beta	0.847***	0.850***	0.818***	0.829***
	(0.018)	(0.014)	(0.015)	(0.013)

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Boostrapped standard errors in parentheses. The row of EQM lists the equilibrium strategies. We use all the data in each session.

C.2 Details of Strategy-fitting Procedure by Camera et al. (2012)

The strategy-fitting procedure of Camera et al. (2012) maps the subject's choices in the different supergames into a set of strategies. It is based on the assumption that a subject's behavior in a supergame can be described by one or more strategies in a predetermined set. For any strategy σ in the set Φ we can determine a *consistency score* between the series of actions prescribed by the strategy and a subject's behavior in a supergame. Given a supergame m faced by subject i, let T_m=|R$_{im}|$ indicates the number of rounds in the supergame. As before, $I^{\sigma}_{imr} = 1$ if in round r of supergame m subject i's choice is consistent with the prescription of strategy σ. The *consistency score* of strategy σ in supergame m is defined as $X^{\sigma}_{im}(T_m) = \sum_{r=1}^{T_m} \frac{I^{\sigma}_{imr}}{T_m}$. If none of the choices made in a supergame is consistent with strategy σ, the score takes value 0. It takes value 1 if the subject's behavior is consistent with the strategy in all rounds of the supergame.

Following Camera et al. (2012), we allow subject to make mistakes (behaving differently from the prescription of a strategy) with probability p_ε starting from the second round. The probability p_ε is the same for all subjects, rounds, supergames, and strategy considered. It follows that the number n_σ of a subject's mistakes relative to the prescription of strategy σ, is distributed according to a binomial distribution with parameters p_ε and $T_m - 1$.

For a given p_ε, a subject in supergame m is *classified* with strategy σ if three conditions hold. First, the action in the first round is consistent with strategy σ. Second, σ must be the strategy has the highest consistency score. Third, the observed number of mistakes n_σ must pass a statistical test. It must be below a critical value, based on a right-tail test at the 10% significance level, given p_ε and T_m. If a strategy does not meet the above conditions, it cannot classify a subject's behavior in the supergame. If there is no strategy that classifies a subject in a supergame, then the subject-supergame observation remains unclassified.

An important thing to notice is that a subject could be classified by more than one strategy in each supergame. As a complement to Table 9 we report the results when $p_\varepsilon = 0.05$ in Table C4. While the number of unclassified observations is larger when players are allowed to make fewer mistakes, the results on the relative ability of different strategies to classify the observations are consistent. In Table C5, we conduct the strategy fitting analysis with $p_\varepsilon = 0.1$ by including BFBr-n, BFBp-n, n=1, 2, 3, s^{NN}, s^{NF}, s^{FF}, and SEM. Different from results from SFEM, we find both BFBp and SEM, as well as s^{FF}, can classify a proportion of observations, although the number of observations classified is still lower than that being classified by BFBr.

Table C4: Individual strategy used - $p_\varepsilon = 0.05$

5 Strategies	Baseline-15	Baseline-11	K-15	K-11
All observations	260	250	230	230
BFBr	129	131	106	106
-BFBr1	107	107	93	79
-BFBr2	109	105	85	88
SEM	103	103	85	61
s^{NN}	120	121	100	54
s^{FN}	113	104	83	99
Unclassified	41	27	44	63

