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Targeted intervention using network characteristics: An experiment☆

Hendrika Geesje Wichers

Royal Holloway, University of London. Department of Economics

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ABSTRACT

In this paper, we experimentally study targeted intervention in a coordination game played in a network. We study two types of bonuses that encourage efficient coordination: a bonus for everyone, and a targeted bonus for less connected nodes only. The bonus for everyone successfully moves the system to the efficient outcome. The targeted bonus performs well initially, but the effect does not persist.

1. Introduction

Network intervention describes the process of using social network data to accelerate behavioural change or improve organisational performance (Valente, 2012). A typical organisation relies on employees interacting and coordinating to provide products and services to customers. The actions of one employee affect those of other employees and can set off cascades of behaviour that ultimately lead to one outcome or another. A cascade that follows undesired actions leads to coordination failure and can cause the organisation to settle into a state that is inefficient and unsatisfactory for everyone, even when better outcomes are possible and would be stable if achieved. Even if the benefits of improved coordination are easy to see, any mechanism designed to bring about a positive shift is not straightforward.

In a modern take on a classic example, imagine a professional services firm introducing a new file-sharing technology to improve efficiency. Workers add their files to a central repository so that colleagues can find information that otherwise would need to be requested or perhaps would be undiscovered. If only one worker uses the repository, they waste their efforts. If, however, a worker can be reasonably sure that their colleagues also use the repository, they should be willing to do the same. To decide whether to use the new technology, the worker needs to estimate their colleagues' efforts and factor in the dynamic with their own effort. A worker who connects with many colleagues is more likely to benefit from adopting the new technology than one who engages with few. However, the ultimate success of the repository is contingent also on the latter group.

The coordination problem described above is of practical importance in political economics too. Consider the issue of promoting a healthy lifestyle. Healthy lifestyles are sustained more easily by those who interact with many others who engage in the same behaviour (see, e.g., Christakis & Fowler 2007), yet the aggregate level of health in society also relies on those who connect with few. The policy question in this context is how to mobilise the latter group to participate in healthy lifestyles.

In both examples, a direct incentive to some agents could cascade and indirectly incentivise others to maintain their efforts, ultimately maximising welfare in the system. In this paper, we experimentally test this hypothesis. Specifically, we try to answer two questions. Firstly, can a direct incentive encourage efficient behaviour in a group of connected agents? Secondly, is it sufficient to provide a direct incentive to some 'key individuals' only?

To answer these two questions, we designed and carried out an experiment where 20 subjects are arranged in a network and play a coordination game. Knowing only their number of connections and the complete structure of the network, players choose between an efficient and risky action (e.g., to participate), and a secure one (e.g., to not participate). We then study the effect of two types of conditional premium incentives. In one type, the premium incentive is available to all players (a *universal premium*), and in the other type, only players with one connection are eligible (a *targeted premium*). The condition to earn the premium is that at least 70 per cent of the players participate. So, we have three treatments: a baseline treatment without an incentive and two treatments with an incentive.

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E-mail address: hendrika.wichers.2013@live.rhul.ac.uk.

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The experimental data yield some interesting answers to our questions. Firstly, a conditional premium increases the average probability of participation for players with one connection, as well as for other players in the network. Secondly, the targeted incentive was not as effective as the universal incentive. The universal incentive led to near-perfect coordination on the efficient outcome, whereas the targeted incentive was less successful.

We now place the paper in the context of the literature. Network intervention is an active subject in economics and other disciplines, such as computer science and sociology. Early research focused on centrality measures (see, for example, Bonacich 1987, Bramoullé et al. 2014, Jackson & Zenou 2015, Jackson et al. 2017, 2019) and recently evolved to considering network intervention strategies (e.g., Bloch et al. 2018, Galeotti et al. 2020). The notion that a small minority of well-connected 'opinion leaders' can determine outcomes in networks has long been popular but does not always apply. For instance, Watts & Dodds (2007) show that cascades of influence are driven by a 'critical mass' of easily influenced individuals who, once activated, also activate the remainder of the network. Other theoretical work (e.g., Akbarpour, Malladi, & Saberi, 2020) and empirical studies using data from online social media platforms lend credence to this idea (see Bakshy et al. 2011, Cha et al. 2010). In a seminal laboratory experiment on coordination in minimum-effort games, Van Huyck et al. (1990) show how groups converge to inefficient equilibria. A vast body of literature investigating factors that can improve coordination on Pareto optimal equilibria followed (see the survey by Devetag & Ortmann (2007) and the recent review by Cooper & Weber, 2020). Most of the evidence shows that coordination failure results from uncertainty about the strategies used by other players (Van Huyck et al., 1990). The problem increases with the number of players (Knez & Camerer, 1994;Goeree & Holt, 2005), the relative cost of effort (Goeree & Holt, 2005; Brandts & Cooper, 2006a) and the cost of exploration (Berninghaus & Ehrhart, 2001). One design feature that improves coordination is giving agents more information about the behaviour of others.

The papers of Brandts and Cooper (2006a) and Hamman et al. (2007) on experimental minimum-effort games are particularly relevant to our research questions. Both find that people coordinate on efficient equilibria more often in the presence of a financial incentive in the form of a bonus. When the bonus is removed, efficient coordination continues in Brandts and Cooper (2006a) but not in Hamman et al. (2007). The difference between the studies is that Hamman et al. (2007) award the bonus only if the minimum effort exceeds a given threshold. But neither paper factors in the connections between players. Networked interventions are more effective than non-networked alternatives (Valente, 2012). Yet, few have been tested in laboratory or real-world settings, and it is unclear which network interventions work best under which conditions. The main contribution of the current paper lies in the experimental use of network characteristics to target and activate a critical mass of susceptible individuals to facilitate efficient coordination.

The rest of the paper is organised as follows. We describe the game and the implementation in Section 2, we set out equilibrium predictions in Section 3, and we outline our research hypotheses in Section 4. We present statistics and findings in Section 5, and finally, we conclude in Section 6.

2. Experimental design

Our experiment is based on the experimental design in Charness et al. (2014), henceforth CFMS (2014). It follows the theoretical framework introduced by Galeotti et al. (2010). A key feature of this framework is individuals' incomplete information: they observe their number of neighbours, but not their exact location in the network. CFMS (2014) test experimentally for the effects of network structure on equilibrium selection in strategic games where payoffs are affected by local network structure.

2.1. Games and implementation

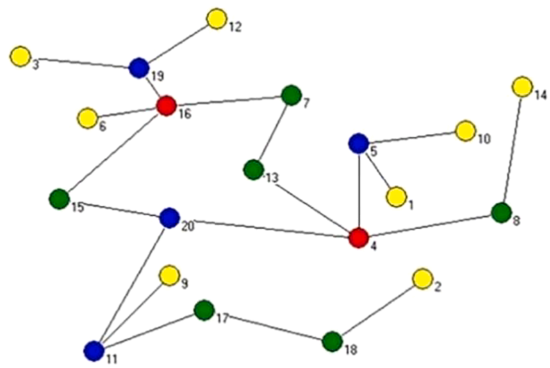
The baseline treatment is described as follows (a copy of the written instructions provided to participants is included in Appendix C). A group of 20 subjects interact for 40 periods in the network shown in Fig. 1. The network remains fixed over all periods. It has 20 positions (*nodes*) and each position is connected by a line (*link*) to one, two, three or four neighbours. We refer to the number of neighbours a player is connected to as their *degree*. A player is affected by their neighbours' actions and their actions also affect their neighbours.

