Contests with network-based externalities: Experimental evidence

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Abstract

We report the findings of a laboratory experiment studying behavior in all-pay Tullock (1980) contests with network-based externalities. We test the predictions of a model in which the prize generates payoff externalities for losing contestants connected to the winner, by systematically varying the network structure and introducing either positive or negative externalities. The data provide robust support for the comparative static predictions of the model, although we also observe considerable over-investment relative to equilibrium predictions. Closer inspection of the observed patterns of over-investment suggests that behavior may be driven by heterogeneous *joy of winning* and *social efficiency concerns*.

Keywords: contests, networks, identity-dependent externalities, network games, experiment

JEL: C72, C91, C92, D72, D74, D85, Z13

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1 Introduction

Economic environments in which individuals expend resources in an attempt to win a valuable prize are extremely common. As such, economists have devoted considerable attention to understanding behavior in these environments, which are most often modeled as *contests*. A standard assumption in the contest literature is that any individual who does not win the contest is indifferent about the identity of the winner. However, in many circumstances, individuals may have more general preferences over the allocation of the prize. This observation is related to a robust body of research examining the impact of *identity-dependent externalities* (IDEs) in various competitive environments (Jehiel, Moldovanu and Stacchetti, 1996; Jehiel and Moldovanu, 1996; Linster, 1993; Esteban and Ray, 1999; Konrad and Schlesinger, 1997; Klose and Kovenock, 2015).

In many cases, these IDEs may arise from some underlying connections between agents, which can be described by a network. For example, consider a network describing the degree of rivalry between competing firms in a consumer product space. In general, we may think of this network as capturing several factors that influence the level of competition, such as regional proximity and the degree of substitutability between firms' products. Beyond this product market competition, firms may also compete in related business ventures (e.g., R&D, patent races, lobbying for licenses), the outcomes of which indirectly affect profits. The level of investment by a firm in these associated competitions is likely influenced by the number of competitors they face in the product market and the degree of rivalry with each. In these instances, it is natural to think of the network as describing negative externalities that may intensify competition between firms in these related business ventures.

Another example emphasizes the potential impacts of positive externalities. Suppose a collection of community councils lobby a city planner tasked with locating a new public facility somewhere among the communities. The ideal outcome for each community is to have the facility located in its own neighborhood, but accessibility and proximity to the selected location may generate positive spillovers for adjacent communities. If the positive externalities are sufficiently strong, or the communities are sufficiently well-connected, the competing communities face free-riding incentives that will tend to reduce the amount of lobbying activity relative to the case where no externalities are present. In each of these examples, there is an underlying network structure that governs the flow of externalities, such that the setting can be modeled as a game with network-based payoff externalities.

Recent advancements in the theory of network games have explored the relationship between individual behavior and the structure of the network connecting interacting agents (see, e.g., Bramoullé and Kranton, 2007; Bramoullé, Kranton and D'Amours, 2014; Jackson and Zenou, 2015). We build upon this literature by examining a version of the *network contest game* (Boosey and Brown, 2022), which was introduced to study the effects of network-based identity-dependent externalities in all-pay Tullock (1980) contest environments. The primary departure of this model from existing contest models is the introduction of a network through which (potentially heterogeneous) externalities flow from the winning agent to their neighbors in the network. This modification accommodates agents having more general preferences over the possible allocations of the prize, which depend on the structure of the network and their position within it.

In this paper, we empirically test the theoretical predictions of the model of network contest games in a controlled laboratory experiment. Analysis of interaction in networks using naturally occurring data is, generally, extremely challenging. As such, laboratory experiments can be especially useful for testing theoretical predictions and identifying additional factors that influence behavior. In our experiment, subjects are placed into groups of six and assigned positions in one of four network configurations—the Complete network, a Circle network, a Star network, and a core-periphery network with two core players, referred to as CP2. We focus on a tractable version of the general model, in which all network links are homogenous, meaning that all of the externalities are of the same sign and size.[1] For each of the four network structures, we implement three different conditions that vary the externality: a strong negative externality, a strong positive externality (of the same magnitude as in the negative condition), and a baseline control in which the network structure is retained but externalities are set equal to zero.

The predictions generated by the model in Boosey and Brown (2022) feature several intuitive properties. These are especially stark in the homogenous-links case examined by our experiment because the externality flows can be described using just a single parameter, $\alpha \in [0, 1)$, in conjunction with a binary network

[1]The theoretical model in Boosey and Brown (2022) allows for arbitrary heterogeneity but derives particularly stark closed-form characterizations and comparative static results for the homogenous-links case.

where $g_{ij} \in \{0, \bar{g}\}$ for all pairs of agents, i, j. The value of α represents the strength of the externality flows, while $\bar{g} \in \{-1, 1\}$ dictates whether the externalities are negative or positive, respectively. In *regular* networks—such as the COMPLETE and CIRCLE networks—there always exists a symmetric Nash equilibrium. Moreover, the symmetric equilibrium investment is strictly (and linearly) decreasing as the value of the externality, $\alpha\bar{g}$, increases over the range $(-1, 1)$. This captures a natural feature of the motivating examples described earlier. When externalities are negative, the intensity of competition increases, leading to higher equilibrium investments; but when they are positive, externalities introduce free-riding incentives for the agents in the contest.

In addition, the rate at which equilibrium investment falls with $\alpha\bar{g}$ is faster for larger values of the *degree* of the regular network. In other words, in more dense networks, a given externality flow has a larger impact on the symmetric equilibrium investment. Both the heightened intensity of competition (for negative externalities) and the strength of free-riding incentives (for positive externalities) are amplified when contestants are more densely connected, as when comparing the COMPLETE network with the CIRCLE network. Furthermore, for sufficiently strong positive externalities, the symmetric equilibrium need not be unique. In particular, for the CIRCLE network, when $\alpha\bar{g} > 0$ is sufficiently large, there can be asymmetric *specialized equilibria*, which are equilibrium investment profiles for which the set of active agents forms a maximal independent set.[2] In these specialized equilibria, competition is concentrated among disconnected agents, allowing their linked neighbors to sit out of the competition and free-ride on the positive externality flows from their active neighbors.

For another class of homogenous-link networks, with a particular core-periphery structure, the theoretical predictions are also intuitive. When externalities are negative, more heavily linked core players are particularly vulnerable, and so in equilibrium, they substantially increase their investment as the size of the negative externality grows. In contrast, peripheral players who are linked only to a single core player are less exposed, so their equilibrium investment is relatively unresponsive to the value of α. A similar argument applies to the case where externalities are positive. The core players, who are structurally more exposed to externality flows, have stronger free-riding incentives as α increases. In fact, for

[2] We refer the reader to Boosey and Brown (2022), section 3.2 for a more detailed discussion of results pertaining to specialized equilibria.

sufficiently strong positive externalities, the semi-symmetric equilibrium is a *specialized equilibrium*, in which the core players are inactive, leaving the peripheral players to compete against one another for the prize.

Overall, our main experimental findings provide strong support for the theoretical predictions. At the aggregate level, the comparative static predictions across treatments are well supported by the observed patterns of mean investment. The lone exception is in the Circle network, where the effect of the positive externality is slightly weaker than predicted when using all rounds of the experiment. However, allowing for the effects of experience (by excluding earlier rounds), we find that even this exceptional case realigns with the predicted comparative static results. Moreover, the Circle network (with positive externalities), is the only condition for which there are multiple equilibria. Thus, we also examine this condition more closely, to see whether behavior is consistent with the symmetric equilibrium, a specialized equilibrium, or neither. We find little support for symmetric equilibrium play. For some groups, investment activity is more consistent with the predicted patterns of specialized equilibrium play. However, the coordination problem that arises with multiple equilibria prevents any clear picture from forming.

In addition, in most treatment conditions, we observe mean over-investment relative to the Nash equilibrium prediction, along with substantial variance across individuals. This finding coincides with the widespread documentation of over-investment (and over-spreading) in standard contest experiments without externalities (see, e.g., Sheremeta (2013)). A prominent explanation for this type of behavior is that individuals derive non-monetary utility from winning (commonly referred to as 'joy of winning') beyond the actual monetary value of the prize. In our baseline conditions (with no externalities), we observe over-investment levels consistent with prior experimental literature. We then offer some support for the 'joy of winning' hypothesis, using an elicitation procedure pioneered by Sheremeta (2010) to measure subjects' preferences for winning *per se*, and showing that subjects with a higher elicited joy of winning also tend to invest more in the main contests.

In the two regular networks (Complete and Circle), we find that over-investment is sensitive to the externality condition. In particular, the degree of over-investment is much smaller for positive externalities than it is for negative externalities. In this case, we explain the differences between treatment conditions by arguing that joy of winning is heightened in the presence of negative externalities, and (partly) suppressed when there are positive externalities. Regression analysis provides statistical support for this argument.

In contrast, for the two core-periphery networks, the patterns of over-investment suggest a different explanation. With negative externalities, we observe no evidence of mean over-investment by the core players but substantial over-investment by the peripheral players. Conversely, with positive externalities, peripheral players exhibit little to no over-investment, on average, while the core players display significant over-investment relative to the equilibrium prediction. Unlike for the regular networks, joy of winning that is sensitive to the externality cannot fully explain these observed patterns of behavior. Instead, we show how the behavior in core-periphery networks may depend on the presence of social efficiency concerns among subjects.

The basic intuition stems from the fact that the equilibrium prediction for core-periphery networks entails a particular kind of inefficiency with regard to the aggregate flows of externalities. For instance, in the Star network, the equilibrium outcomes generate (i) a high probability of widespread harm with negative externalities, and (ii) minimal aggregate flow of benefits with positive externalities. In the former case, peripheral players with a collective concern for social efficiency may over-invest in hopes of reducing the chance that the core player wins (thereby harming everyone else). In the latter case, a concern for social efficiency would explain more restrained investment by peripheral players and greater participation by the core player, since the aggregate flow of externalities is maximized when the prize is awarded to the core player. A closer inspection of the data at the group level offers some support for this argument.

Our study contributes to and draws upon recent experimental research on strategic behavior in games played on a network. For the most part, experiments on network games have focused either on coordination problems and games with strategic complementarities (see, e.g., Keser, Ehrhart and Berninghaus, 1998; Berninghaus, Ehrhart and Keser, 2002; Cassar, 2007; Gallo and Yan, 2015) or on public goods games where actions are strategic substitutes (Rosenkranz and Weitzel, 2012; van Leeuwen et al., 2019). Charness et al. (2014) examine both games of strategic complements and strategic substitutes, varying whether subjects in the experiment have complete or incomplete information about the network, in order to test the predictions of Galeotti et al. (2010) for network games.[3] Thus, the experimental literature has largely focused on games with a relatively simple structure (e.g., binary actions, linear-quadratic utility, local interaction, or core-periphery networks).[4] We provide the first experimental study of a contest game with network-based payoff externalities. As such, our work both broadens the experimental literature on network games and provides a novel extension to the rich body of work on contest experiments.