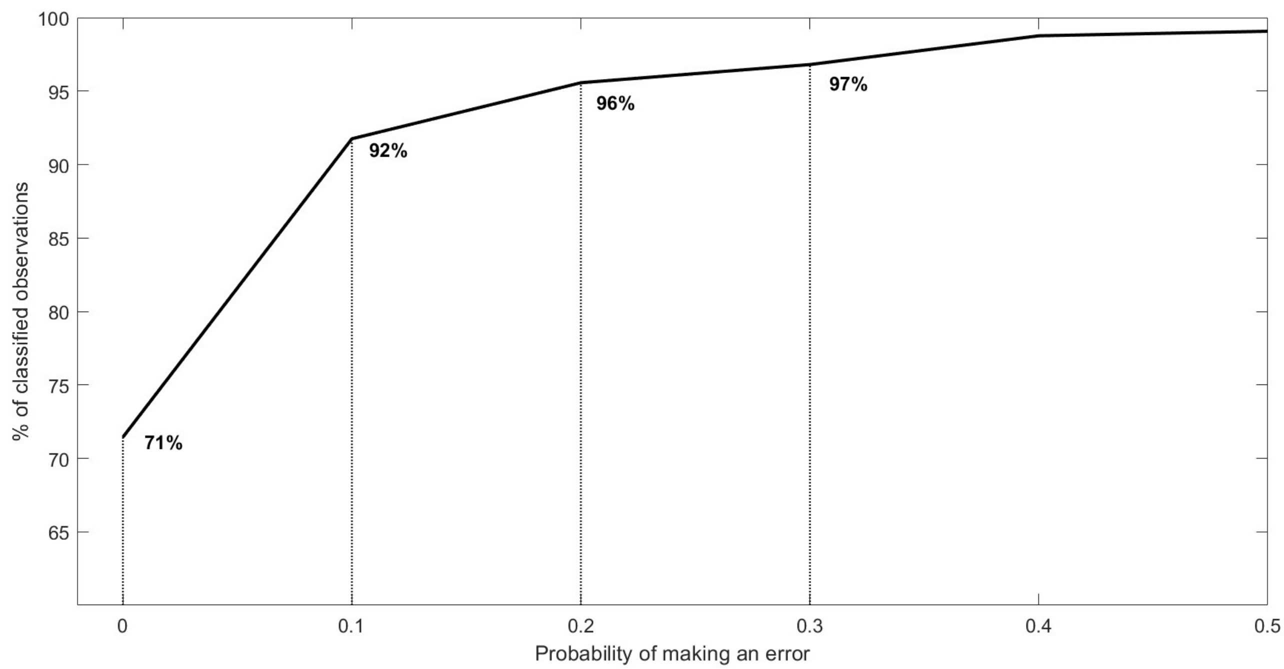
Notes: The unit of an observation is all choices of a subject in a supergame. We use the data of last 5 supergames in each session.

Table C5: Individual strategy used - $p_\varepsilon = 0.1$

10 Strategies	Baseline-15	Baseline-11	K-15	K-11
All observations	260	250	230	230
BFBr	146	135	113	123
-BFBr1	113	107	95	82
-BFBr2	115	103	87	92
-BFBr3	117	100	86	92
BFBp	134	120	98	111
-BFBp1	93	86	65	54
-BFBp2	113	96	81	79
-BFBp3	113	101	87	88
SEM	109	103	88	64
s^{NN}	125	125	102	61
s^{FN}	119	102	86	102
s^{FF}	42	38	38	33
Unclassified	14	13	28	25

Notes: The unit of an observation is all choices of a subject in a supergame. We use the data of last 5 supergames in each session.

Figure C1: Percentage of classified observations



Notes: We use the data of last 5 supergames in each session.

D Instructions

D.1 Instructions for K-15 Treatment

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 $15 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:

Table D1: Joint probability

		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%

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. Your payoff in each round 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.

Table D2: Payoff table

Your decision	Your matched player's decision	
	Do a favor	Do not do a favor
Do a favor	10 – cost, 10 – cost'	– cost, 10
Do not do a favor	10, – cost'	0, 0

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 (10 – cost) points and your matched player earns (10 – cost') points.

- (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 (– cost) points, and your matched player earns 10 points.

- (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 10 points, and your matched player earns (– 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 0 points.

Final Earnings

Your total payoff for each sequence will be the sum of the points you obtain from each round of that sequence. At the end of the session, the computer will calculate your payoffs from playing the game as the average of the total points you earn from all the rounds of each sequence and convert it to Canadian dollar at the exchange rate of 1 point=$1.

Your final earnings will be equal to the payoffs from playing the game plus $15 show-up fee.

In the rare case, in which your actual payoff from playing the game is negative, you will receive $15 show-up fee as your final earnings.

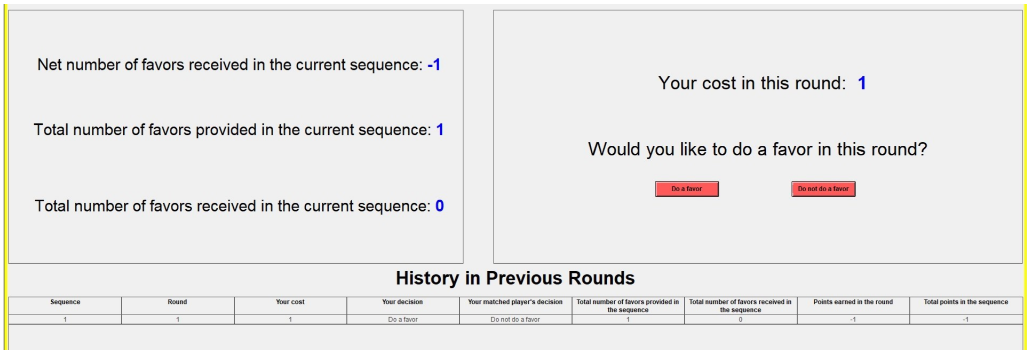
Information shown at the computer screen

The following screenshot gives you an example of the information you will see on the screen before making a decision in each round. In addition to observing your private cost (see the upper right panel of Figure D1), you will also observe the current information on your net number of favors received in the current sequence, your total number of favors provided in the current sequence, and your total number of favors received in the current sequence (see the upper left panel of Figure D1).

