A Successive Analysis of Online Networked Common Knowledge Experiments

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Abstract. Common knowledge (CK) is a phenomenon where a group of individuals each knows some collection of information, and, in essence, everyone knows that everyone knows the information. There are many applications involving CK, including business decision making, protests and rebellions, and online advertising. CK can lead to contagion and collective action but in ways that are fundamentally different from classic (e.g., Granovetter) threshold models used in the social sciences. Researchers developed CK models to enable the computation of contagion in networked populations. But these models have largely not been investigated using experiments with human subjects. In this work, we conduct a successive analysis of online CK experiments. We devise a flexible and interpretable statistical method to investigate the effects of significant factors, such as network structure and communication type. Among our findings, we demonstrate a phase change in group payout in the games that is caused by prohibiting player communication.

Keywords: Common knowledge · Human subjects games · Contagion · Social networks · Phase change

1 INTRODUCTION

1.1 Background and Motivation

Social **contagions** are information, actions, emotions, etc., that are transmitted among people in a population [3]. Contagion is often studied (e.g., [3, 7]) by representing a population as a network $G(V,E)$, where V is the set of individuals $v_i \in V$ (with $n = |V|$) and E is the undirected edge set of pair-wise interactions among v_i, $i \in \{1,2,\ldots,n\}$, e.g., $\{v_i, v_j\} \in E$. Two models are presented here; each uses a different mechanism to propagate contagion.

Under the **Granovetter model** [7], early adopters initiate some action. Then, a neighboring node v_i contracts a contagion when the number (or fraction) of v_i's distance-1 neighbors in G that have *previously* acted is at least a **threshold** θ_i [7, 15]. When a node contracts a contagion, it is *participating*. This is a *sequential* or *incremental* process. Another important characteristic is that an individual *unilaterally* makes her decision to act.

Common knowledge is a more recently studied mechanism for collective action. It may induce significantly different contagion dynamics compared to those of the Granovetter model [5]. CK considers a set of information $\mathbb{I}$ such that each member v_i of a group $M \subseteq V$ knows $\mathbb{I}$, each v_i knows that every other member v_j $(i \neq j)$ knows $\mathbb{I}$, each v_i knows that every other member v_j $(i \neq j)$ knows that v_i knows $\mathbb{I}$, and so on, ad infinitum [1, 4, 5, 11–13].

Under CK, which can be represented as a coordination game [5, 11], individuals of M may *cooperatively* and *simultaneously* participate, even when no members have yet acquired the contagion. This is because CK enables individuals to *anticipate* what others will do. To acquire a contagion, individuals in M must (a) generate CK of $\mathbb{I}$ at time t, (b) generate CK for reasoning about the action each person will take in the future, i.e., at time $(t + \Delta t)$, and (c) act simultaneously at $(t + \Delta t)$.

Figure 1 provides an example of CK, based on the Chwe model [5], in a *network structure* (NS) that is a star graph, i.e., NS=star. Node (i.e., player) thresholds are given, and taking $\theta = 3$ to be a large threshold, the *number of high thresholds* (NTH) is 2. Assume each node only has local *network knowledge* (NK), i.e., NK=local: a node only knows about the existence of itself and its distance-1 neighbors in G. (NK=global, means that each node knows the entire network structure.) Furthermore in this example, *communication type*, CT, is specified as CT=none, i.e., nodes do not communicate their intentions to participate or not. (In experiments where CT is *bilateral communication*, each pair of nodes forming an edge can send messages to each other. A node selects one of two messages: "I will participate." or "I will NOT participate.") Each leaf node knows only about the hub node v_1, and so there are four distinct CK sets, each of size two, containing one leaf node and v_1; see middle graphic, Figure 1. The information I_i that each node v_i contributes to $\mathbb{I}$ of one CK set is $I_i = (v_i, \theta_i, s_i)$, where s_i is the state of v_i, with $s_i = 0$ meaning that the node is not participating and $s_i = 1$ meaning that the node is participating. In contrast, nodes v_2 and v_3 cannot share CK because they do not share an edge and thus do not know each other's threshold and state. In fact, for NK=local, v_2 and v_3 do not even know that the other exists.