The rest of the paper is organized as follows. In Section 2, we provide an overview of the relevant theoretical framework developed in Boosey and Brown (2022). Section 3 describes the design and procedures of the experiment, before summarizing the predictions for each treatment condition. The main results are presented in Section 4, with further results and a discussion of over-investment patterns presented in Section 5. We offer brief concluding remarks in Section 6.

2 Theoretical Framework

Here, we describe a tractable version of the model presented in Boosey and Brown (2022), which informs our experimental design, in which the network is characterized by homogeneous link weights. That is, the weight of the link between any pair of agents connected by the network is the same. Consider an environment with a set of players $N = \{1, \ldots, n\}$, with $n \geqslant 2$, arranged in a network, described by the adjacency matrix $\mathbf{G}$, where $g_{ij} \in \mathbb{R}$ is the link weight between two agents i and j. The network is assumed to be undirected, with $g_{ij} = g_{ji} = \bar{g}$ if agents i and j are linked; $g_{ij} = g_{ji} = 0$ otherwise. Additionally, we adopt the standard convention that $g_{ii} = 0$ for all $i \in N$.

All individuals invest an amount $x_i \geqslant 0$ in the contest and face identical, linear cost functions, $c(x_i) = x_i$. Denoting by $\mathbf{x}_{-i}$ the vector of investments by all other individuals, the probability that player i wins the contest is given by the Tullock

[3] There is also a substantial amount of experimental research on cooperation in prisoners' dilemma games played on networks, and on social learning in networks, which is summarized nicely in the chapter by Choi, Gallo and Kariv (2016) on networks in the laboratory.

[4] There is also a related, though distinct literature on *conflict networks* (see, e.g., Goyal and Vigier, 2014; Franke and Öztürk, 2015; Matros and Rietzke, 2018; Kovenock and Roberson, 2018; Xu, Zenou and Zhou, 2019; Corrales and Rojo Arjona, 2022). In contrast with our setting, these studies typically focus on environments where the network is used to describe the structure of conflict between agents who participate in *multiple battles*.

(1980) contest success function.

$$P_i(x_i, \mathbf{x}_{-i}) = \begin{cases} \frac{1}{n}, & \text{if } \sum_{h=1}^{n} x_h = 0, \\ \frac{x_i}{\sum_{h=1}^{n} x_h}, & \text{otherwise} \end{cases} \qquad [1]$$

The agent that wins the contest receives a prize with value $V > 0$. The payoff of an agent that does not win the contest depends on their position in the network, relative to the winner. Specifically, if an agent i wins the contest, an externality $\alpha g_{ij} V$, with $\alpha \in [0, 1)$ is imposed on each agent j. Thus, an externality $\alpha \bar{g} V$ is imposed on each agent connected to the winner of the contest and no externality is imposed on agents not connected to the winner. Then, the expected payoff of each player i given a profile of investments $(x_i, \mathbf{x}_{-i})$ can be expressed as follows.

$$\pi_i(x_i, \mathbf{x}_{-i}; \mathbf{G}) = P_i(x_i, \mathbf{x}_{-i})V - x_i + \alpha \sum_{j=1}^{n} g_{ij} P_j(x_j, \mathbf{x}_{-j})V \qquad [2]$$

As previously mentioned, we restrict attention to networks with homogeneous link weights. Thus, the size and sign of the externality are reflected by the value of $\alpha\bar{g}$. We examine the case where $\bar{g} = 1$ (positive externalities) and $\bar{g} = -1$ (negative externalities). Then, the assumption that $\alpha \in [0, 1)$ implies that externalities are proportional to the prize and strictly smaller (in magnitude). Requiring $\alpha\bar{g} < 1$ guarantees that no individual ever prefers to lose the contest. No technical problems arise from allowing negative externalities larger in magnitude than the prize, but for simplicity, we rule out this possibility.

In the experiment, we restrict attention to two classes of networks that contain many structures commonly examined in the prior literature. First, we consider *regular* networks. For any network $\mathbf{G}$, we let $d_i(\mathbf{G}) = \sum_j |g_{ij}|$ denote the degree of agent j and note that, in the framework described here, an agent's degree describes the number of neighbors they have in the network. Then, a network $\mathbf{G}$ is said to be regular of degree k if $d_i(\mathbf{G}) = k$ for all $i \in N$. The second class of networks we consider is *core-periphery* networks. These networks are comprised of two types of agents–highly connected core players and less connected peripheral players. In our experiment, we restrict attention to core-periphery networks in which (i) all core players are directly connected to one another, (ii) each core player is connected to the same number of peripheral players, and (iii) each peripheral player is connected to a single core player and no other peripheral players.

2.1 Equilibria in the Network Contest Game

Proof of the existence of a pure strategy Nash equilibrium in the network contest game is established in Boosey and Brown (2022); however, uniqueness is not necessarily guaranteed.[5] In general, there may be multiple equilibria, and depending upon the structure of the network $\mathbf{G}$, these equilibria may be quite different. In particular, in some equilibria, not all agents will be active participants in the contest (i.e., some agents will optimally invest zero).

Lemma 1 in Boosey and Brown (2022), which we describe below, provides necessary and sufficient conditions for an investment profile to be an equilibrium of the network contest game. Let A denote the set of agents who are active in the contest (i.e., those with $x_i > 0$) and $N - A$ denote the set of agents who are inactive (i.e., those with $x_i = 0$).

Lemma (Boosey and Brown (2022), Lemma 1)**.** *An investment profile,* $\mathbf{x}$*, is a Nash equilibrium of the network contest game with network* $\mathbf{G}$ *if and only if the following hold.*

(i) $|A| \geqslant 2$

(ii) *for all* $i \in A$*,*

$$\sum_{j \in A}(1 - \alpha g_{ij})x_j - x_i = \left(\sum_{j \in A} x_j\right)^2 \qquad [3]$$

(iii) *for all* $i \in N - A$*,*

$$\sum_{j \in A}(1 - \alpha g_{ij})x_j \leqslant \left(\sum_{j \in A} x_j\right)^2 \qquad [4]$$

With negative and small positive externalities, equilibria will be fully interior and symmetric (semi-symmetric) in regular (core-periphery) networks. However, when externalities are positive and sufficiently large it may be optimal for some agents to invest zero in the contest. In core-periphery networks, the equilibrium remains semi-symmetric and is characterized by inactive (active) core (peripheral) players. Intuitively, core players are most structurally exposed to the externality, and therefore when externalities are positive and large these individuals are better off dropping out of the contest and free-riding off the investments of their (many) neighbors, who remain active.

[5] Sufficient conditions for equilibrium uniqueness, which depend on the structure of the network, are also derived in Boosey and Brown (2022).

Despite the fact that in a regular network all agents are equally exposed to the externality, a similar outcome, where some agents choose to not participate in the contest, can actually occur; this yields what we refer to as a specialized equilibrium. Specifically, a Nash equilibrium $\mathbf{x}$ is a *specialized equilibrium* if the set of active players A forms a maximal independent set—that is, when for any two agents $i, j \in A$ we have $g_{ij} = 0$ and for every $k \in N - A$ we have $g_{kj} = \bar{g}$ for some $j \in A$. The underlying logic is the same as in the case of core-periphery networks. With sufficiently large positive externalities, inactive (non-specialist) agents are content to sit out of the contest and free-ride off of their active (specialist) neighbors. Furthermore, it will often be the case that multiple specialized equilibria (with different maximal independent sets of specialists) exist simultaneously. In our experiment, there are two specialized equilibria (in addition to the symmetric equilibrium) for the Circle network with strong positive externalities. In every other treatment condition, the Nash equilibrium is unique.

3 The Experiment

3.1 Design of the Experiment

The basic decision environment in our experiment is a network contest game with groups of $n = 6$ players. Each participant is given an initial endowment of 800 tokens and asked to choose an amount between 0 and 800 tokens to invest in a project. Within each group, only one player's project can be successful, and the probability of success for each group member is given by the Tullock (1980) lottery contest success function in [1].

We set the value of the prize to be $V = 500$ tokens, and note that the restriction $\alpha\bar{g} \in (-1, 1)$ results in an externality that is proportional to the prize. The resulting material payoffs to player i who invests x_i in the contest, accounting for the network $\mathbf{G}$, are $1300 - x_i$ if player i wins the contest, $800 + 500\alpha\bar{g} - x_i$ if player i does not win but is directly linked to the winner by $\mathbf{G}$, and $800 - x_i$ if player i does not win and is not directly linked to the winner.

We introduce two sources of treatment variation. First, we examine the four network structures shown in Figure 1, varied across sessions (i.e., between subjects). The Complete and Circle networks are both *regular* networks (with degree $k = 5$ and $k = 2$, respectively). The Star and CP2 networks are both *core-periphery* networks. Second, we examine three values of effective externality,

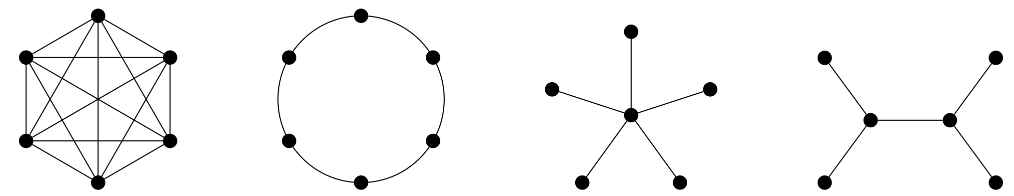


Figure 1. The set of networks

Table 1. Summary of experimental treatments.

Network	Treatment Order (Blocks 2–4)	Sessions	Groups	Subjects
Complete	NPB, PNB, BNP, BPN	4	10	60
Circle	NPB, PNB, BNP, BPN	4	11	66
Star	NPB (2), PNB (2), BNP, BPN	6	18	108
CP2	NPB (2), PNB (2), BNP, BPN	6	16	96

$\alpha\bar{g}$, in every session (i.e., within-subjects). The first value $\alpha\bar{g} = 0$, represents the baseline environment with no externality. The other values capture a (strong) negative externality ($\alpha\bar{g} = -0.8$) and a (strong) positive externality ($\alpha\bar{g} = 0.8$).[6] Altogether, this generates 12 treatment conditions, distinguished by the network and the externality parameter.

3.2 Procedures

In total, we conducted 20 sessions at the XS/FS laboratory at Florida State University (FSU) between October 2018 and June 2019. Subjects could only participate in one session. The experiment was implemented using z-Tree (Fischbacher, 2007), with a total of 330 subjects, randomly recruited via ORSEE (Greiner, 2015) from a sub-population of FSU students who had all pre-registered to receive announcements about participation in experiments. Table 1 summarizes the treatment design, number of sessions, and number of independent groups.