Your net number of favors received in the current sequence **equals** your total number of favors received in the current sequence **minus** your total number of favors provided in the current sequence.

Before you make a decision in each round, a History Table will provide information on the history of all previous rounds and sequences (see the lower panel of Figure D1), which includes your private cost, your 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

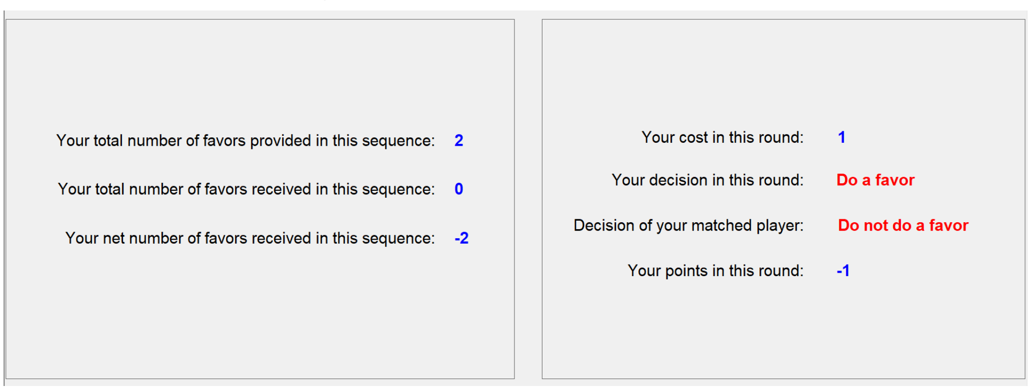
Figure D1: Pre-decision information



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 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, your total number of favors provided/received in this sequence and your net number of favors received in this sequence), you will also observe the decision made by your matched player. However, you will never observe the cost of your matched player.

Figure D2: Post-round information



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.

D.2 Quiz

Before we start today's session, we ask that you answer the following quiz questions that are intended to check your comprehension of the written instructions. Your answers to this quiz will not affect your earnings. After everyone has completed the quiz, the answers will be reviewed. If there are any incorrect answers, we will go over the relevant part of the instructions once again.

1. Suppose it is the 2nd round of a sequence. The chance that this sequence continues with a 3rd round is _________ percent and the chance that this sequence ends after the 2nd round is _________percent. If we were instead considering whether the sequence continued beyond the 12th round to a 13th round, my answers to this same question would:

a. be different b. remain the same.

2. You will be matched with a same player for a new sequence.

True or False?

3. You will be matched with the same player for each round in the same sequence.

True or False?

4. If you receive a low cost in this round, you will have high probability to receive low cost in next round.

True or False?

5. Suppose the cost you receive is 1 for this round, what is the cost your matched player receives?

a. 1 b. 15 c. 5 d. 9

6. Suppose the cost you receive is 15, then the cost your matched player receives is 15 as well. True or False?

7. Suppose your private cost is 1 and only you choose "Do a favor" in the current round, what is your payoff in this round? __________, what is the payoff for your matched player in this round? ____________.

a. -1 b. -5 c. 0 d. 10 e. -15

8. Suppose your private cost is 15 and only you choose "Do a favor" in the current round, what is your payoff in this round? ____________, what is the payoff for your matched player in this round? ____________.

a. -1 b. -5 c. 0 d. 10 e. -15

9. Suppose your private cost is 15 and the cost of your matched player is 1. Only your matched player chooses "Do a favor" in the current round, what is your payoff in this round? ____________, what is the payoff for your matched player in this round? ____________.

a. -1 b. -5 c. 0 d. 10 e. -15

10. Suppose your total number of favors provided in the current sequence and your total number of favors received in the current sequence are 9 and 11, respectively. What is your current net number of favors received in this sequence before making a decision in this round?

a. 9 b. 11 c. 0 d. 2 e. 20

11. Suppose your total number of favors provided in the previous sequence and your total

number of favors received in the previous sequence are 10 and 8, respectively. The computer starts a new sequence in this round. What is your current net number of favors received in this sequence before making a decision in this round?

a. 9 b. 11 c. 0 d. 2 e. 20

12. Your payoffs from playing the game is:

a. the total points earned from all the rounds of all the sequences.

b. the average of the total points earned from all the rounds of each sequence.

c. the total points earned from all the rounds of a randomly chosen sequence.

d. the average of the points earned from all the rounds in the session.