At the start of each period, each player is randomly assigned to one of the 20 nodes. They are privately informed of their degree but not of their exact position. For example, they learn that they have four neighbours. Therefore, they know that they can be in either position 4 or position 16 with equal probability. They now face a choice to be *active* (e.g., adopt the file sharing technology) or to be *inactive* (e.g., not adopt the file sharing technology). If they choose to be active, they earn 33.33 points times the number of neighbours who are also active. That is, the game has strategic complements: the marginal payoff from the active choice increases when more players take the same action. If they choose to be inactive, they earn 50 points regardless of their neighbours' choices. After they submit their choice, they are privately informed of the position they were in, how many of their neighbours chose to be active and inactive, and their payoffs. Before the start of the next period, they are presented with a history table that shows for each previous period their degree, their position, their choice, their neighbours' choices, and their payoffs. At the end of 40 periods, three periods are selected at random for payment.

The games with the conditional premiums have an additional layer of global interaction: a player who chooses to be active receives 33.33 bonus points in each period with at least 14 active players across the network. Note that to receive the bonus a player needs to be active themselves, and thus that the design does not allow free riding. In the "*universal premium treatment*", the bonus is available to all players. In the "*targeted premium treatment*" only players with degree 1 are eligible. The motivation for this choice is that for players with degree 1 the active action can be profitable only when the premium is paid. CFMS (2014) observe convergence to inactivity for all degrees in their experiment 3, which is the same as our baseline. Without a premium, the choice to be active is relatively risky for players with degree 2 because they are connected to many nodes with degree 1. Hence, the effect of a premium for degree 1 could cascade to degree 2, and ultimately to degrees 3 and 4. Finally, at the end of each period, players in the conditional premium treatments receive additional private information about the number of players that chose to be active in the network, whether the condition was met and if the bonus is paid.

In summary, we consider three treatments in the same 20-person network: (i) a baseline treatment; (ii) a universal premium treatment; and (iii) a targeted premium treatment aimed at players who have one connection.

We conducted four sessions of each treatment, summing to a total of 12 sessions involving 240 unique subjects. Participants were recruited from the student population of Royal Holloway, University of London. The sessions were held at the University's ExpReSS Lab using z-Tree software for computerised economic experiments (Fischbacher, 2007). Subjects were not allowed to participate in more than one session of the experiment. Earnings averaged around £10 per subject for a 1-hour



	# nodes
degree = 1	8
degree = 2	6
degree = 3	4
degree = 4	2
Total	20

Fig. 1. The network and characteristics.

session.

3. Equilibrium predictions

Our equilibrium analysis considers only pure strategy Bayesian Nash Equilibria (BNE) in which all players of the same degree take the same action. Let us label the choice to be active as action 1 and the choice to be inactive as action 0. Then, a symmetric strategy profile is represented by the vector $s = (s_1, s_2, s_3, s_4)$, where $s_j \in \{0, 1\}$ is the action chosen by an agent with degree $j \in \{1, 2, 3, 4\}$. CFMS (2014) show that the baseline game has two equilibria: (i) $(0, 0, 0, 0)$ is a *full-inactivity equilibrium*, where all players choose to be inactive, and (ii) $(0, 1, 1, 1)$ is a Pareto-dominant *partial-activity equilibrium*, where players with degree 1 choose to be inactive and players with degrees 2, 3 and 4 choose to be active. The universal premium game has the same two equilibria, plus a third: $(1, 1, 1, 1)$ is a *full-activity equilibrium* where all players choose to be active. The third equilibrium is Pareto-dominant due to the bonus.

Proposition 1. *The universal premium game has three equilibria, (i) a full-inactivity equilibrium, where players of all degrees choose the inactive action, (ii) a partial-activity equilibrium where players with degree 1 choose the inactive action and players with higher degrees choose the active action, and (iii) a full-activity equilibrium, where players of all degrees choose the active action.*

Proof: All proofs are provided in Appendix A.

The targeted premium game has the same three equilibria as the universal premium game and one further partial-activity equilibrium $(1, 0, 1, 1)$, where players with degree 2 choose the inactive action and players with degrees 1, 3 and 4 choose the active action.[1]

Proposition 2. *The targeted premium game has four equilibria, (i) a full-inactivity equilibrium, where players of all degrees choose the inactive action, (ii) a partial-activity equilibrium where players with degree 1 choose the inactive action and players with higher degrees choose the active action, (iii) a partial-activity equilibrium where players with degree 2 choose the inactive action and players with all other degrees choose the active action, and (iv) a full-activity equilibrium, where players of all degrees choose the active action.*

Note that the efficient equilibrium varies between games: in the baseline treatment only nodes with degrees 2, 3 and 4 are active, while in the conditional premium treatments all nodes are active. Table 1 summarises the equilibrium predictions. The equilibria are Pareto-ranked and for each treatment the efficient equilibrium is the one with most active degrees.

[1] The full-activity equilibrium remains Pareto-dominant but has lower payoffs for players with degrees 2, 3 and 4 since the bonus is available only to players with degree 1.

Table 1
Bayesian Nash equilibria.

Game	Equilibrium	Active Degrees	Inactive Degrees
Baseline	full-inactivity	–	1, 2, 3, 4
	partial-activity i	2, 3, 4	1
Universal premium	full-inactivity	–	1, 2, 3, 4
	partial-activity i	2, 3, 4	1
	full-activity	1, 2, 3, 4	–
Targeted premium	full-inactivity	–	1, 2, 3, 4
	partial-activity i	2, 3, 4	1
	partial-activity ii	1, 3, 4	2
	full-activity	1, 2, 3, 4	–

Lastly, CFMS (2014) apply the concept of generalised-risk dominance proposed by Peski (2010) to prove that none of the equilibria in the baseline game are ordinal generalised-risk dominant (*ordinal GR-dominant*). We use the same approach and prove that equilibria in the conditional premium games are also not ordinal GR-dominant.

4. Research hypotheses

Each of our games has multiple equilibria and theory is silent on the issue of equilibrium selection. We form three behavioural research hypotheses concerning the effects of a conditional premium on activity rates and on coordination.

Firstly, the conditional premium increases the profitability of the active choice for all players. Therefore, we predict that the premium positively affects the choice to be active for all degrees. Our first hypothesis is:

H1: The premium effect. *The conditional premium increases the rate of active choices for players with every degree. Hence, the full-activity equilibrium (1,1,1,1) is more likely to be played.*

Secondly, we predict that the targeted premium has the same effect as the universal premium. The set of equilibria in the targeted premium game includes all equilibria present in the universal premium game. In particular, the strategy profile $(1, 1, 1, 1)$ is the payoff dominant equilibrium in both games. The increase in activity of players with degree 1 could cascade to players with higher degrees and result in full network activity, and thus facilitate coordination on the full-activity equilibrium. People have a taste for social efficiency (Charness & Rabin, 2002), so we anticipate that players with degree 1 are prepared to try. Hence, we expect that the targeted premium has the same effect as the universal premium. We capture this in our second hypothesis:

H2. *The targeted premium has the same effect as the universal premium.*

The anticipated increase in the rate of active choices with the targeted premium may not induce full network activity. The choice to be active is riskier for players with degree 1 than for players with higher degrees. Recall that in the baseline game it is never profitable for a player with degree 1 to choose the active action. The active choice produces a maximum potential payoff of 33.33 points, whilst the inactive action results in 50 points for sure. The conditional premium increases the maximum potential payoff to 66.66 points, but the condition of 14 active players needs to be met to earn this. If the condition is not met, the maximal payoff potential is 33.33 points once again. So, players with degree 1 may prefer the secure action. In this case, the cascade does not occur, and we expect the result to be the same as in the baseline game, matching the outcome observed in CFMS (2014). Then, we can state an alternative hypothesis to the one above.