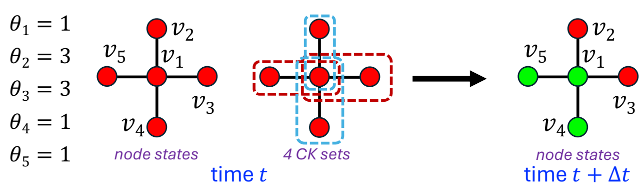


Fig. 1: Effect of CK in a game using a star graph. All nodes are in non-participating state 0 (red) at time t, with the given threshold assignments. There are four CK sets of size two according to the Chwe model [5]: the hub node with each of the leaf nodes. Nodes v_1, v_4, and v_5 transition to state 1 (green), i.e., participate. See text for details.

Consider the CK set $M = \{v_1, v_4\}$. Each of these nodes' thresholds' is $\theta = 1$, so each needs one other node besides itself to participate in order for it to participate. And it has this "other node" in the node with which it forms the edge. Here, $\mathbb{I} = I_1 \cup I_4 = (v_1, \theta_1, s_1) \cup (v_4, \theta_4, s_4)$. Now, v_4 knows (i) $\mathbb{I}$ and (ii) that v_4 and v_1 can participate; v_4 knows that v_1 knows (i) and (ii); v_4 knows that v_1 knows that v_4 knows (i) and (ii); etc. The same is true for v_1 with respect to v_4, and therefore the two nodes share CK of information and decisions and consequently, simultaneously participate. By symmetry, the CK set $M = \{v_1, v_5\}$ behaves in the same way as set $\{v_1, v_4\}$: both nodes participate. If even one node of the two in these two CK sets has $\theta = 2$ instead of $\theta = 1$, then the nodes in that particular M would not participate because $|M| < 3$; the low threshold of 1 is critical in this example for generating CK.

Figure 2 is a schematic of the online game screen (in a web browser) displayed for player v_1 of Figure 1. (Owing to space limitations, we omit game introductions given to each player, including instructions and example game plays.) The player is labeled with v_1 and her threshold is shown. v_1's local network (i.e., distance-1 neighborhood) is provided with neighbor IDs and their thresholds. (All nodes are initially non-participating.) If an experiment incorporates messaging, v_1 can select a neighbor, select a message, and send it. A message can be sent to each neighbor, at v_1's discretion. At this time, v_1, if she chooses, engages in reasoning similar to that provided in describing Figure 1, as it pertains to the sets M in which she is a member. When v_1 is done messaging and reasoning, she clicks the gray button and then chooses whether to participate or not. This is one game for a single node, and is a one-shot game; a human subject plays 15 games in one seating.

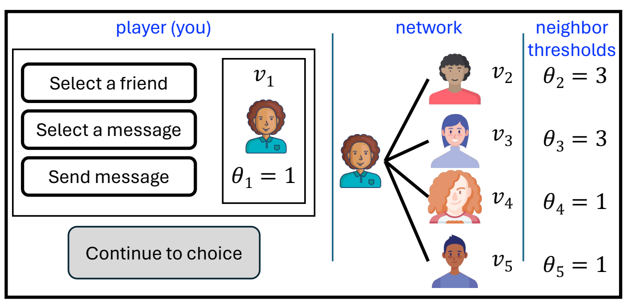


Fig. 2: Stylized illustration of the online game. View of player v_1's computer screen, which is consistent with Figure 1.

At issue is how players act under different conditions—NS, NK, CT, and NTH—in the games and although there are many different aspects, this is the overarching issue of the study. In this work, we consider three NS: star, circle, and clique. We study predominantly team or group payoffs, that is, the sum of the earnings of five players in a scenario (this is defined more concretely in Section 3). In each scenario, a player earns 100 units if she chooses to participate and her threshold is met by other participating players; a player receives 0 units if she chooses to participate but her threshold is not met; a player receives 50 units if she does not participate, regardless of other considerations.

If players v_2 and v_3 of Figure 1 choose to "not participate" and the other players choose "participate," then the *group payoff* for this game is 400 units ($= 3(100) + 2(50)$).

Finally, we note that CT and messages are not part of v_i's information $I_i = (v_i, \theta_i, s_i)$ that contributes to $\mathbb{I}$. That is, message communication is not required for players to recognize and exploit CK.

1.2 Contributions

There are several contributions on both methodology and application in analyzing CK experiments. Our first contribution, called **conditional treatment effect** (CTE), enables successively quantifying the effects of factors on response variables when conditioned on other factors. It introduces a more flexible and interpretable statistic that allows the specification of a linear combination of levels for a factor of interest. Estimates of CTE and the corresponding hypothesis testing are established. Our second contribution is the application of these methods to CK human subjects experimental data of the kind given in the example in Section 1.1. The analyses demonstrate that main effects CT, NS, and NTH are all significant for group payout. Subsequent analyses reveal that the effect of NS on group payout varies by NTH and CT. Moreover, our analyses reveal a phase change in group payout as a function of NTH that only occurs for NS=clique and CT=none. Explanation of this phase change is provided in terms of user choices in the games.