Each session consisted of four blocks, with multiple rounds in each block. In all sessions, Block 1 consisted of 10 rounds with $\alpha\bar{g} = 0$ (the Baseline condition). For the other three blocks, we implemented the Negative condition (15 rounds),

[6] For notational convenience, we occasionally describe the different treatment conditions by attaching a B (for Baseline) to indicate $\alpha\bar{g} = 0$, N (for Negative) to indicate $\alpha\bar{g} = -0.8$, or P (for Positive) to indicate $\alpha\bar{g} = 0.8$, at the end of the network name. For example, Complete-B refers to the Complete network with $\alpha\bar{g} = 0$, while Star-P refers to the Star network with positive externality, $\alpha\bar{g} = 0.8$.

the Positive condition (15 rounds), and another Baseline condition (10 rounds), varying the order of the three conditions across sessions. For the COMPLETE and CIRCLE networks, we ran one session each of NPB (i.e., Negative in Block 2, Positive in Block 3, Baseline in Block 4), PNB, BNP, and BPN. For the STAR and CP2 networks, we ran two sessions each of NPB and PNB, and one session each of BNP and BPN. The additional sessions of NPB and PNB ensured that we were able to collect enough observations for the core player in the STAR network.

At the beginning of each session, subjects were randomly divided into groups of six. Groups were fixed across all rounds and all blocks in every session. Participants were seated randomly at private computer terminals and given a set of written instructions. The experimenter then read the instructions aloud to facilitate common understanding.[7] Additionally, participants completed a short set of control questions to ensure they understood the instructions. The instructions were framed in terms of a general externality, X. Then, before each block, the experimenter announced the value of $X = \alpha\bar{g}V$ and reminded participants of the way payoffs are calculated. Participants were not informed about the number of blocks or the details of any future blocks until after the previous block was completed.

Each player in a group was randomly assigned a letter ID from A to F. The letter ID and position in the network were fixed across the entire experiment. In each round, players were shown the network, with their own ID and position highlighted in red. In addition, their direct neighbors in the network were highlighted in yellow, while those members of the group with whom they were not connected were shown in black. They were also reminded about the externality at the top of the screen and prompted to enter the number of tokens they would like to invest in their project. After all players had made their decisions, an interim summary screen displayed a table showing all players' investments, the total investment, and the corresponding probability of winning. After a few moments, the same screen was updated to also show the letter ID of the winner, whether or not the player was affected by the externality (if they were not the winner), and the calculation of their payoffs for the round.

Before the four blocks that constituted the main part of the experiment, we also elicited subjects' attitudes towards risk, ambiguity, and losses, using a list-style procedure similar to the methods used by Holt and Laury (2002) and Sutter

[7]A copy of the experimental instructions (for the CIRCLE) are provided in Appendix C.

et al. (2013). We also included a decision task *after* the four blocks were completed, designed to provide a measure of each subject's *joy of winning*, following an approach introduced by Sheremeta (2010). For this task, subjects were rematched into new groups of six subjects for a single decision round. They were given the same endowment of 800 tokens and asked to choose a project investment, just as in the four main blocks. In contrast with the other four blocks, there were no network connections (and thus no network externalities) and the winner received a prize of 0 tokens.

At the end of the experiment, subjects were paid for one randomly chosen period from each block, for the single decision round in the joy of winning task, and for one (randomly selected) of the risk, loss, or ambiguity aversion elicitation tasks. Tokens were converted to US dollars according to the exchange rate 400 tokens = \$1. Average earnings (including the \$7 show-up fee) amounted to \$17.46.

3.3 Predictions

Table 2 summarizes the equilibrium predictions for each treatment condition.[8] First, for all networks, when $\alpha\bar{g} = 0$ (Baseline), the unique equilibrium investment is symmetric across positions and corresponds to the standard equilibrium investment for a contest with six players and a prize of $V = 500$. Furthermore, in the Complete network, the unique equilibrium is the symmetric one corresponding to a standard contest with prize value equal to $V(1 - \alpha\bar{g})$. Accordingly, the equilibrium investment declines sharply as the externality increases from $\alpha\bar{g} = -0.8$ (Negative) to $\alpha\bar{g} = 0$ (Baseline), to $\alpha\bar{g} = 0.8$ (Positive). This key comparative static is highlighted in Figure 2a.

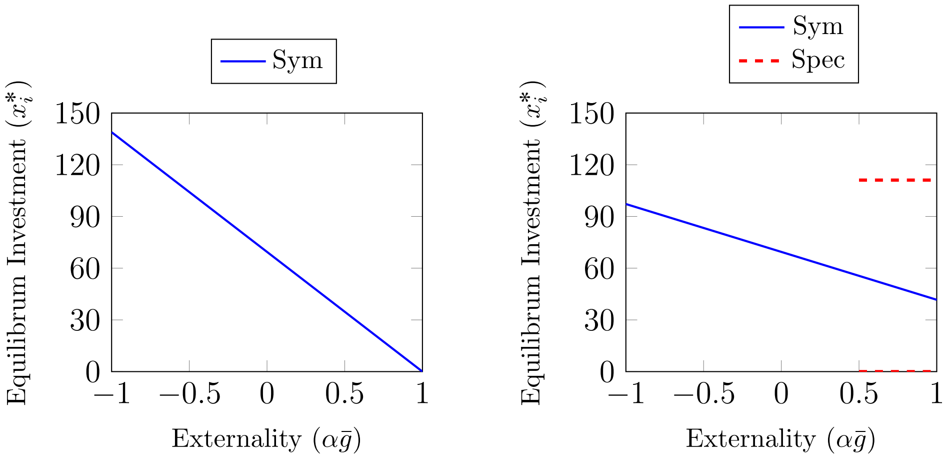
In the Circle network, there is a unique equilibrium for the Negative condition and the Baseline condition. In the Positive externality condition, there exists both a symmetric equilibrium with $x^* = 47.22$ and a pair of specialized equilibria, each consisting of three players who invest $x_A = 111.11$ and three inactive players.[9] This poses a potential coordination problem for the players in Circle-P, since players may hold different beliefs about whether or not they are playing the symmetric equilibrium, the specialized equilibrium in which they are active, or the specialized

[8] In Appendix A, we provide general closed-form results for equilibrium investment as a function of α in the class of regular and core-to-periphery structures. See Boosey and Brown (2022) for further details and complete proofs.

[9] The two specialized equilibria can be obtained by switching the sets of active players.

Table 2. Equilibrium predictions by treatment condition.

Network (position)	Externality Negative	Externality Baseline	Externality Positive
Complete	125.00	69.44	13.89
Circle – *Symmetric*	91.67	69.44	47.22
Circle – *Specialized*			
(active)	–	–	111.11
(inactive)	–	–	0.00
Star (core)	206.63	69.44	0.00
Star (peripheral)	74.39	69.44	80.00
CP2 (core)	157.89	69.44	0.00
CP2 (peripheral)	60.73	69.44	93.75



(a) Complete network **(b)** Circle network

Figure 2. Equilibrium investment in the Complete and Circle networks with $n = 6$ and $V = 500$. For specialized equilibria in the Circle network with $\alpha\bar{g} \geqslant 0.5$, players' investments are shown by dashed (red) lines at 111.11 (active) and 0 (inactive).

equilibrium in which they are inactive.[10] Compared with the Complete network, the predicted investment in the symmetric equilibrium exhibits a much flatter decline as the externality increases. This difference is depicted, along with the specialized equilibrium investment, in Figure 2b.

For the Star and CP2 networks, we examine the core player(s) and peripheral players separately. In both networks, the equilibrium is unique for all three

[10]In our initial analysis of this treatment condition, we focus on the comparative static predictions, which are similar whether we use the symmetric equilibrium or the specialized equilibrium. Subsequently, we examine the possibility that players are able to coordinate over time, and investigate whether play within groups is consistent with characteristics of a specialized equilibrium.

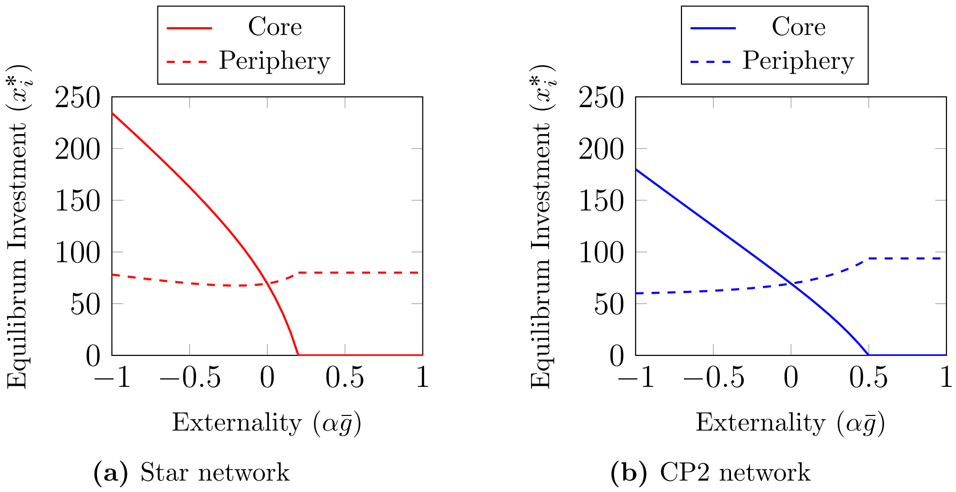


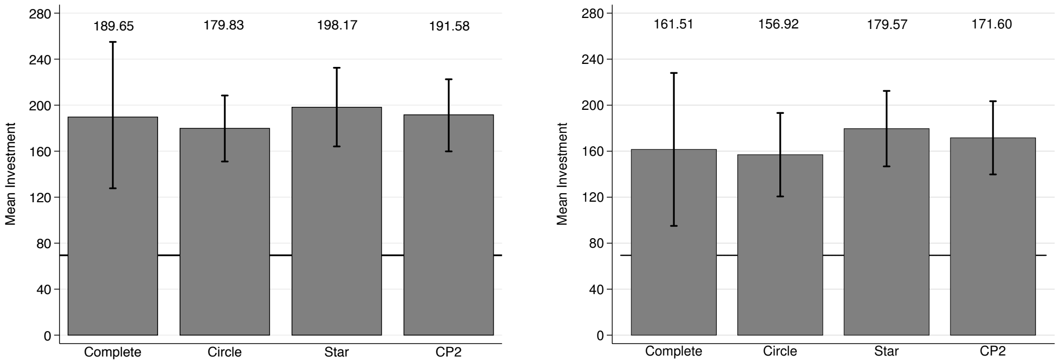
Figure 3. Semi-symmetric equilibria in the Star and CP2 networks.

externality conditions, is interior when $\alpha\bar{g} = -0.8$ and $\alpha\bar{g} = 0$, and specialized (with the core players inactive) when $\alpha\bar{g} = 0.8$. Thus, the equilibrium investment for the core player(s) is very high in the Negative condition, but equals zero in the Positive condition, reflecting their incentive to free ride in the specialized equilibrium. In contrast, for the peripheral players, equilibrium investment is fairly similar across all three values of $\alpha\bar{g}$. Figure 3 illustrates the equilibrium predictions for every value of $\alpha\bar{g} \in (-1, 1)$ when $n = 6$ and $V = 500$, with the precise predictions for $\alpha \in \{-0.8, 0, 0.8\}$ summarized in Table 2.