H2b. *The targeted premium fails to motivate players with degree 1. The full-inactivity equilibrium (0,0,0,0) is more likely to be played.*

5. Experimental results

Table 2 reports the observed mean frequencies of activity by treatment and degree in the top panel and differences in activity rates between treatments with the significance of Wilcoxon rank-sum tests in the bottom panel.[2] We see a degree effect on activity, as the rates increase by degree in all three treatments and for each degree. This finding aligns with CFMS (2014). Overall activity in the baseline is 33.8%, and it is higher with both the universal premium (83.5%) and the targeted premium (51.1%).

In Fig. 2, we observe the evolution of activity over 40 periods of the game in each treatment by degree. We see convergence to the full-inactivity equilibrium in the baseline and the targeted premium game, and clear adherence to the full-activity equilibrium with the universal premium. In what follows, we compare statistics and dynamics between the treatments.

Table 2
Statistics by treatment and degree.

Frequencies of activity by treatment and degree	Baseline		Universal premium		Targeted premium	
	# %	Total	# %	Total	# %	Total
overall	1081 33.8	3200	2671 83.5	3200	1635 51.1	3200
degree = 1	72 5.6	1280	950 74.2	1280	400 31.3	1280
degree = 2	327 34.1	960	809 84.3	960	484 50.4	960
degree = 3	387 60.47	640	594 92.81	640	477 74.53	640
degree = 4	295 92.2	320	318 99.4	320	274 85.6	320

Percentage point difference in activity rate	Universal premium vs Baseline	Targeted premium vs Baseline	Targeted premium vs Universal premium
overall	49.7**	17.3	−32.4
degree = 1	68.6**	25.6**	−43.0
degree = 2	50.2*	16.4	−33.9
degree = 3	32.3**	14.1	−18.3
degree = 4	7.2*	−6.6	−13.8*

Wilcoxon Mann-Whitney: ***, **, * denote significance at 1%, 5% and 10% levels, respectively, in a two-tailed test.

First, we consider the universal premium and the baseline. Activity rates with the universal premium are significantly higher, both overall ($p = 0.029$) and for each degree ($p = 0.029$ for degrees 1 and 3, $p = 0.057$ for degree 2, and $p = 0.086$ for degree 4). We see similar results when we consider the first and second halves of the game separately (details are included in Appendix D). In the first 20 periods, activity is significantly higher with the universal premium overall and for degrees 1, 2 and 3 ($p = 0.029$ in each case). Activity for degree 4 did not improve, because degree 4 was nearly always active already in the baseline. In the last 20 periods, activity remains high with the universal premium. The difference with the baseline is significant overall and for degrees 3 and 4 ($p = 0.057$ in each case), but not for degrees 1 and 2.[3] We can now state our first result.

Result 1: The premium effect. *The universal premium increases the rate of active choices for players with every degree, and play shows convergence to the full-activity equilibrium (1,1,1,1).*

Next, we consider the targeted premium and the baseline. The targeted premium has systematically higher activity rates than the baseline for degrees 1, 2 and 3, but it is significant for degree 1 only ($p = 0.029$). Degree 4 has lower activity rates than the baseline. In the first 20 periods, activity is significantly higher with the targeted premium overall ($p = 0.057$) and for degrees 1, 2 and 3 ($p = 0.029$ for degree 1, $p = 0.086$ for degree 2, and $p = 0.057$ for degree 3). But the increase in activity does not reach degree 4. In the last 20 periods, activity remains higher overall but fails to be significantly different from the baseline in any comparison. In three of four sessions with the targeted premium, groups settled on the full-inactivity equilibrium, and in one session play converged to the full-activity equilibrium. The latter explains the higher overall rate with the targeted premium.

Lastly, we consider the targeted premium and the universal premium. Activity with the targeted premium is significantly different from the universal premium only in the last 20 periods of the game, when it is lower for degree 3 ($p = 0.086$) and for degree 4 ($p = 0.057$). We can now state our second result.

Result 2. *The targeted premium has the same effect as the universal premium in the first half of the game, but it does not persist in the second half.*

We observe heterogeneity in groups. With the universal premium, three groups coordinated on the full-activity equilibrium and one group settled on the full-inactivity equilibrium. The result with the targeted premium is the reverse: one group coordinated on the full-activity equilibrium and three groups settled on the full-inactivity equilibrium. This variation in combination with our small sample size means that our tests lack the power to detect all effects. Therefore, we complement our analysis with an econometric model. For the first and last ten periods separately, we estimate the probability of being active as a logistic function of the following explanatory variables: dummies for treatment, player degree, period, and interactions between these variables. The data are arranged as a panel where the unit of observation is a participant who is observed in the applicable time frame. The models are estimated using random effects with errors clustered at the session level (see Appendix E for details). Finally, we calculate the marginal effects of treatment on the probability to be active by degree. The results are displayed in Table 3.

The universal premium yields a significantly higher probability to be

[2] We use the Wilcoxon rank-sum test, where an independent observation is the average decision by degree within a twenty-player group over 40 periods of the game. Therefore, we have four independent observations. We follow the methodology in Harris & Hardin (2013) and calculate exact statistics. Note that we cannot reach sensitivity at the 1% level due to the low number of independent observations.

[3] Our test narrowly fails to detect significance for degrees 1 and 2 in the last 20 periods ($p = 0.114$ for both). In the baseline, average activity rates were low in all four sessions. With the universal premium, average activity rates were high in three sessions, and low in one session.