2 RELATED WORK

Conceptual and theoretical works on CK are [1, 2, 11, 12]. There are few formal network models of CK. A model where CK is formed in clique substructures, where all members are in direct communication with each other, is described in [5]. That model is the inspiration for the experiments reported on here. A game-theoretic CK model for Facebook, where an individual's timeline or wall provides a mechanism for establishing CK, is provided in [11].

In another study [10] using similar game data to those in this work, it was found that participation rates increased with NK=global, compared to NK=local. Also, CT=bilateral resulted in player participation choices that were more in agreement with the CK model, compared to the CT=none case. Participants in games with NK=local and CT=none chose participation at a high rate. Our analyses have a different focus and neither set of results (ours or those in [10]) can be derived or inferred from the other.

There are many contexts in which CK operates, including driving behaviors, social gatherings, and advertising on television, e.g., [4, 6]. Group decision-making in business is also studied in the context of CK [9]. Several stylized social situations are summarized in [6], where peoples' actions are strongly affected by whether or not CK is present among those involved. They also evaluated various scenarios with private, shared, and common knowledge [14].

There are two major statistical areas related to the conditional treatment effects used in this work. In the area of experimental design, the conditional main effect is introduced in [16]. In the area of causal inference, the average treatment effect (ATE) is widely used for assessing the impact of treatment factors [8]. Inspired by these concepts, we devise the conditional treatment effect (CTE) as a more flexible and interpretable measure of the effects and patterns of factors conditioning on other factors.

3 EXPERIMENTS

The experiments are designed to test the effects of the four factors in Table 1 on earnings of human subjects; see the example in Section 1 for a review of these factors. The only factor not detailed above is NS. The three types of NS used in the games are provided in Figure 3.

Table 1: Factors of interest and their levels with notations.

Factor	Factor Notation	Levels	Level Notation
NK	$X^{(1)}$	global, local	$l_1^{(1)}, l_2^{(1)}$
NS	$X^{(2)}$	circle, clique, star	$l_1^{(2)}, l_2^{(2)}, l_3^{(2)}$
CT	$X^{(3)}$	none, bilateral	$l_1^{(3)}, l_2^{(3)}$
NTH	$X^{(4)}$	0, 2, 3, 4, 5	$l_1^{(4)}, l_2^{(4)}, l_3^{(4)}, l_4^{(4)}, l_5^{(4)}$

The actual games are played with one difference from the game description in the example. That is, to control a human subject's environment and to make data analysis less complicated, only one of the nodes in a game network is a human. The other players are bots (the human was not told this) and the bots' actions are dictated by the Chwe model [5], which is demonstrated in the example. Since each of the three NS has five nodes, for each set of game conditions, the game is played five times, where a human occupies each of the five positions in a network (not the same human). The **group payoff** is the sum of the five human payoffs across the five games, under the same game conditions. In total, 270 human subjects participated in 4050 games.

The experiment is designed under a nested structure, and it may be decomposed into three layers, namely session, participants group, and individual participants, which are experiment units for CT and NK, NS, and NTH, respectively.

Layer 1: Session The data contain 18 sessions, where each session is assigned to a combination of levels of CT $\times$ NK. Since there are two levels for each of NK and CT, this results in four combinations in total. The combinations of (bilateral, global) and (none, global) are replicated five times and (bilateral, local) and (none, local) are replicated four times.

Layer 2: Participant groups Within each session, participants are arranged in groups of five to play 15 total rounds of games: each human plays five rounds in each of the three networks of Figure 3.

Layer 3: Individual participants The five rounds, for each NS in Layer 2 and each group of five human players, are used for different threshold assignments to players. These are given in Table 2. NTH is the number of $\theta = 3$ players.

There are 4050 observations of players' responses (to participate or not). With five responses per group payoff, there are 810 group payout values across the factors in Table 1.

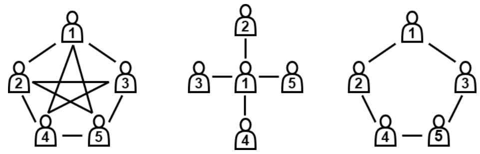


Fig. 3: Illustration of three types of NS. From left to right, the NS type is clique, star, and circle, respectively.