4 Results of the Experiment

The results are organized as follows. First, we report aggregate results concerning mean investment levels across networks and externality conditions. We concentrate on the comparative statics predictions in order to highlight the main treatment effects. In addition, we conduct a closer examination of behavior in the Circle-P condition, where there is both a symmetric equilibrium and a pair of specialized equilibria. In Section 5, we shift attention to the evidence regarding over-investment relative to the point predictions, and discuss alternative behavioral explanations for the differences between observed and predicted investment patterns.

Throughout the analysis, we rely on non-parametric tests for treatment comparisons and on the wild cluster bootstrap method (Cameron, Gelbach and Miller, 2008) for post-estimation hypothesis tests on regression coefficients. When the rel-



(a) All rounds

(b) Final six rounds

Figure 4. Mean investment levels in the Baseline condition ($\alpha\bar{g} = 0$) from Block 1, by network. The solid reference line indicates the NE point prediction (69.44). Error bars indicate 95% wild cluster bootstrap confidence intervals.

evant test is not indicated, the reported p-values correspond to a Wald test (with wild cluster bootstrap) comparing the estimated constant in a linear regression to the NE prediction. Furthermore, in all figures, error bars indicate 95% wild cluster bootstrap confidence intervals.

4.1 Aggregate Results

We first compare the mean investment level across networks in Block 1, where $\alpha\bar{g} = 0$. In this case, the network is payoff irrelevant and thus there should be no systematic differences across networks. Figure 4 shows that mean Block 1 investment is 189.65 in Complete, 179.83 in Circle, 198.17 in Star, and 191.58 in CP2. Consistent with the prediction, we find no significant differences between networks (Kruskal-Wallis test, $p = 0.89$; also, for all pairwise comparisons between networks using the Wilcoxon ranksum test, $p > 0.401$). However, there is substantial over-investment, on average, relative to the Nash Equilibrium prediction (69.44) in all networks, which is consistent with the experimental literature on standard contests.

Result 1. *Mean investment in the Baseline condition (Block 1) does not differ across networks.*

Nevertheless, in all networks, mean investment is trending down towards the Nash Equilibrium point prediction over the course of Block 1, which is consistent with some learning by the subjects as they gain experience with the strategic envi-

Table 3. Summary statistics for mean investment in Blocks 2-4 by treatment condition

	Externality					
	Negative ($\alpha\bar{g} = -0.8$)		Baseline ($\alpha\bar{g} = 0$)		Positive ($\alpha\bar{g} = 0.8$)	
Network	Observed	[NE]	Observed	[NE]	Observed	[NE]
COMPLETE	180.28	[125.00]	123.36	[69.44]	53.85	[13.89]
CIRCLE	168.90	[91.67]	114.72	[69.44]	103.06	[47.22]
						[55.55]†
STAR						
core	256.06	[206.63]	161.43	[69.44]	71.79	[0.00]
peripheral	179.16	[74.39]	143.15	[69.44]	126.14	[80.00]
CP2						
core	213.03	[157.89]	125.33	[69.44]	102.28	[0.00]
peripheral	168.37	[60.73]	137.36	[69.44]	140.09	[93.75]

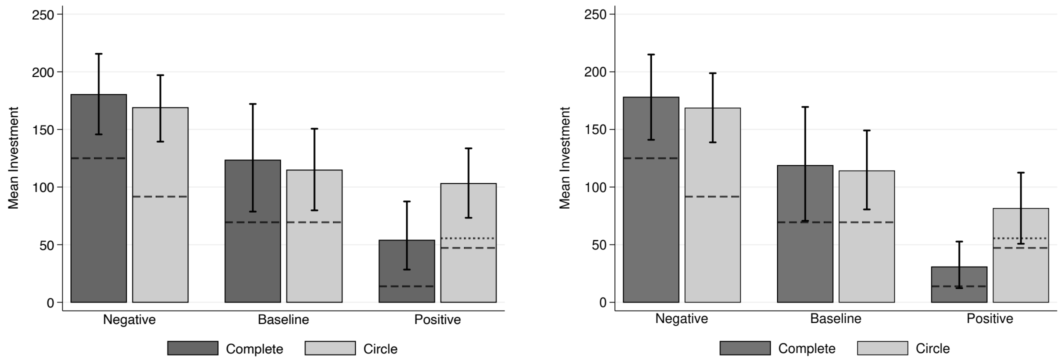
Notes: † denotes the average equilibrium investment in the specialized equilibria for CIRCLE-P.

ronment.[11] Thus, in order to account for experience, we also replicate the analysis using only the final six rounds of the block (see Figure 4b).[12] The corresponding mean investments are 161.51 in COMPLETE, 156.92 in CIRCLE, 179.57 in STAR, and 171.60 in CP2, which are also not significantly different from each other (Kruskal-Wallis test, $p = 0.772$; for all pairwise comparisons using the Wilcoxon ranksum test, $p > 0.322$). Although these investment levels are lower than when we use all 10 rounds, over-investment relative to the NE prediction persists.

Next, we compare mean investment across networks and externality conditions using the data collected in Blocks 2–4. Table 3 reports the mean investment for each network and each externality condition, alongside the corresponding Nash equilibrium (NE) point predictions. As is typical in contest experiments, and consistent with behavior in Block 1, we observe considerable over-investment (over-dissipation) relative to the NE in all conditions. However, we postpone a more detailed discussion of over-investment until Section 5. In the rest of this section, we concentrate on treatment comparisons and comparative static predictions. We begin by considering the two regular networks, COMPLETE and CIRCLE, before turning our attention to the core-periphery structures, STAR and CP2.

[11] We provide visual support for this downward trend in Figure B.1 in Appendix B.

[12] All of our results are qualitatively similar using only the last five rounds, or only the last ten rounds.



(a) All rounds

(b) Final six rounds

Figure 5. Mean investment levels by externality in the Regular networks. Dashed lines indicate symmetric NE point predictions, while the short-dashed line for Circle-P indicates specialized NE point prediction. Error bars indicate 95% wild cluster bootstrap confidence intervals.

4.1.1 Regular Networks

Figure 5a illustrates the mean investment reported in Table 3 (using all rounds) for each externality in the two regular networks, Complete and Circle. Comparisons within network (between externality) are generally consistent with the comparative static predictions. In both networks, investment is highest for the negative externality (180.28 in Complete, 168,90 in Circle) and lowest for the positive externality (53.85 in Complete, 103.06 in Circle), as predicted by the theory.

Using the mean investment across all rounds of a block within each independent group as a single observation, we observe significant differences for all pairwise comparisons between externality conditions in the Complete network (Wilcoxon Signed-Rank tests, $p = 0.047$ for N vs. B, $p = 0.005$ for N vs. P, $p = 0.007$ for P vs. B). Similarly, in the Circle network, we observe significantly higher mean investment in the negative condition compared with the other two conditions (Wilcoxon Signed-Rank tests, $p = 0.016$ for N vs B, $p = 0.008$ for N vs. P). However, mean investment in the Circle network is not significantly different between the baseline (zero externality) and positive externality conditions (Wilcoxon Signed-Rank test, $p = 0.374$), consistent with Figure 5a. We summarize our findings in the following two results.

Result 2. *For the Complete network, mean investment is strictly decreasing in the externality level, in line with the comparative static predictions.*

Result 3. *For the* Circle *network, mean investment is significantly higher with the negative externality than with either of the other externality conditions. However, mean investment is no different with the positive externality than with zero externality.*

Discussion. The second part of the result for Circle may be driven in part by the multiplicity of equilibria in the positive externality condition. In particular, while the symmetric equilibrium predicts lower investments in Circle-P than in Circle-B, the difference is quite small.[13] Furthermore, the predicted difference is even smaller if we posit that subjects play a specialized equilibrium (69.44 vs. 55.55). In addition, the likelihood of some coordination failure, especially in the early rounds could explain why average investment remains at a similar level when $\alpha\bar{g}$ increases from 0 to 0.8. Given that it is the only condition in which there are multiple equilibria, we investigate the Circle-P condition in more detail in Section 4.2.

Final six rounds. We also examine investment using only the final six rounds of each block. Figure 5b shows that for the Negative and Baseline externality conditions, the mean investment levels using the final six rounds are no different than those reported in Table 3 and Figure 5a (which use all rounds). For both the Complete and Circle networks, over-investment relative to the NE prediction remains statistically significant. However, for the Positive externality condition, the mean investment over the final six rounds is considerably lower than it is using all rounds.[14] More importantly, when using only the final six rounds of each block, the comparative static prediction that investment in Circle-B is higher than in Circle-P is now supported (Wilcoxon Signed-Rank test, $p = 0.0076$). Thus, if we allow for learning (or experience) to take place in each block, we can remove the qualified support for the comparative static predictions in the Circle network altogether.

[13] Note, however, that the difference is no smaller than the difference between Circle-N and Circle-B.

[14] In fact, over the final six rounds, over-investment in the Complete-P condition is only marginally significant ($p = 0.0925$). Similarly, while the difference between mean investment and the symmetric equilibrium in Circle-P over the final six rounds is still significant ($p = 0.032$), the difference relative to the average predicted investment in a specialized equilibrium is only marginally significant ($p = 0.0954$).

Comparing across networks. Next, we hold fixed the externality condition and compare investment levels *between* the two regular networks. As expected, in the Baseline condition, we find no significant differences, while in the Positive condition, investment is significantly higher in CIRCLE than in COMPLETE, which is consistent with both the symmetric and specialized equilibria for CIRCLE-P.[15] However, contrary to the theoretical prediction, mean investment in the Negative condition is not significantly different between COMPLETE and CIRCLE (Wilcoxon ranksum test using group-level means, $p = 1.000$ using all rounds, $p = 0.622$ using the final six rounds).