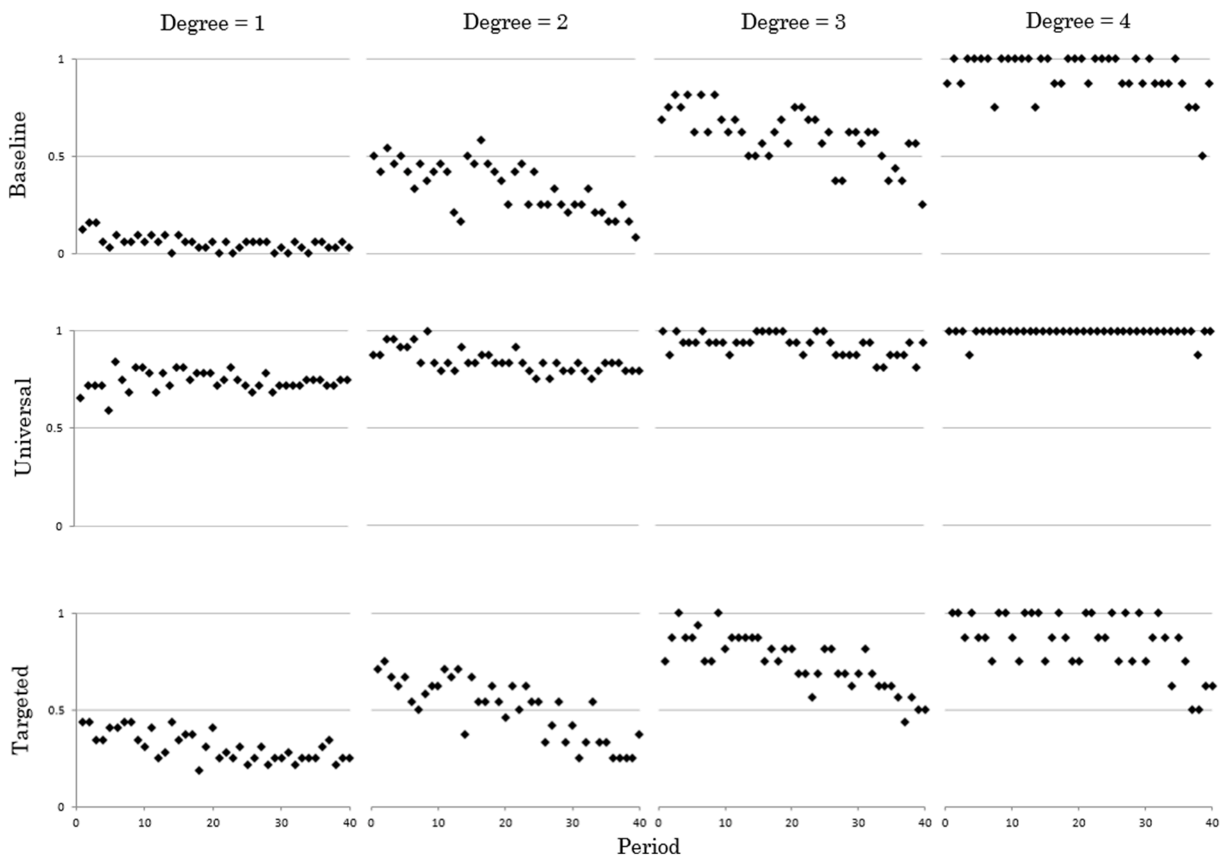


Fig. 2. Observed activity rates by treatment and degree.

Table 3
Marginal effects of treatment by degree.

	Universal premium vs Baseline		Targeted premium vs Baseline		Targeted premium vs Universal premium	
	First 10	Last 10	First 10	Last 10	First 10	Last 10
degree = 1	0.4780***	0.7059***	0.2491***	0.2145	−0.2289	−0.4914**
degree = 2	0.2936***	0.5954***	0.0885	0.1141	−0.2051**	−0.4813**
degree = 3	0.1198	0.4468***	0.0329	0.1210	−0.0869	−0.3258*
degree = 4	0.0336	0.1872***	−0.0658	−0.1267	−0.0993	−0.3139**

***, **, * denote significance at 1%, 5% and 10% levels, respectively.

active for degree 1 (47.8%, $p = 0.001$) and degree 2 (29.4%, $p = 0.001$) in the first ten periods when compared to the baseline. Activity cascades to higher degrees and persists. The targeted premium also motivates players with degree 1. In the first ten periods, they are 24.9% ($p = 0.005$) more likely to be active than in the baseline, but activity does not spread to higher degrees or persist. Finally, we can confirm our alternative hypothesis H2b:

Result 2b. *The targeted premium motivates players with degree 1, but activity does not cascade to higher degrees. Play shows convergence to the full-inactivity equilibrium (0,0,0,0).*

We find that, in practice, our targeted premium does not facilitate efficient coordination. Whilst effective initially when compared to the baseline, the probability for degree 1 to be active in the first ten periods is only 24.9% versus 47.8% with the universal premium. The choice to be active is riskier for degree 1 with the targeted premium than with the universal premium, and a minor adjustment to our mechanism design could mitigate that risk. For example, a guaranteed minimum payoff of 50 points for either the active or inactive choice makes the decision risk-free.

Finally, Brandts & Cooper (2006a) find that an increase in the benefit of coordination leads to improved coordination, and that the size of the benefit does not matter. However, in our network environment, we need the universal premium rather than the targeted premium to facilitate efficient coordination. This observation may suggest that asymmetries in bonus eligibility reduce the effectiveness of financial incentives.

6. Conclusion

Networks are a ubiquitous feature of the social and economic landscape. The question of efficient network intervention is critical for central planners, whether involved with business decisions or government policy. In this paper, we use network characteristics to study targeted intervention in the laboratory. We financially incentivise agents with only one connection to participate because they take the most risk. The objective is to create a critical mass of activity that cascades to higher degrees and ultimately settles the system on the best outcome. Our mechanism was successful in only one of four sessions, but we gained some insights into the practical application of targeted network intervention. Firstly, to help improve coordination, the mechanism should mitigate all risks for the targeted subset of agents. Secondly, asymmetries in bonus eligibility may reduce the effectiveness of financial incentives. It would be interesting to understand better the intricacies of the second point in the network environment. Also worthy of mention and further exploration is the role of "strong leaders". In Brandts & Cooper (2006a), strong leaders raise their effort by at least two levels in response to the bonus and succeed in leading their groups to better outcomes. We see a similar pattern in our sessions. Four groups coordinated on the efficient equilibrium: three with the universal premium and one with the targeted premium. Average activity rates of degree 1 in the first ten periods were above 50 per cent only in these sessions (see Appendix B). These groups, perhaps, had a greater population of strong leaders. Our data are sparse in this respect, but a systematic study into the role of strong leaders in networks may yield novel insights for targeted intervention. A final avenue for further research is persistence. Brandts & Cooper (2006a,b) find that once coordination on an efficient equilibrium has been achieved with the use of financial incentives, the coordination gains persist when the incentives are removed. The compelling question in this context is how network features can be used to facilitate coordination with temporary incentives.

Theoretical and experimental work is critical to understand better what targeted interventions work under which circumstances. Identifying key individuals is increasingly feasible in our digital world. Data about agents' interests, behaviours, and connections are more accessible than ever. A precise understanding of targeted interventions enables us to leverage this information and achieve desired results more efficiently. We hope that others will join in this exciting direction of research.

Declaration of Competing Interest

None.

Data availability

Data were uploaded with the first submission.

Appendix

A. Proofs

Proposition 1. *The universal premium game has three equilibria, (i) a full-inactivity equilibrium, where players of all degrees choose the inactive action, (ii) a partial-activity equilibrium where players with degree 1 choose the inactive action and players with higher degree choose the active action, and (iii) a full-activity equilibrium, where players of all degrees choose the active action.*

Proof. A player knows only her degree, so she can only condition her behaviour on this information when she chooses to be active (action 1) or inactive (action 0). Thus, a symmetric strategy profile is represented by the vector $= s \ = (s_1, s_2, s_3, s_4)$, where $s_j \in \{0, 1\}$ is the action chosen by an agent with degree $j \in \{1, 2, 3, 4\}$.

Let $\pi_i^j(x_i, x_{-i}) \equiv \pi_i^j(x_i)$ be the payoff of an agent $i \in N \equiv \{1, 2, \cdots, 20\}$ with degree $j \in \{1, 2, 3, 4\}$ from action $x_i \in \{0, 1\}$ when other players choose action x_{-i}.

Note that strategy $(0, 0, 0, 0)$ is a strict Bayes-Nash equilibrium in any case because a deviation to action 1 yields a payoff of 0, against a payoff of 50 for action 0.

There are five candidates to be a pure-strategy Bayes-Nash equilibrium: all possible combinations of s_1, s_2, s_3, s_4 in s where 14 of more agents choose action 1 in symmetric strategies. Strategy $(1, 1, 0, 0)$ is not an equilibrium because $\pi_i^4(1, x_{-i}) = 116.66 > 50 = \pi_i^4(0, x_{-i})$. Strategy $(1, 1, 1, 0)$ is not an equilibrium because $\pi_i^4(1, x_{-i}) = 166.66 > 50 = \pi_i^4(0, x_{-i})$. Strategy $(1, 1, 0, 1)$ is not an equilibrium because $\pi_i^3(1, x_{-i}) = 116.66 > 50 = \pi_i^3(0, x_{-i})$. Strategy $(1, 0, 1, 1)$ is not an equilibrium because $\pi_i^2(1, x_{-i}) = 77.77 > 50 = \pi_i^2(0, x_{-i})$. Finally, strategy $(0, 1, 1, 1)$ is a strict equilibrium because $\pi_i^4(1, x_{-i}) = 116.66 > 50 = \pi_i^4(0, x_{-i})$, $\pi_i^3(1, x_{-i}) = 58.33 > 50 = \pi_i^3(0, x_{-i})$, $\pi_i^2(1, x_{-i}) = 55.55 > 50 = \pi_i^2(0, x_{-i})$, $\pi_i^1(0, x_{-i}) = 50 > 33.33 = \pi_i^1(1, x_{-i})$ and strategy $(1, 1, 1, 1)$ is a strict equilibrium because $\pi_i^4(1, x_{-i}) = 166.66 > 50 = \pi_i^4(0, x_{-i})$, $\pi_i^3(1, x_{-i}) = 133.33 > 50 = \pi_i^3(0, x_{-i})$, $\pi_i^2(1, x_{-i}) = 99.99 > 50 = \pi_i^2(0, x_{-i})$, $\pi_i^1(1, x_{-i}) = 66.66 > 50 = \pi_i^1(0, x_{-i})$.