Table 2: Design for Layer 3 to study threshold. H represents a high threshold ($\theta = 3$) for a player and L represents a low threshold ($\theta = 1$). The player numbers are mapped to Figure 3 and so in each game instance, four of these players are bots.

Round	Player 1	Player 2	Player 3	Player 4	Player 5
1	H	H	H	H	H
2	L	L	L	L	L
3	L	H	H	H	H
4	L	H	L	H	H
5	H	L	H	L	L

4 ANALYSIS AND RESULTS

4.1 Analysis Method

Conventional ANOVA analysis is generally insufficient to ascertain effects masked by confounding factors for the unbalanced and nested design structure described in Section 3, especially if we want to quantify the patterns under distinct factor levels. Therefore, we propose a successive analytical approach that begins with an examination of the main effects and sequentially focuses in on conditional interaction effects to thoroughly analyze such complex designs.

We define **conditional treatment effect** (CTE) to quantify the conditional effect of factors as:

$$CTE(X^{(i)}, \boldsymbol{\alpha}) = \sum_{k=1}^{n_i} \alpha_k E[y(\cdot)|X^{(i)} = l_k^{(i)}], \tag{1}$$

where $X^{(i)}$ is a factor in Table 1; n_i is the number of levels for factor $X^{(i)}$; α_k is the k^{th} linear combination coefficient of $\boldsymbol{\alpha} = (\alpha_1, \alpha_2, ..., \alpha_{n_i})$; and $y(\cdot)$ is the response (i.e., group payoff here) over all $X^{(i)} = l_k^{(i)}$, with $k \in \{1, 2, \ldots, n_i\}$.

CTE in Equation (1) can be extended by conditioning on other factors. Without loss of generality, we define:

$$CTE(X^{(i)}, \boldsymbol{\alpha}|X^{(j)} = l_h^{(j)}) = \sum_{k=1}^{n_i} \alpha_k E[y(.)|X^{(i)} = l_k^{(i)}, X^{(j)} = l_h^{(j)}], \tag{2}$$

which considers group payoff over all $X^{(i)}$ conditioning on $X^{(j)} = l_h^{(j)}$. The notation in Equation (2) can be generalized by conditioning on multiple factors (e.g., $CTE(X^{(i)}$,

$\boldsymbol{\alpha}|X^{(j)} = l_h^{(j)}, X^{(m)} = l_g^{(m)})$ is well defined). Depending on specific relations of interest, the values of α_i may be customized for hypothesis tests. The procedures of the proposed successive analysis method can be described as follows.

Step 1. Test the main effect of the factors. For example, to test whether two levels of the factor $X^{(1)}$ (i.e., NK) have significant differences in the response, the hypothesis can be considered:

$$H_0 : CTE(X^{(1)}, \boldsymbol{\alpha}^{(1)}) = CTE(X^{(1)}, \boldsymbol{\alpha}^{(2)}), \tag{3}$$

where $\boldsymbol{\alpha}^{(1)} = (1,0)$ and $\boldsymbol{\alpha}^{(2)} = (0,1)$.

Step 2. Test the conditional effects. Perform pairwise tests when conditioning on other factors by the following hypothesis,

$$H_0 : CTE(X^{(i)}, \boldsymbol{\alpha}|X^{(j)} = l_1^{(j)}) = CTE(X^{(i)}, \boldsymbol{\alpha}|X^{(j)} = l_2^{(j)}), \tag{4}$$

where $l_1^{(j)}$ and $l_2^{(j)}$ can be any distinct levels of $X^{(j)}$.

Step 3. Based on findings from Step 2, one can further zoom in to study effects of target factor $X^{(i)}$ conditioning on multiple factors (i.e., $H_0 : CTE(X^{(i)}, \boldsymbol{\alpha}|X^{(j)} = l_1^{(j)}, X^{(m)} = l_1^{(m)}) = CTE(X^{(i)}, \boldsymbol{\alpha}|X^{(j)} = l_2^{(j)}, X^{(m)} = l_2^{(m)})$).