Result 4. *Average investment is significantly lower in* COMPLETE-P *than in* CIRCLE-P*, and is not significantly different between* COMPLETE-B *and* CIRCLE-B*, consistent with the predictions. In contrast, and contrary to the theoretical prediction, average investments in* COMPLETE-N *and* CIRCLE-N *are not significantly different from each other.*

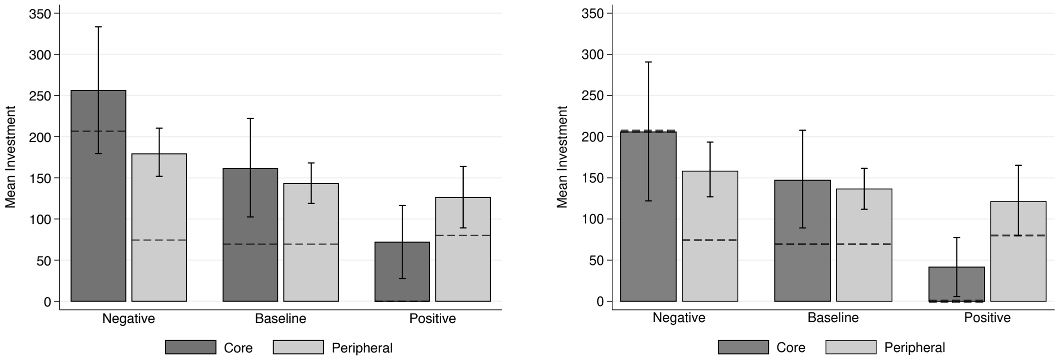
4.1.2 Core-Periphery Networks

For the STAR and CP2 networks, we compare mean investment levels separately for core players and peripheral players. We concentrate first on the impacts of the externality condition in the STAR network, then in the CP2 network, before turning our attention to the comparison between networks while holding the externality fixed.

Star network. Figure 6a shows the mean investment across externality conditions for the core player and peripheral players in the STAR network. Core players invest significantly more than the NE point predictions in the Baseline and Positive conditions, but not in the Negative condition. Nevertheless, comparisons between the three conditions for core players are all in line with the comparative static predictions. Specifically, investment in Negative is higher than in Baseline (Wilcoxon Signed-Rank test, $p = 0.018$) and Positive ($p < 0.001$), and investment in Baseline is higher than in Positive ($p = 0.004$).

For peripheral players, the NE investment levels are very similar across the three externality conditions (cf. Table 2). However, Figure 6a shows that the

[15] For the Wilcoxon ranksum test, using mean investment over all rounds for a single group as one observation, we have $p = 1.000$ for Baseline and $p = 0.029$ for Positive. Nothing substantive changes if we use the final six rounds, with $p = 0.994$ for Baseline and $p = 0.006$ for Positive.



(a) All rounds

(b) Final six rounds

Figure 6. Mean investment levels by externality in the STAR network. Dashed lines indicate NE point predictions. Error bars indicate 95% wild cluster bootstrap confidence intervals.

mean investment is, in fact, slightly higher in Negative than in Baseline and Positive, which do not differ from one another.[16] The comparative static results for core players are all robust to using only the final six rounds of each block (see Figure 6b). However, the differences between mean investment of peripheral players for the different externality conditions are no longer statistically significant when we restrict attention to the final six rounds.[17] Our next result summarizes these findings for the STAR network.

Result 5. *For the* STAR *network,*

(i) mean investment by the core players is strictly decreasing in the externality level, in line with the comparative static predictions;

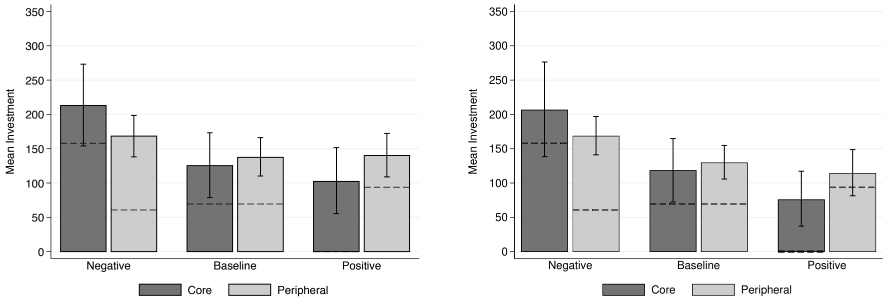
(ii) mean investment by the peripheral players is significantly higher with the negative externality than with the other two externality conditions when using all rounds, but does not differ between the three externality conditions when using the final six rounds of each block.

One interesting feature of the data that is highlighted by Figure 6a is the differential over-investment by peripheral players across externality conditions. In particular, we find that the percentage over-investment by peripheral players declines from 140.8% in Negative, to 106.11% in Baseline, to 57.7% in Positive.[18]

[16]Wilcoxon Signed-Rank tests, $p = 0.043$ for N vs. B, $p = 0.003$ for N vs. P, $p = 0.223$ for P vs. B.

[17]Wilcoxon Signed-Rank tests, $p = 0.396$ for N vs. B, $p = 0.085$ for N vs. P, $p = 0.122$ for P vs. B.

[18]Note, however, that when using only the final six rounds of each block, the over-investment



(a) All rounds **(b)** Final six rounds

Figure 7. Mean investment levels by externality in the CP2 network. Dashed lines indicate NE point predictions. Error bars indicate 95% wild cluster bootstrap confidence intervals.

CP2 network. Figure 7a shows the mean investment in the CP2 network. As in the Star network, the core players invest significantly more than the NE point predictions in the Baseline and Positive conditions, but not the Negative condition. Nevertheless, the comparisons between externality conditions are all consistent with the comparative static predictions for the core players. Mean investment in Negative is higher than in both Baseline (Wilcoxon Signed-Rank test, $p = 0.007$) and Positive ($p = 0.006$), while investment in Baseline is higher than in Positive ($p = 0.0303$). Figure 7b shows that each of these comparisons is also robust to using only the final six rounds of each block ($p < 0.01$ for each pairwise comparison).

The pattern of behavior for peripheral players in CP2 is also very similar to what we observe in the Star network. Mean investment is higher in Negative than in Baseline ($p = 0.010$) but only marginally higher than in Positive ($p = 0.079$), while Baseline and Positive are not significantly different ($p = 0.796$). Moreover, using only the final six rounds actually widens the difference between investment in the Negative condition and investment in the other two externality conditions by the peripheral players (Wilcoxon Signed-Rank tests, $p < 0.001$ for N vs. B; $p = 0.008$ for N vs. P; $p = 0.234$ for P vs. B).

Result 6. *For the* CP2 *network,*

(i) mean investment by the core players is strictly decreasing in the externality level, in line with the comparative static predictions;

rates for Negative (112.5%) and Baseline (96.5%) are similar, though both are much larger than the rate for Positive (51.6%). In fact, the difference between mean investment and the NE prediction for peripheral players in Star-P is only marginally significant ($p = 0.051$).

(ii) mean investment by the peripheral players is significantly higher with the negative externality than with the other two externality conditions, and does not differ between the baseline and positive externality.

Alongside these results, we observe the same feature of behavior in CP2 as in the Star with regards to the percentage over-investment by peripheral players. Over-investment falls from 177.2% in Negative, to 97.8% in Baseline, to 49.4% in Positive. Using the final six rounds only, the over-investment rates are 177.3% in Negative, 96.5% in Baseline, and just 21.7% in Positive. Furthermore, the difference between mean investment by peripheral players and the NE prediction in the CP2-P condition is not statistically significant ($p = 0.234$).

Comparing across networks. Finally, we compare behavior of the core players and peripheral players in the Star and CP2 networks, holding the externality level fixed. Core players' mean investment is less in CP2 than in Star when the externality is negative and in the Baseline condition, and higher in CP2 than in Star when the externality is positive, but none of the differences are statistically significant (Wilcoxon ranksum test, $p = 0.370$ for Negative, $p = 0.309$ for Baseline, and $p = 0.124$ for Positive). Similarly, mean investment by the peripheral players is not different between Star and CP2 for any of the externality conditions (Wilcoxon ranksum test, $p = 0.581$ for Negative, $p = 0.605$ for Baseline, and $p = 0.448$ for Positive).

4.2 Symmetric vs. Specialized Equilibrium Play in Circle-P

In this section, we provide a closer examination of the patterns of investment behavior in the Circle-P condition. In particular, we investigate whether play is consistent with either the symmetric or the specialized equilibria that arise for the Circle network when $\alpha\bar{g} = 0.8$. As a starting point, Figure 8 shows a scatter plot of all the data in Circle-P by round. Some of the notable features of the data are the concentration of observations at or around zero (in all rounds) and the gradual decline (and compression) of observations across rounds.

Focusing on the final six rounds of the data (rounds 10–15), there is still a considerable amount of heterogeneity, although the majority of the observations are no greater than 200. The clustering of observations around zero and the (smaller) clusters around 100 and 200 offer some hope for the emergence of specialized equilibria. However, as in most contest experiments, the spread of investment levels

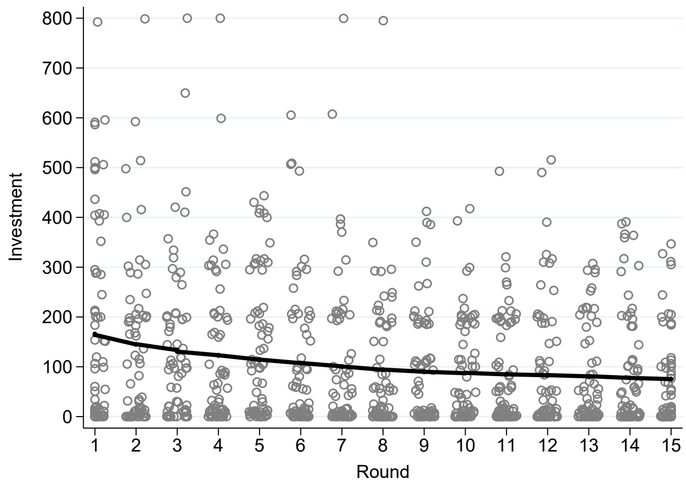


Figure 8. Scatter plot of investment by round in CIRCLE-P with Lowess smoother (bandwidth = 0.5).

across individuals is hardly encouraging evidence of symmetric equilibrium play.

Group-level analysis. In order to explore the evidence regarding specialized equilibrium play, we examine the data at the group level. Our analysis concerns three key features of specialized equilibria. First, in any specialized equilibrium of the CIRCLE-P condition, the three active agents must form a maximal independent set. Second, the three active agents invest just over 100 tokens into the contest (equilibrium investment is 111.11). Third, the other three agents, who are inactive, invest zero. Realistically, subjects face a coordination problem, due to the fact that there are two specialized equilibria in the CIRCLE network.

We begin by examining individual investment levels in each independent group, in order to provide an initial test of consistency with specialized equilibrium play. In order to allow for the possibility that players gain experience and require time to coordinate, we focus in the main text on just the final six rounds (rounds 10–15).[19] Figure 9 plots the investment choices for each player over the final six rounds, for each independent group in the CIRCLE-P condition. Based on this figure, there appears to be heterogeneity across groups. For instance, in some groups (IDs 7, 9, 10, 12, 31, 32, and 41), there are consistently two to four players who are inactive (or invest close to nothing) and at least two players who invest significantly more (most often 100 tokens or more). At least in terms of investment

[19]For each group, we also plot the individual investments by each player over all 15 rounds (see Figure B.2 in Appendix B.