Q.E.D.

Proposition 2. *The targeted premium game has four equilibria, (i) a full-inactivity equilibrium, where players of all degrees choose the inactive action, (ii) an partial-activity equilibrium where players with degree 1 choose the inactive action and players with higher degree choose the active action, (iii) an partial-activity equilibrium where players with degree 2 choose the inactive action and players with all other degrees choose the active action, and (iv) a full-activity equilibrium, where players of all degrees choose the active action.*

Proof. Notation and strategy $(0, 0, 0, 0)$ are the same as in Proposition 1.

There are five candidates to be a pure-strategy Bayes-Nash equilibrium: all possible combinations of s_1, s_2, s_3, s_4 in s where 14 of more agents choose action 1 in symmetric strategies. Strategy $(1, 1, 0, 0)$ is not an equilibrium because $\pi_i^4(1, x_{-i}) = 83.33 > 50 = \pi_i^4(0, x_{-i})$. Strategy $(1, 1, 1, 0)$ is not an equilibrium because $\pi_i^4(1, x_{-i}) = 133.33 > 50 = \pi_i^4(0, x_{-i})$. Strategy $(1, 1, 0, 1)$ is not an equilibrium because $\pi_i^3(1, x_{-i}) = 83.33 > 50 = \pi_i^3(0, x_{-i})$. Finally, strategy $(1, 0, 1, 1)$ is a strict equilibrium because $\pi_i^4(1, x_{-i}) = 66.66 > 50 = \pi_i^4(0, x_{-i})$, $\pi_i^3(1, x_{-i}) = 83.33 > 50 = \pi_i^3(0, x_{-i})$, $\pi_i^2(1, x_{-i}) = 44.44 < 50 = \pi_i^2(0, x_{-i})$, $\pi_i^1(1, x_{-i}) = 58.33 > 50 = \pi_i^1(0, x_{-i})$, and strategy $(1, 1, 1, 1)$ is a strict equilibrium because $\pi_i^4(1, x_{-i}) = 133.33 > 50 = \pi_i^4(0, x_{-i})$, $\pi_i^3(1, x_{-i}) = 99.99 > 50 = \pi_i^3(0, x_{-i})$, $\pi_i^2(1, x_{-i}) = 66.66 > 50 = \pi_i^2(0, x_{-i})$, and $\pi_i^1(1, x_{-i}) = 66.66 > 50 = \pi_i^1(0, x_{-i})$.

Q.E.D.

Ordinal generalized risk-dominance

Proof. Let N be the set of players and let $\boldsymbol{a} = (a_1, \cdots, a_n)$ be an action (strategy) profile. Players can have maximum degree 4, and for each player $i \in N$, $a_i = (a_{i,1}, a_{i,2}, a_{i,3}, a_{i,4}) \in \{0,1\}$. For each $k \in \{1, 2, 3, 4\}$, $a_{i,k} = 0$ ($a_{i,k} = 1$) represents the choice of inactive (active) in the event in which player i has degree k.

Definition 1: Given an action profile $\boldsymbol{a}$, two action profiles, $\boldsymbol{\eta}$ and $\overline{\boldsymbol{\eta}}$, are a-associated if, for each $i \in N$, either $\boldsymbol{\eta}_i = a_i$ or $\overline{\boldsymbol{\eta}}_i = a_i$

Definition 2: An action profile $\boldsymbol{a}$ is ordinal GR-dominant if, for each player i, and for each pair of $\boldsymbol{a}$ a-associated action profiles, $\boldsymbol{\eta}$ and $\overline{\boldsymbol{\eta}}$, a_i is a best response of player i to either $\boldsymbol{\eta}$ or $\overline{\boldsymbol{\eta}}$.

(i) We first show that the action profile $\boldsymbol{a}$ such that for each $i \in N$, $a_i = (0, 1, 1, 1)$ is not ordinal GR-dominant. Consider, without loss of generality, player 1. There exist two $\boldsymbol{a}$-associated action profiles, $\boldsymbol{\eta}$ and $\overline{\boldsymbol{\eta}}$, such that for each $i \in \{2, \ldots, 10\}$, $\boldsymbol{\eta}_i = (0, 0, 0, 0)$ and $\overline{\boldsymbol{\eta}}_i = (0, 1, 1, 1)$, and for each $j \in \{11, \ldots, 20\}$, $\boldsymbol{\eta}_j = (0, 1, 1, 1)$ and $\overline{\boldsymbol{\eta}}_j = (0, 0, 0, 0)$. Consider the event in which $\boldsymbol{\eta}_1 = 2$. Clearly, if $a_{1,2} = 1$ is not a best response to profile $\boldsymbol{\eta}$, it will neither be to profile $\overline{\boldsymbol{\eta}}$, since the latter has one more player choosing the full-inactivity strategy (10 vs. 9 players) and all the remaining players choose the same strategy $(0, 1, 1, 1)$ (recall that all players are randomly allocated in the network with uniform probability. Thus, to prove the result is suffices to show that $a_{1,2} = 1$ is not a best response to profile $\boldsymbol{\eta}$.

To this aim, consider a profile $\boldsymbol{\eta}'$ such that, for each $i \in \{2, \ldots, 10\}$, $\boldsymbol{\eta}_i' = (0, 0, 0, 0)$, and for each $j \in \{11, \ldots, 20\}$, $\boldsymbol{\eta}_i' = (1, 1, 1, 1)$. In profile $\boldsymbol{\eta}'$ there are ten players in $N\backslash\{1\}$ that are always active (regardless of their degree), and nine players in $N\backslash\{1\}$ that are always inactive. It is straightforward to see that if $a_{1,2} = 1$ is not a best response to profile $\boldsymbol{\eta}'$, it cannot be a best response to profile $\boldsymbol{\eta}$. Hence, it suffices to prove that $a_{1,2} = 1$ is not a best response to profile $\boldsymbol{\eta}'$. Under profile $\boldsymbol{\eta}'$, when $\boldsymbol{\eta}_1 = 2$, the probability that player 1 has $k \in \{0, 1, 2\}$ active neighbours is $p_k' = \frac{\binom{10}{k}\cdot\binom{9}{2-k}}{\binom{19}{2}}$.

Thus, in such a case, the expected payoff to player 1 by choosing $a_{1,2} = 1$ is $\sum_{k=0}^{k=2} p_k' \cdot k \cdot \frac{100}{3} = 35.1 < 50$. Thus, $a_{1,2} = 1$ is not a best response to profile $\boldsymbol{\eta}'$. It follows that $a_{1,2} = 1$ (and, therefore, a_1) is neither a best response to $\boldsymbol{\eta}$ nor to $\overline{\boldsymbol{\eta}}$ and, thus, $\boldsymbol{a}$ is not ordinal GR-dominant.