To establish the test statistics, denote the estimates for $CTE(X^{(1)}, \boldsymbol{\alpha}^{(1)})$ and $CTE(X^{(i)}, \boldsymbol{\alpha}|X^{(j)} = l_1^{(j)})$ in Equations (3) and (4) as $\widehat{CTE_L}$; and $CTE(X^{(1)}, \boldsymbol{\alpha}^{(2)})$ and $CTE(X^{(i)}, \boldsymbol{\alpha}|X^{(j)} = l_2^{(j)})$ as $\widehat{CTE_R}$ (i.e., the left-hand-side and right-hand-side of the equations). The test statistic can be written:

$$t = (\widehat{CTE_L} - \widehat{CTE_R})/(s_p\sqrt{1/n_1 + 1/n_2}), \tag{5}$$

where s_p is the pooled standard deviation [16]. Here n_1 and n_2 represent the number of observations in $\widehat{CTE_L}$ and $\widehat{CTE_R}$. Under the normal assumption of response y, the test in (5) can be conducted using two-sample t-tests.

The proposed procedure is not limited to test factors with two levels or pairwise tests. Hypotheses involving multiple levels of factors, which test whether there is a statistically significant difference among three or more groups of observations, are also well-defined. The following hypotheses can be constructed.

$$H_0 : CTE(X^{(j)}, \boldsymbol{\alpha}^{(1)}) = \ldots = CTE(X^{(j)}, \boldsymbol{\alpha}^{(n_j)}), \tag{6}$$

$$H_0 : CTE(X^{(i)}, \boldsymbol{\alpha}|X^{(j)} = l_1^{(j)}) = \ldots = CTE(X^{(i)}, \boldsymbol{\alpha}|X^{(j)} = l_{n_j}^{(j)}), \tag{7}$$

where $\boldsymbol{\alpha}^{(j)} = (0,\ldots,1,\ldots,0) = \boldsymbol{e_j}$ (i.e., $\boldsymbol{\alpha}^{(j)}$ represents a vector with j^{th} element equal to 1, and 0 otherwise). The $\boldsymbol{\alpha}$ in Equation (7) is a user-defined vector depending on the interest of testing. Correspondingly, the hypotheses tests in Equations (6) and (7) can be conducted using F-test statistics [16].

4.2 Results

Figure 4 displays the plots of the main effects for CT, NK, NS and NTH. Only the factor of NK has a relatively flat line as a main effect. For the factors that are significant, there is a greater group payoff for bilateral communication compared to no communication. Also, groups with clique structures have greater payoffs compared to those with circle or star structures. Finally, groups with greater NTH are expected to have lower payoff (because greater thresholds present greater barriers to participating), but there is an inflection point at NTH$=4$. To perform hypothesis tests regarding main effects, we adopt the F-test specified in Equation (6). The F-values and associated p-values support these observations. However, the visualizations and tests of the main effects may obfuscate interactions among input variables; this is explored next.

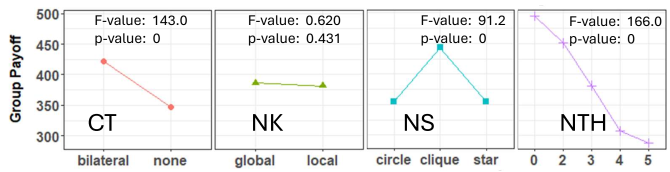
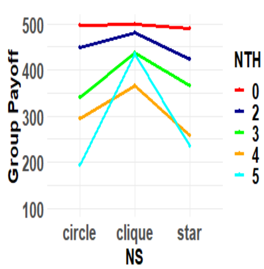
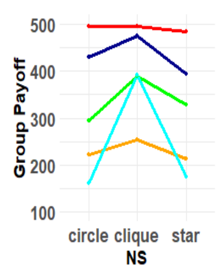


Fig. 4: Main effects on group payoff. F-values and p-values are given in each plot for the specified factor (variable).

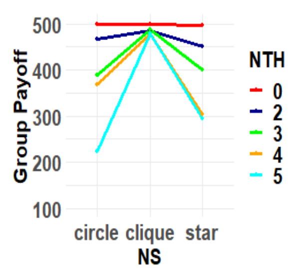
Figure 5a decomposes the effect of NS, showing that payouts are different for different NTH levels. There is a phase change induced by NTH for the clique NS, because the payout decreases as NTH goes from 0 to 4, but increases for NTH of 5. (The effect of NTH is monotonic for the other two NS.) Figure 5b and Figure 5c further decompose these differences for each NS to show the effect of CT. Figure 5b and Figure 5c illustrate that the phase change is caused by a lack of communication (i.e., CT=none).