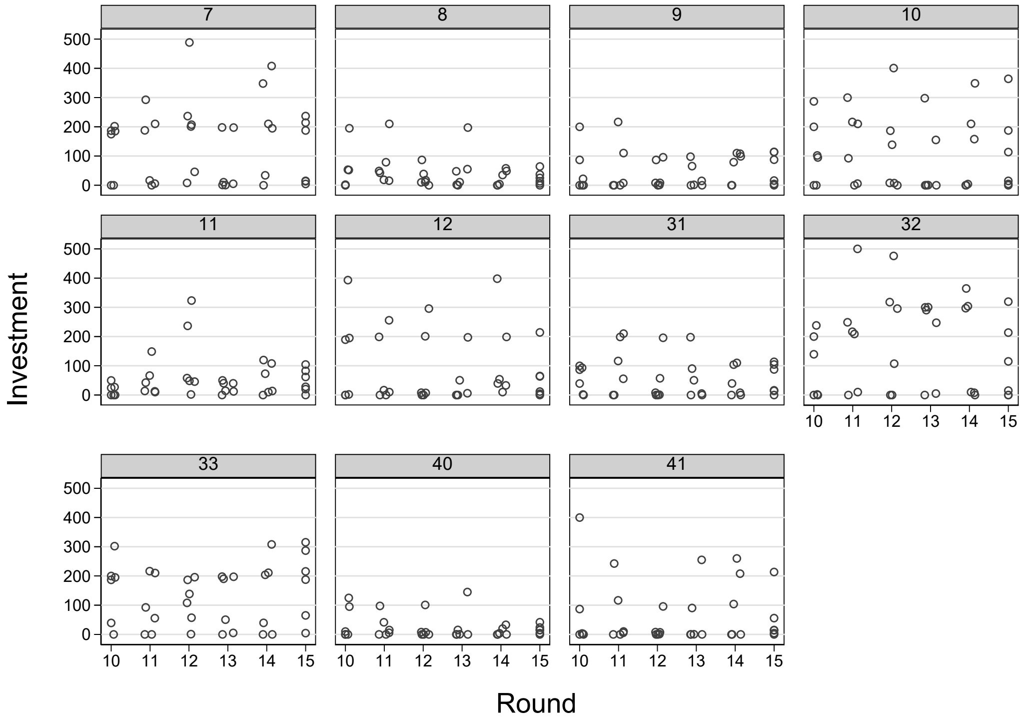


Figure 9. Scatter plot of investments in rounds 10 – 15 by group in the CIRCLE-P condition.

levels, the pattern in these groups appears consistent with specialized equilibrium play. In other groups (IDs 8, 11, and 40), the investments are typically more clustered together (consistent with more symmetric play), with only an occasional (single) high investor who separates from the other five group members.

One limitation of the plots in Figure 9 is that they contain no information regarding the configurations of active players within the network. In order to address this aspect of specialized equilibrium play, we next explore how often the subjects choosing the three highest investments in a group form a maximal independent set. In the CIRCLE-P condition, there are 11 groups and 15 rounds. Out of the resulting 165 observations, there are only 18 instances in which the three highest investments are all *strictly* higher than the others and come from agents who form a maximal independent set. If we allow for the possibility that there are ties at the median (so that the third and fourth highest investments are equal), there are 49 instances (out of 165) in which the three highest investments come from agents who form a maximal independent set. This suggests that even if groups are choosing investments consistent with a specialized equilibrium, they are rarely successful in coordinating on which sets of agents are active and which are inactive.

Another way to examine the consistency of play with a specialized equilibrium is to compare average investment by each maximal independent set of agents in the CIRCLE network. Consider the two subsets of agents, denoted by their position labels in the experiment, $M_A = \{A, D, E\}$ and $M_B = \{B, C, F\}$.[20] For each of the two subsets M_A and M_B, we compute the average investment by its constituent members in each round. Then, in Figure 10, we plot the average investments for M_A and M_B in the final six rounds, for each independent group in CIRCLE-P.[21] Consistent with the heterogeneity across groups observed in Figure 9, we observe a mix of patterns between the two maximal independent sets. For instance, in groups 7, 31, and 41, average investment is consistently higher for players in the maximal independent sets M_B than for those in M_A, whereas in groups 9 and 32, average investment is higher for players in M_A than for those in M_B. In contrast, in groups 8, 11, 33, and 40 (all of which exhibited more clustering in Figure 9), the mean investment levels are roughly similar across the two maximal independent sets.

Nevertheless, even when there is a gap between average investment for the two maximal independent sets, it may not necessarily reflect specialized equilibrium play. To assess whether or not it does, it is useful to compare the patterns observed in Figure 10 for the CIRCLE-P condition with the average investment by the same groups in the CIRCLE-N and CIRCLE-B conditions. Figure B.4 in Appendix B shows the corresponding plots for the CIRCLE-N condition. For several of the groups (including 9, 10, 12, 31, and 32), there are similar gaps between average investment for the two maximal independent sets. Similarly, Figure B.5 shows that for the CIRCLE-B condition, there are comparable gaps between average investment for M_A and M_B in groups 12, 31, 32, and 41. Together these findings suggest that the gaps may be driven by factors other than the presence of a specialized equilibrium, since no such equilibria exists for the CIRCLE-N or CIRCLE-B conditions.

One possibility is that there are different types of subjects, some of whom are inclined to over-invest in the contest (for instance, due to high non-monetary utility–or 'joy'–of winning), and others for whom the resulting best response is to remain inactive. We discuss this idea alongside other possible influences as part

[20]These two subsets correspond to the two maximal independent sets given the labeling used in the experiment. See, for example, Figure C.1 in Appendix C.

[21]Corresponding plots with all 15 rounds are presented in Figure B.3 in Appendix B.

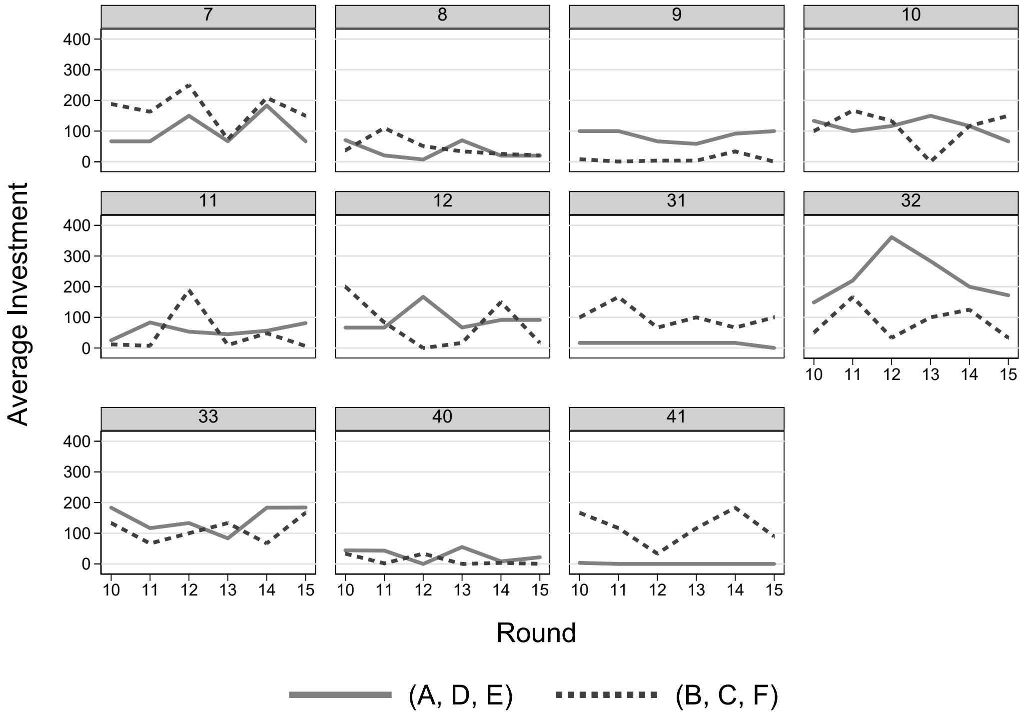


Figure 10. Average investment by maximal independent sets $M_A = \{A, D, E\}$ and $M_B = \{B, C, F\}$ over the final six rounds in the Circle-P condition. Each cell represents one independent group.

of the analysis of over-investment, in the next section.

5 Discussion—Explaining Patterns of Over-Investment

Mean over-investment relative to the NE point prediction has been widely documented in standard lottery contest experiments without externalities (see, e.g., Sheremeta (2013)). Given the wealth of evidence, several alternative explanations have been proposed for over-investment, and these have been well summarized by Dechenaux, Kovenock and Sheremeta (2015) and tested systematically by Sheremeta (2016). One such explanation is that individuals derive some non-monetary utility from winning *per se*, commonly referred to as the 'joy of winning', beyond the actual value of the prize (Goeree, Holt and Palfrey, 2002; Sheremeta, 2010; Brookins and Ryvkin, 2014; Boosey, Brookins and Ryvkin, 2017).[22] In this

[22]Other explanations contend that individuals who care about status or relative payoffs may invest more in a contest (see, e.g., Hehenkamp, Leininger and Possajennikov (2004); Mago, Samak and Sheremeta (2016)), or that individuals are boundedly rational and subject to making mistakes. A standard approach to modeling the noise associated with these mistakes is the Quantal Response Equilibrium (QRE) framework (McKelvey and Palfrey, 1995). Supporting

section, we consider the evidence of (mean) over-investment relative to NE predictions and discuss some alternative behavioral considerations that can help to explain the patterns we observe. For each treatment condition, we briefly review the aggregate patterns that were highlighted in the previous section, to help organize the subsequent discussion.

5.1 Baseline Condition

Recall that in the Baseline condition ($\alpha\bar{g} = 0$), the network structure is theoretically irrelevant. In Section 4.1, it was demonstrated that average investment is significantly above the NE point prediction in all four networks. Moreover, the amount of over-investment does not differ significantly across networks. Neither of these results change when using only the final six rounds of each block. Here, we also examine the Baseline conditions implemented in Blocks 2 and 4 of the experiment. Figure B.6 in Appendix B shows the mean investment levels for each network, pooling together the sessions from Blocks 2 and 4.[23]

Overall, we find no significant differences between networks (Kruskal-Wallis test, $p = 0.142$), although pairwise comparisons using the Wilcoxon ranksum test suggest that investments in the Star network are higher than in the Complete ($p = 0.084$) and Circle ($p = 0.053$) networks. Focusing on the final six rounds of each block, we again find no significant differences between networks overall (Kruskal-Wallis test, $p = 0.249$) and higher mean investment in the Star network as compared to the Circle, though the difference is only marginally significant (Wilcoxon ranksum test, $p = 0.096$). We summarize these observations with the following result.