(ii) We now show that the action profile $\boldsymbol{a}$ such that for each $i \in N$, $a_i = (0, 0, 0, 0)$ is not ordinal GR-dominant. Consider, without loss of generality, player 1. There exist two $\boldsymbol{a}$-associated action profiles, $\boldsymbol{\eta}$ and $\overline{\boldsymbol{\eta}}$, such that for each $i \in \{2, \ldots, 10\}$, $\boldsymbol{\eta}_i = (1, 1, 1, 1)$ and $\overline{\boldsymbol{\eta}}_i = (0, 0, 0, 0)$, and for each $j \in \{11, \ldots, 20\}$, $\boldsymbol{\eta}_j = (0, 0, 0, 0)$ and $\overline{\boldsymbol{\eta}}_j = (1, 1, 1, 1)$. In profile $\boldsymbol{\eta}$ (profile $\overline{\boldsymbol{\eta}}$) there are nine (ten) players in $N\backslash\{1\}$ that are always active (regardless of their degree), and ten (nine) players in $N\backslash\{1\}$ that are always inactive. Consider the event in which $\boldsymbol{\eta}_1 = 4$. Clearly, if $a_{1,4} = 0$ is not a best response to profile $\boldsymbol{\eta}$, it will neither be to profile $\overline{\boldsymbol{\eta}}$ (recall that all players are randomly allocated in the network with uniform probability. Thus, to prove the result is suffices to show that $a_{1,4} = 0$ is not a best response to profile $\boldsymbol{\eta}$.

Under profile $\boldsymbol{\eta}$, when $\boldsymbol{\eta}_1 = 4$, the probability that player 1 has $k \in \{0, 1, 2, 3, 4\}$ active neighbours is $q_k' = \frac{\binom{9}{k}\cdot\binom{10}{4-k}}{\binom{19}{4}}$. Thus, in such a case, the expected payoff to player 1 by choosing $a_{1,4} = 0$ (i.e. 50) is lower than the expected value he would get by choosing action 1, i.e. $\sum_{k=0}^{k=4} p_k' \cdot k \cdot \frac{100}{3} = 63.2$. It follows that $a_{1,4} = 0$ (and, therefore, a_1) is neither a best response to $\boldsymbol{\eta}$ nor to $\overline{\boldsymbol{\eta}}$ and, thus, $\boldsymbol{a}$ is not ordinal GR-dominant.

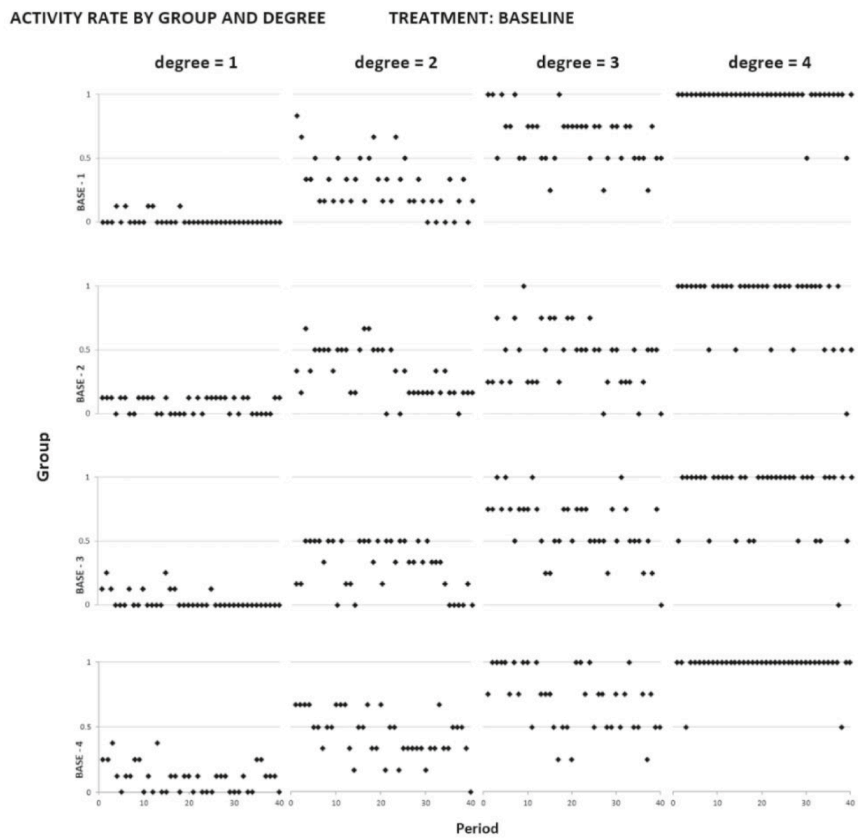
(iii) We now show that the action profile $\boldsymbol{a}$ such that for each $i \in N$, $a_i = (1, 1, 1, 1)$ is not ordinal generalised-risk dominant. Consider, without loss of generality, player 1. There exist two a-associated action profiles, η and $\overline{\eta}$, such that for each $i \in \{2, \ldots, 10\}$, $\eta_i = (0, 0, 0, 0)$ and $\overline{\eta}_i = (1, 1, 1, 1)$, and for each $j \in \{11, \ldots, 20\}$, $\eta_i = (1, 1, 1, 1)$ and $\overline{\eta}_i = (0, 0, 0, 0)$. In profile η (profile $\overline{\eta}$) there are ten (nine) players in $N\backslash\{1\}$ that are always active (regardless of their degree), and nine (ten) players in $N\backslash\{1\}$ that are always inactive. The condition of 14 active players is not met in either profile η or profile $\overline{\eta}$ and therefore the bonus is not received. Consider the event in which $\eta_1 = 1$. Clearly, if $a_{1,1} = 1$ is not a best response to profile η, it will neither be to profile $\overline{\eta}$ since profile η has a higher average activity rate than profile $\overline{\eta}$ and therefore profile η has a higher expected payoff than profile $\overline{\eta}$ (recall that all players are randomly allocated in the network with uniform probability). Thus, to prove the result it suffices to show that $a_{1,1} = 1$ is not a best response to profile η. Under profile η, when $\eta_1 = 1$, the probability that player 1 has $k \in \{0, 1\}$ active neighbours is $r_k = \frac{\binom{10}{k}\cdot\binom{9}{1-k}}{\binom{19}{1}}$. Thus, in such a case, the expected payoff to player 1 by choosing $a_{1,1} = 1$ is $\sum_{k=0}^{k=1} r_k \cdot k \cdot \frac{100}{3} = 17.54 < 50$. Thus, $a_{1,1} = 1$ is not a best response to η. It follows that $a_{1,1} = 1$ (and therefore a_1) is neither a best response to η nor to $\overline{\eta}$ and, thus, a is not ordinal GR-dominant.

(iv) We lastly show that the action profile a such that for each $i \in N$, $a_i = (1, 0, 1, 1)$ is not ordinal GR-dominant. Consider, again, the event in which $\eta_1 = 1$ and $a_{1,1} = 1$. The case is the same as in part (iii) and the proof is identical.