(a) NS $\times$ NTH



(b) NS $\times$ NTH | CT = none



(c) NS $\times$ NTH | CT = bilateral

Fig. 5: Figure 5a shows the two-way interaction of NS $\times$ NTH. Figure 5b and Figure 5c show the two-way interaction of NS $\times$ NTH for group payoff conditional on CT values.

Since the phase change is primarily observed when NS=clique, we conduct hypothesis tests of the form in Equation (4) to validate our observation in Figure 5a. Specifically, we first perform sequential pairwise two-sample tests: $H_0 : CTE(X^{(2)}, \boldsymbol{\alpha} = (0,1,0)|X^{(4)} = l_i^{(4)}) = CTE(X^{(2)}, \boldsymbol{\alpha} = (0,1,0)|X^{(4)} = l_j^{(4)})$ for different pairs of (i, j) levels of NTH, with $j = i+1$ (here the first, second, and third elements in $\boldsymbol{\alpha}$ correspond to NS=circle, clique, and star, respectively). Then, similar tests are performed by sub-setting (i.e., conditioning) on CT levels to validate our observation in Figure 5b and Figure 5c. The resulting test statistics are shown in Table 3, where the test statistic turns negative when NTH changes from 4 to 5 as shown in Figure 5a and Figure 5b. The pairwise tests when CT=bilateral reveal insignificant results, so the phase change pattern observed from Figure 5a for clique is indeed caused by the CT condition of no communication.

Table 3: Pairwise tests for Figure 5a, Figure 5b, and Figure 5c for NS=clique, confirming that the phase change in group payout is caused by CT=none.

NTH Pairs	CT combined		CT = none		CT = bilateral	
	t-val	p-val	t-val	p-val	t-val	p-val
0 vs 2	3.78	0.0004	3.32	0.0021	2.13	0.0431
2 vs 3	2.99	0.0040	3.63	0.0011	-0.23	0.8221
3 vs 4	2.70	0.0083	3.46	0.0011	0.61	0.5474
4 vs 5	-2.39	0.0187	-3.25	0.0021	0.10	0.9219

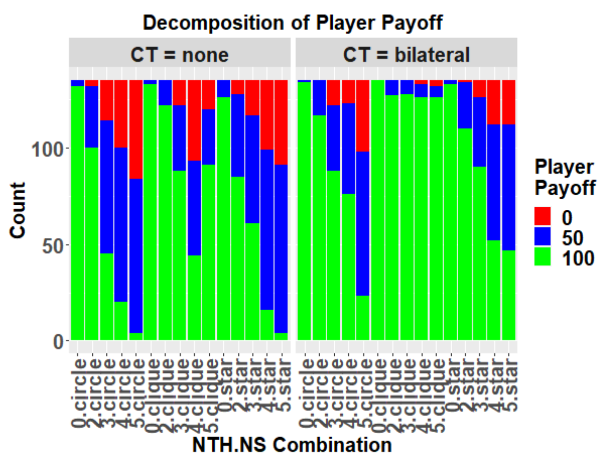


Fig. 6: Decomposition of group payoff to player level.

Figure 6 shows a further decomposition of the group payoffs at each level for combinations of factors NS, NTH, and CT, i.e., how many players choose to participate and make the correct (green bars) and wrong (red bars) decisions, and how many choose not to participate (blue bars). We observe that when there is no communication (or even lack of communication due to network structure), players choose to not participate in significant numbers when NTH exceeds 2. We previously observed in Figure 5b that NTH = 4 and NTH = 3 may have lesser payoff than NTH = 5 for NS=clique. This is explained by Figure 6 in that comparing NTH = 4 and 5 (i.e., CT=none, NS=clique, and NTH = 4 and 5), more players choose to not participate when NTH = 4 and also more players make the wrong decision when they choose to participate. However, the decomposition for NTH = 3 and NTH = 5 are very similar, which is why the results for NTH = 3 and 5 are essentially the same for NS=clique in Figures 5a and 5b (and also, in Figure 5c).

5 SUMMARY AND FUTURE WORK

In this work, we analyze human subjects common knowledge experiments using a new conditional treatment effect approach. We demonstrate a phase change in group payout under certain conditions. Our contributions are provided in Section 1.2. With respect to future work, we will provide further analyses of the type shown in Figure 6 for explaining the phase change. There is a number of interesting phenomena analogous to those in Figure 5a, to be elaborated upon as was done in Figures 5b and 5c.

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