Result 7. *In the Baseline condition, over-investment levels are similar across networks and consistent with the robust evidence of over-investment in standard contest experiments.*

Another well-documented finding in the contest experiments literature is that

evidence for this approach is reported in Sheremeta (2011), Chowdhury, Sheremeta and Turocy (2014), Lim, Matros and Turocy (2014), and Brookins and Ryvkin (2014). Yet another suggested explanation is that individuals are subject to judgmental biases, such as non-linear probability weighting, or the hot hand fallacy, which may lead to higher investment than the standard NE prediction (Parco, Rapoport and Amaldoss, 2005; Amaldoss and Rapoport, 2009; Sheremeta, 2011).

[23] In these later Baseline blocks, the network structure is, similarly, theoretically irrelevant; although, it is technically possible that in Block 4 individuals' investment behavior is influenced by previous exposure to the Negative and Positive conditions.

Table 4. Distribution of Joy Investment (investments in the zero prize contest) and corresponding Block 1 investments

Joy Investment	Percent of subjects	Mean Baseline Investment (Block 1)
0	77.88%	175.18
1	11.21%	206.95
2–15	3.03%	240.74
16–100	3.63%	259.14
> 100	4.22%	346.20

mean over-investment is accompanied by considerable variance (or overspreading), with many subjects investing less than the NE while others substantially over-invest. Following the approach introduced by Sheremeta (2010), at the end of the main experiment we elicited a measure of subjects' non-monetary value of winning (their *joy of winning*), by asking them to choose an investment for a contest with a prize of zero. The data obtained from this experimental elicitation of joy of winning reveals that about 22% of subjects submitted non-zero levels of investment for a prize with value zero. While the majority of these were relatively small, about 6% of investments in this part of the experiment were larger than 80 tokens (10% of their total endowment) and about 4% were larger than 200 tokens (25% of their total endowment).

In Table 4, we report the percentage of subjects who chose different ranges of investment in the zero prize contest, alongside the mean Baseline (Block 1) investment for the subjects in each range. The main takeaway is that the mean Baseline investment in Block 1 is higher for subjects who choose higher "joy investments". In particular, subjects who invested more than 100 in the zero prize contest also invested nearly twice as much (on average) in the Baseline condition as subjects who invested nothing in the contest with a prize of zero.

We also estimate a mixed effects model regressing Baseline investment in Block 1 on investment in the zero prize contest (Joy Investment). Specifically, we estimate the model in the following equation,

$$\text{Invest}_{it} = \beta_0 + \beta_1 \text{Joy Investment}_i + \gamma(1/t) + u_{0i} + u_{1i}\text{Joy Investment} + \epsilon_{it}, \quad [5]$$

allowing for subject-level fixed effects and between-subject heterogeneity in the effects of Joy Investment (random slope coefficients), and include a time trend (the reciprocal of the round number) to account for learning during Block 1.[24]

[24] A likelihood ratio test confirms that including random slopes with respect to the explanatory

Table 5. Multilevel mixed effects model with between subjects random slopes, regressing Baseline Investment (from Block 1) on Joy Investment.

Dependent variable: Individual investment in round t					
	Overall	Complete	Circle	Star	CP2
Joy Invest	0.396***	2.676***	0.539***	−0.060	0.302**
	(0.138)	(0.479)	(0.044)	(0.151)	(0.145)
1/t	75.105***	126.198***	54.882	61.847***	71.990***
	(13.436)	(32.436)	(39.499)	(20.533)	(21.108)
Constant	161.366***	134.461***	155.277***	181.118***	159.233***
	(9.753)	(31.197)	(17.755)	(16.375)	(16.749)
$\hat{\sigma}^2_{u_0}$ (Constant)	17180.50***	18450.80***	14992.30***	18599.59***	14237.84***
$\hat{\sigma}^2_{u_1}$ (Joy Invest)	0.125***	2.761***	–	–	0.067***
$\hat{\sigma}^2_{\epsilon}$ (Residual)	26409.22***	28985.74***	25251.39***	26042.89***	25844.08***
Groups	55	10	11	18	16
Observations	3300	600	660	1080	960
Wald $\chi^2(2)$	40.44***	45.58***	161.53***	9.10**	18.19***

Robust standard errors, adjusted for clustering at the group level, in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Standard errors are clustered at the group level, to account for the dependence across individuals. The results are reported in Table 5, both overall and separately for each network.

Overall, the relationship between a subject's Joy Investment and her investment levels in the Baseline condition is positive and highly significant. Disaggregating the data by network, we find that the effect is heterogeneous, although significantly positive for each case except the Star network. There is significant variance in the slope coefficients overall and for the Complete and CP2 networks, whereas the estimation results for the Circle and Star networks are no different than from a standard random effects regression. The time trend is also significant (except in the Circle network), consistent with the evidence that investment in Block 1 declines (non-linearly) with experience in each block. We summarize our findings in the following result.

Result 8. *Subject-level investment in the Baseline condition (Block 1) is increasing in the elicited measure of the subject's joy of winning.*

variable 'Joy Investment' significantly improves the fit of the model when the data are pooled across networks. The same is true for the Complete and CP2 networks on their own, although not for the Circle or Star networks, where the coefficient on Joy Investment does not exhibit any subject-level variation.

5.2 Regular Networks

Next, we consider over-investment in the regular networks, for the Negative and Positive externality conditions. For regular networks, Table 3 provides clear evidence of mean over-investment in all conditions (including the Baseline in Blocks 2 and 4), although it is only marginally significant over the final six rounds of Complete-P and Circle-P.[25] One possible explanation for the differences between conditions could be that subjects' joy of winning is elevated in the presence of negative externalities. We examine this possibility by estimating a multilevel mixed effects model for investment over the final six rounds of each block.

The full specification of interest is the following model,

$$\begin{aligned}\text{Invest}_{it} = &\beta_0 + \beta_1 \text{Joy Investment}_i + \beta_2 \text{Neg} + \beta_3 \text{Pos} + \boldsymbol{\gamma}\mathbf{X} \\ &+ \alpha_1(\text{Neg} \times \text{Joy Investment}_i) + \alpha_2(\text{Pos} \times \text{Joy Investment}_i) \\ &+ u_{0i} + u_{1i}\text{Joy Investment}_i + \epsilon_{it},\end{aligned} \qquad [6]$$

where Neg and Pos are dummy variables for the externality condition, $\mathbf{X}$ is a vector consisting of the individual elicited measures of ambiguity aversion (AA), risk aversion (RA), and loss aversion (LA). We allow for both random intercepts (corresponding to Baseline investment) and random slope coefficients on Joy Investment. The results are reported in Table 6. In the first column, we estimate the model under the restrictions that $\alpha_1 = \alpha_2 = 0$ and $u_{1i} = 0$. That is, we exclude interactions between Joy Investment and the externality condition, and exclude random slope coefficients on Joy Investment. In the second column, we allow for subject-level random slope coefficients on Joy Investment, and in the third column, we further include interactions between Joy Investment and the externality condition.

In all three columns, Joy Investment has a strongly significant positive effect on investment. The third column mirrors the result obtained for the Baseline condition in Block 1, that Joy Investment has a significant positive effect on Baseline investment, but for the Baseline condition implemented during the main part of the experiment (Blocks 2 and 4). More importantly, the effect of Joy Invest-

[25] Wald tests (with wild cluster bootstrap): Complete-N ($p = 0.003$ for all rounds, $p = 0.010$ for last six rounds), Circle-N ($p < 0.001$ for all rounds, $p < 0.001$ for last six rounds), Complete-P ($p = 0.002$ for all rounds, $p = 0.093$ for last six rounds), Circle-P symmetric ($p = 0.002$ for all rounds, $p = 0.032$ for last six rounds), Circle-P specialized ($p = 0.032$ for all rounds, $p = 0.095$ for last six rounds).

Table 6. Multilevel mixed effects model with between subjects random slopes, regressing Investment (final six rounds) on Joy Investment and externality condition; Regular networks.

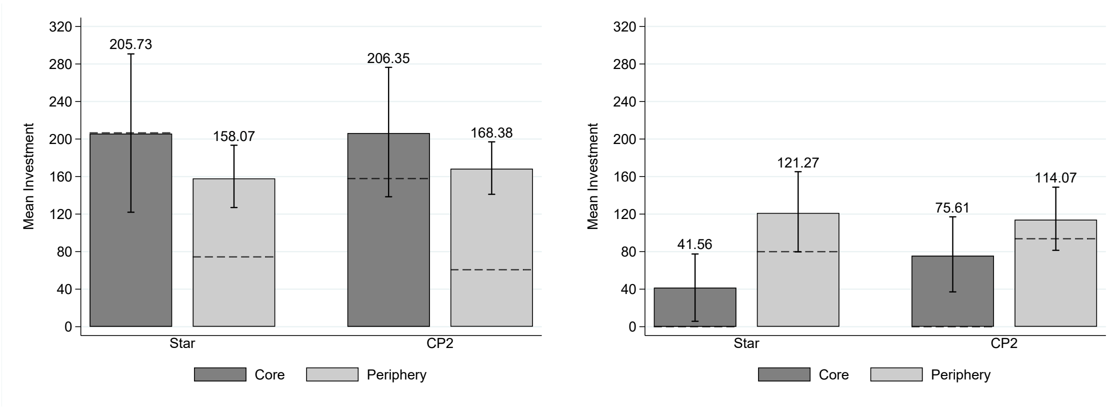
Dependent variable: Individual investment in round t			
	Regular	Regular	Regular
Joy Invest	0.44**	0.63***	0.68***
	(0.21)	(0.23)	(0.25)
Neg	56.76***	56.76***	55.94***
	(13.61)	(13.61)	(13.51)
Pos	−58.97***	−58.97***	−56.39***
	(12.26)	(12.26)	(12.31)
AA	−5.33*	−5.68**	−5.68**
	(2.83)	(2.77)	(2.77)
RA	−2.78	−3.56*	−3.56*
	(1.78)	(1.83)	(1.83)
LA	−1.60	−1.92	−1.92
	(1.96)	(1.98)	(1.98)
Joy Invest × Neg	–	–	0.06
			(0.08)
Joy Invest × Pos	–	–	−0.20***
			(0.06)
Constant	154.81***	163.98***	163.39***
	(25.90)	(27.57)	(27.40)
$\widehat{\sigma}_{u_0}$ (Constant)	90.89***	88.06***	88.08***
$\widehat{\sigma}_{u_1}$ (Joy Invest)	–	0.319***	0.319***
$\widehat{\sigma}_{\epsilon}$ (Residual)	134.42***	134.42***	134.13***
Groups	21	21	21
Observations	2268	2268	2268
Wald $\chi^2(6)$	130.70***	145.71***	172.43***

Robust standard errors, adjusted for clustering at the group level, in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

ment is no different when the externality is negative (since the coefficient estimate $\widehat{\alpha}_1 = 0.06$ is not significantly different from zero), but is significantly weaker when the externality is positive ($\widehat{\alpha}_2 = -0.20$).[26] Thus, we find support for the hypothesis that joy of winning has a significantly weaker influence on investment in regular networks when there are positive externalities than it does when there are negative externalities or no externalities at all.