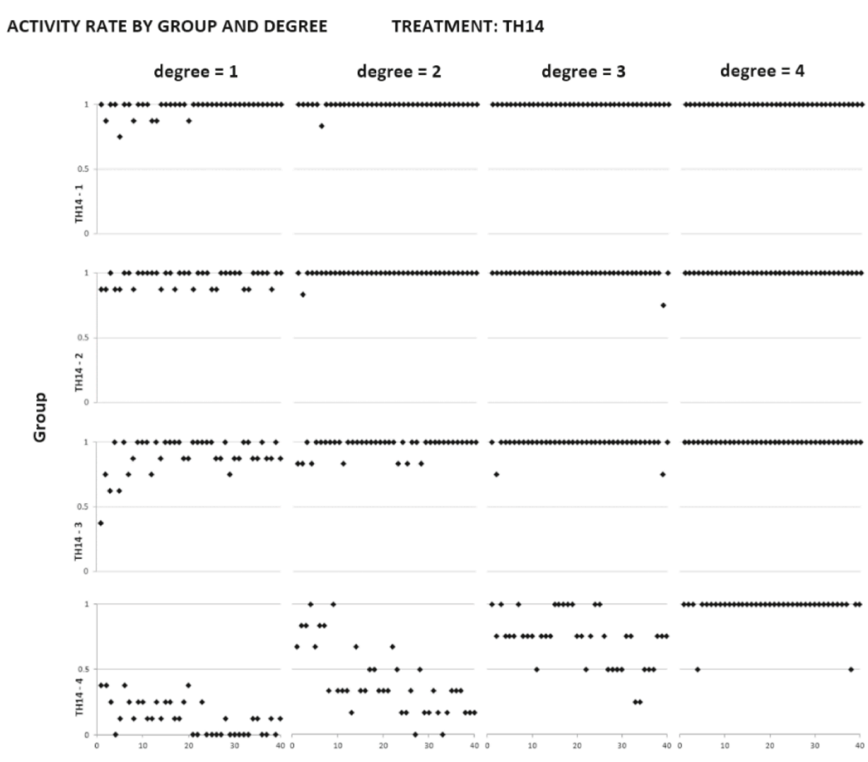
Q.E.D.

B. Evolution of play by treatment and by session

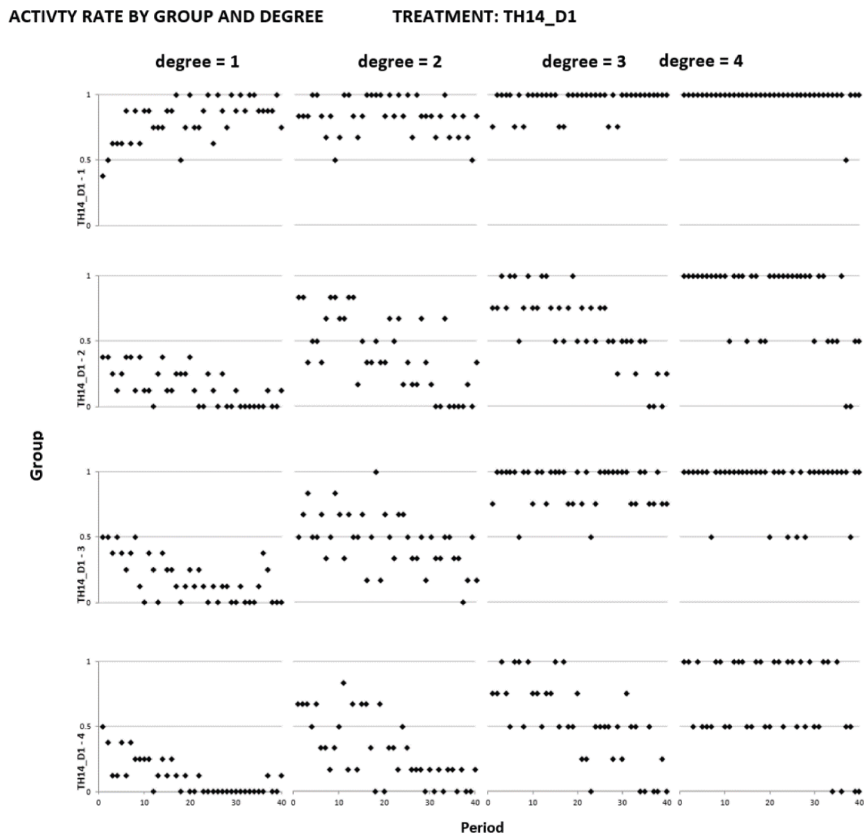
B.1. Baseline treatment



B.2. Universal premium treatment



B.3. Targeted premium treatment



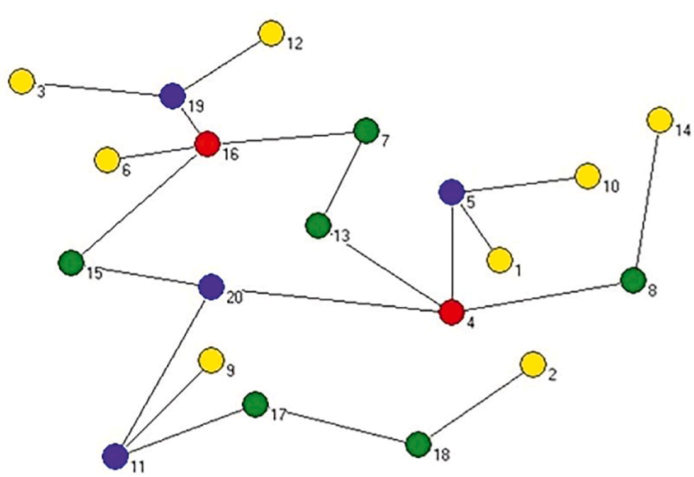
C. Instructions

Only instructions for the Universal Premium game are included. The corresponding instructions for the Targeted Premium game and the baseline are analogues.

Instructions

The aim of this experiment is to study how individuals make decisions in certain contexts. The instructions are simple. If you follow them carefully you will earn a non-negligible amount of money in cash (GBP) at the end of the experiment. During the experiment, your earnings will be accounted in ECU (Experimental Currency Units). Individual earnings will remain private, as nobody will know the other participants' earnings. Any communication amongst you is strictly forbidden and will result in an immediate exclusion from the experiment.

1.- The experiment consists of 40 periods, and there are 20 participants, including yourself. The participants will remain the same throughout the experiment. At each period, you and each of the remaining nineteen participants will be assigned one position of the following NETWORK. The positions in the network are numbered from 1 to 20.



2.- In the network, a link is represented by a line (connection) between two positions. For example, position 16 has four links: it is linked to positions 6, 7, 15 and 19 (but it is not linked to the remaining positions).

Note that there are four classes of positions in the network, identified by different colours.

- There are eight yellow positions: Those positions with one link (1, 2, 3, 6, 9, 10, 12 and 14).
- There are six green positions: Those positions with two links (7, 8, 13, 15, 17 and 18).
- There are four blue positions: Those positions with three links (5, 11, 19 and 20).
- There are two red positions: Those positions with four links (4 and 16).

3.- At each period, you (and the other participants) are randomly assigned by the computer to a position from 1 to 20 in the network, all of them being equally likely. The assignment process is random: At each period, you are equally likely to be located in each of the 20 positions of the network.

At each period, you will only be informed of the colour of your position, that is, you will know how many links your assigned position has: 1 link (yellow), 2 links (green), 3 links (blue) or 4 links (red). However, you will not be informed of which is your exact position.

For example, if at a particular period you are informed that your position has 3 links (blue), then you know that you can be in position 5, 11, 19 or 20, and that you can be in any of them with the same probability. Note that, in such a case, you also know that you cannot be in yellow, green or red positions.

Your earnings for the period are affected by your decisions and the decisions of the other participants, as specified below.

4.- At each period, knowing the network and your position, you will be asked to make a choice: to be ACTIVE or INACTIVE (the other participants are asked to make the same choice). Your payoff for the period will depend on your choice and on the choices of those participants located in positions linked to yours, as well as overall activity in the network. If you choose to be INACTIVE, your period payoff is 50 ECU. If you choose to be ACTIVE, your period payoff is calculated as follows: First, add 100 ECU per participant linked to you that also chooses to be ACTIVE; then, divide the result by 3. If in any period 14 or more participants in the network, including yourself, are active, 33,33 ECU are added to your period payoff. Hence,

If you choose to be ACTIVE your period payoff can be:

- $166,66$ ECU if 4 participants linked to you choose to be ACTIVE and any 14 or more participants, including yourself, are ACTIVE: $\left[\frac{100+100+100+100}{3}\right]+33,33$, or
- $133,33$ ECU if 4 participants linked to you choose to be ACTIVE and less than 14 participants, including yourself, are ACTIVE: $\left[\frac{100+100+100+100}{3}\right]$, or
- $133,33$ ECU if 3 participants linked to you choose to be ACTIVE and any 14 or more participants, including yourself, are ACTIVE: $\left[\frac{100+100+100}{3}\right]+33,33$, or
- $100,00$ ECU if 3 participants linked to you choose to be ACTIVE and less than 14 participants, including yourself, are ACTIVE: $\left[\frac{100+100+100}{3}\right]$, or
- $100,00$ ECU if 2 participants linked to you choose to be ACTIVE and any 14 or more participants, including yourself, are ACTIVE: $\left[\frac{100+100}{3}\right]+33,33$, or
- 66,66 ECU if 2 participants linked to you choose to be ACTIVE and less than 14 participants, including yourself, are ACTIVE: $\left[\frac{100+100}{3}\right]$, or
- 66,66 ECU if 1 participant linked to you chooses to be ACTIVE and any 14 or more participants, including yourself, are ACTIVE $\left[\frac{100}{3}\right]+33,33$, or
- 33,33 ECU if 1 participant linked to you chooses to be ACTIVE and less than 14 participants, including yourself, are ACTIVE: $\left[\frac{100}{3}\right]$, or
- 33,33 ECU if no participant linked to you chooses to be ACTIVE and any 14 or more participants, including yourself, are ACTIVE $\left[\frac{0}{3}\right]+33,33$, or
- 0,00 ECU if no participant linked to you chooses to be ACTIVE and less than 14 participants, including yourself, are ACTIVE: $\left[\frac{0}{3}\right]$

If you choose to be INACTIVE your period payoff is 5000 ECU for sure.

5.- At the end of every period, you will get information about current and past periods. The information consists of:

- Your position in the network.
- Your choice (ACTIVE or INACTIVE).
- The number of participants linked to you that chose to be ACTIVE.
- The number of participants in the network that chose to be ACTIVE.
- Your (period) payoff from participants linked to you (component A).
- Your (period) payoff from overall activity (component B).
- Your total (period) payoff.

6.- Payoffs. At the end of the experiment, you will be paid the earnings that you achieved in 4 periods, that will be randomly selected across the 40 periods of play (all periods selected with the same probability).

These earnings are transformed to cash at the exchange rate of 40 ECU = 1 GBP. In addition to your earnings in the experiment, you will receive GBP 4.00 for your participation.

7.- The experiment starts with 5 trial periods that do not count for earnings. Trial periods are indicated as such in the top left corner of the screen. After the 5 trial periods the experiment starts without a break.

D. Frequencies of activity by treatment and degree, split by first and second half of the game

Frequencies of activity by treatment and degree. First half (period 1–20) and second half (period 21–40).

	Baseline		Universal premium		Targeted premium	
	First half # %	Second half # %	First half # %	Second half Total	First half # %	Second half Total
overall	615	466	1366	1305	939	696
	38.4	29.1	85.4	81.6	58.7	43.5
degree = 1	48	24	480	470	233	167
	7.5	3.8	75.0	73.4	36.4	26.1
degree = 2	203	124	421	388	291	193
	42.3	25.8	87.7	80.8	60.6	40.2
degree = 3	212	175	306	288	271	206
	66.3	54.7	95.6	90.0	84.7	64.4
degree = 4	152	143	159	159	144	130
	95.0	89.4	99.4	99.4	90.0	81.3

Percentage point difference in activity rate

	Universal premium vs Baseline		Targeted premium vs Baseline		Targeted premium vs Universal premium	
	First half	Second half	First half	Second half	First half	Second half
overall	46.9**	52.4*	20.3*	14.4	−26.7	−38.1
degree = 1	67.5**	69.7	28.9**	22.3	−38.6	−47.3
degree = 2	45.4**	55.0	18.3*	14.4	−27.1	−40.6
degree = 3	29.4**	35.3*	18.4*	9.7	−10.9	−25.6*
degree = 4	4.4	10.0*	−5.0	−8.1	−9.4	−18.1*

Wilcoxon Mann-Whitney: ***, **, * denote significance at 1%, 5% and 10% levels, respectively, in a two-tailed test.

E. Econometrics

E.1. Logistic regression for the first and last 10 periods

Independent variable: choice to be active

Dependent variables: dummy for treatment, player degree, period, and interactions across these variables

VARIABLES	(1) Logit first 10 periods	(2) Logit last 10 periods
0.treat#1.links#c.period	−0.640***	−0.304***
	(0.117)	(0.0545)
0.treat#2.links#c.period	−0.115**	−0.200***
	(0.0509)	(0.0464)
0.treat#3.links#c.period	0.166***	−0.120***
	(0.0524)	(0.0425)
0.treat#4.links#c.period	0.668***	−0.014
	(0.0920)	(0.0471)
1.treat#1.links#c.period	0.049	−0.030
	(0.165)	(0.0429)
1.treat#2.links#c.period	0.297	0.006
	(0.182)	(0.0394)
1.treat#3.links#c.period	0.442*	0.070**
	(0.232)	(0.0280)
1.treat#4.links#c.period	1.054**	0.209***
	(0.417)	(0.0388)
2.treat#1.links#c.period	−0.216**	−0.188***
	(0.0907)	(0.0416)
2.treat#2.links#c.period	−0.015	−0.162***
	(0.0524)	(0.0347)
2.treat#3.links#c.period	0.222***	−0.082*
	(0.0373)	(0.0446)
2.treat#4.links#c.period	0.371**	−0.062
	(0.176)	(0.0421)
Constant	0.853**	4.215***
	(0.354)	(1.280)
Observations	2400	2400
Number of id	240	240

0.treat = baseline, 1.treat = universal premium, 2.treat = targeted premium.
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

E.2. Marginal effects for the first 10 periods

VARIABLES	(1) Universal premium vs baseline first 10 periods	(2) Targeted premium vs baseline first 10 periods	(3) Targeted premium vs Universal Premium first 10 periods
degree = 1	0.478***	0.249***	−0.229
	(0.139)	(0.0888)	(0.153)
degree = 2	0.294***	0.0885	−0.205**
	(0.0901)	(0.0575)	(0.0909)
degree = 3	0.120	0.0329	−0.0869
	(0.0742)	(0.0385)	(0.0662)
degree = 4	0.0336	−0.0658	−0.0993
	(0.0273)	(0.0623)	(0.0655)
Observations	2400	2400	2400

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

E.3. Marginal effects for the last 10 periods

VARIABLES	(1) Universal premium vs baseline last 10 periods	(2) Targeted premium vs baseline last 10 periods	(3) Targeted premium vs Universal Premium last 10 periods
degree = 1	0.706***	0.214	−0.491**
	(0.150)	(0.175)	(0.234)
degree = 2	0.595***	0.114	−0.481**
	(0.125)	(0.153)	(0.198)
degree = 3	0.447***	0.121	−0.326*
	(0.0603)	(0.173)	(0.167)
degree = 4	0.187***	−0.127	−0.314**
	(0.0531)	(0.163)	(0.148)
Observations	2400	2400	2400

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

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