Result 9. *In the regular networks, non-monetary utility of winning has a strongly*

[26]Nevertheless, the effect of Joy Investment in the Positive condition is still significant. That is, we reject the hypothesis that $\beta_1 + \alpha_2 = 0$, with $p = 0.0165$.



(a) Negative **(b)** Positive

Figure 11. Mean investment levels in the final six rounds of the Negative ($\alpha = -0.8$) and Positive ($\alpha = 0.8$) conditions, by network. Dashed lines indicate NE point predictions. Error bars indicate 95% wild cluster bootstrap confidence intervals.

significant positive effect on investment in the Baseline and Negative conditions. However, the effect in the Positive condition is significantly weaker than in the other conditions, although it remains statistically significant.

5.3 Core-Periphery Networks

We turn next to the two core-periphery networks. Figure 11 highlights three key patterns of over-investment across externality conditions for the different types of player in Star and CP2. First, we observe significant mean over-investment by the core players in the Positive conditions, where they are predicted to be inactive. Second, there is no mean over-investment by core players in the Negative condition, for either network. Third, peripheral players exhibit considerably higher over-investment rates in the Negative condition than in the Positive condition, for which mean over-investment loses significance over the final six rounds.[27]

Result 10. *In the core-periphery networks, we observe a stark reversal in the patterns of mean over-investment for the Negative and Positive externalities.*

(i) *With negative externalities, peripheral players exhibit mean over-investment while core players' investments are in line with the NE prediction.*

(ii) *With positive externalities, core players exhibit significant mean over-investment,*

[27]For completeness, refer to Figure B.7 in Appendix B, which shows mean investment levels using all rounds.

while peripheral players' mean investment levels are close to the NE prediction.

One might argue, as we did for the regular networks, that the patterns of over-investment by peripheral players are consistent with non-monetary utility of winning that is sensitive to the externality condition. That is, if joy of winning is elevated in the presence of negative externalities and diminished in the presence of positive externalities, it may explain, at least in part, why the peripheral players over-invest by substantially more in the Negative condition than they do in the Positive condition. We estimate the same model as in Equation [6], separately for core players and peripheral players. The results are reported in Table 7.

The first two columns examine the Star network and the third and fourth columns examine the CP2 network. For the Star network, the effect of Joy Investment for peripheral players is only statistically significant for the Negative externality condition.[28] In contrast, for the core players, Joy Investment has a strongly significant impact in the Baseline condition, an even stronger impact in the Negative condition, and a weaker, statistically insignificant effect in the Positive condition (Wald test, $p = 0.718$). The results are similar for the peripheral players in the CP2 network, where the effect is significant only in the Negative condition (Wald test, $p = 0.028$). However, for the core players, the effect is only significant in the Baseline condition (Wald test, $p = 0.022$), although it is stronger in the Positive condition than in the Negative condition.[29] We summarize these findings as follows.

Result 11. *In the core-periphery networks, non-monetary utility of winning*

(i) *is significantly positively correlated with peripheral players' investment in the Negative condition, but is not correlated with their behavior in the other externality conditions;*

(ii) *is strongly and significantly positively correlated with investment by the core players in the Baseline conditions and in* Star-N *but is not correlated with core players' investments in the other core-periphery treatment conditions.*

Thus, the same argument we appeal to for regular networks (cf. Result 9) does not receive the same support in the context of core-periphery networks. Joy

[28] We reject the null hypothesis that $\beta_1 + \alpha_1 = 0$ (Wald test, $p = 0.029$) for the Negative condition. For the other two conditions, we fail to reject, with $p > 0.335$.

[29] We fail to reject the null hypotheses that $\beta_1 + \alpha_1 = 0$ ($p = 0.839$) or $\beta_1 + \alpha_2 = 0$ ($p = 0.245$).

Table 7. Multilevel mixed effects model with between subjects random slopes, regressing Investment (final six rounds) on Joy Investment and externality condition; by player type in Core-Periphery networks.

Dependent variable: Individual investment in round t				
	STAR		CP2	
	Peripheral	Core	Peripheral	Core
Joy Invest	0.15	4.17***	0.40	0.71**
	(0.21)	(0.95)	(0.26)	(0.31)
Neg	19.56	48.15**	32.34***	116.10***
	(19.19)	(22.77)	(10.95)	(39.70)
Pos	−15.98	−88.21***	−13.16	−29.01**
	(17.63)	(20.13)	(10.72)	(14.08)
Joy Invest × Neg	0.10	2.34***	0.15	−0.64***
	(0.15)	(0.38)	(0.16)	(0.09)
Joy Invest × Pos	0.04	−3.83***	−0.05	−0.31***
	(0.05)	(0.61)	(0.12)	(0.05)
AA	3.63*	4.05	1.21	−6.53
	(2.20)	(3.17)	(2.93)	(4.09)
RA	0.98	13.34***	−2.36	−6.53**
	(2.84)	(3.75)	(4.11)	(2.62)
LA	−2.53	−7.69***	0.83	−2.33
	(2.13)	(2.31)	(2.45)	(1.81)
Constant	152.04***	95.99***	127.07***	175.93***
	(27.58)	(35.25)	(41.45)	(34.48)
$\widehat{\sigma}_{u_0}$ (Constant)	96.62***	53.43***	74.98***	68.45***
$\widehat{\sigma}_{u_1}$ (Joy Invest)	0.19***	–	0.46***	0.47***
$\widehat{\sigma}_{\epsilon}$ (Residual)	144.31***	124.52***	144.22***	147.69***
Groups	18	18	16	16
Observations	1620	324	1152	576
Wald $\chi^2(8)$	72.34***	3057.92***	140.67***	483.51***

Robust standard errors, adjusted for clustering at the group level, in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

of winning does not appear to explain the differential patterns of over-investment by the peripheral players in the different externality conditions. Furthermore, the argument clearly does not explain the observed investment patterns of the core players. Instead, we argue that subjects take into consideration the impact of the allocative externalities on *social efficiency*.

Social efficiency concerns. Consider the following line of reasoning. In the core-periphery networks, a greater number of neighbors are impacted when the prize is allocated to a core player. As a result, the sum of payoffs can be altered (perhaps quite significantly) by the allocation.[30] For instance, consider the Star network, in which there is just one core player. In the Negative externality condition, the unique equilibrium involves the core player winning with higher probability than an individual peripheral player.[31] However, when the core player wins, every other player is impacted severely. If, instead, a peripheral player were to win the contest, the only player who suffers is the core player.

Thus, from a social efficiency standpoint, the total harm is minimized if the prize is allocated to a peripheral player. If subjects share some concern for social efficiency, we might expect to see the peripheral players collectively over-invest, so as to reduce the chances of the widespread harm that will arise in the event that the core player wins the contest. This can be interpreted as an alternative explanation to the joy of winning hypothesis, or as a foundation for the elevated joy of winning on the part of the peripheral players in Star-N. A similar concern with social efficiency may mitigate the joy of winning for the core players in the Star-N condition, leading them to reduce their investment levels in consideration of others. However, even those core players who are unconcerned with the harm they may inflict upon others may rationally reduce their investment, as a best response to the over-investment by peripheral players.

An analogous argument can be made to explain the opposite patterns of over-investment observed in the presence of positive externalities. In this case, the total externality flows are maximized when the core player wins the contest. However, in equilibrium, the probability that the core player wins is zero, since the equilibrium investment profile involves the core player choosing to be inactive. Thus, equilibrium and efficiency are in direct conflict with each other. If the core and peripheral players care about social efficiency, they may be able to coordinate on an investment profile in which the peripheral players remain inactive, allowing the core player to win the contest and provide externality benefits to all. Indeed, we find some evidence in support of these patterns for some of the groups in the Star-P condition.

[30] In contrast, in the regular networks, the structure of the network is such that the flow of externalities, while identity-dependent, has no effect on the sum of payoffs (holding fixed the effort investments), since regardless of which agent is allocated the prize, the number of neighbors (who are impacted by the externality) is the same. As such, social efficiency concerns should not come into play.

[31] The core player's equilibrium probability of winning is about 0.357, while each peripheral player wins with approximately 0.129 probability.

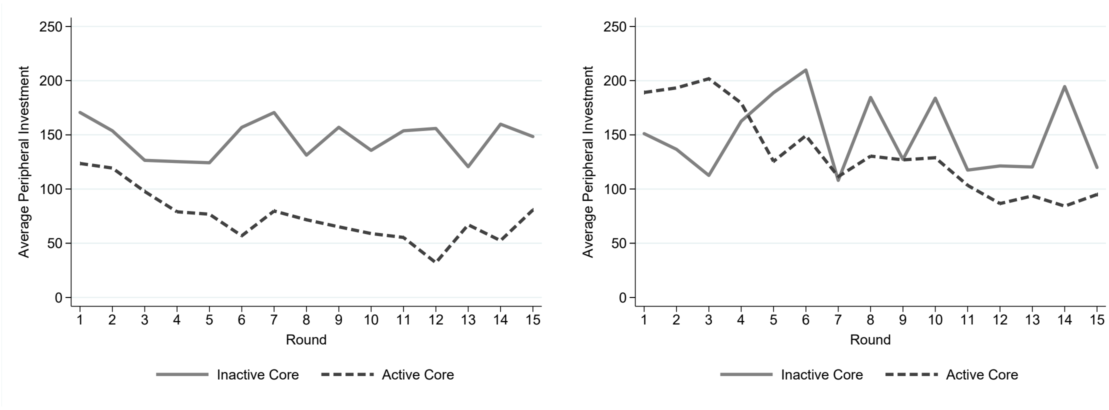
Figure 12 displays average investment levels among peripheral players over time for the Positive externality condition, depending on the median investment level (across all rounds) of the core player(s). In the case of the Star network, we calculate the median investment level of the lone core player across all 15 rounds in Star-P.[32] We find that 13 of 18 core players have a median investment level of one or less and we classify these individuals as *inactive*; the remaining five core players all have median investment levels of 100 tokens or more, and so are classified as *active*. In the case of the CP2 network, we first calculate the sum of the core players' investments in each round and then calculate the median of the aggregate investment by core players, collectively, across the 15 rounds. We find that four out of 16 cores have a median aggregate investment of five or less and classify these cores as *inactive*; the remaining 12 cores all have median aggregate investment levels of 120 or more and are classified as *active*.

In Star-P, we see a clear disparity between the average investment levels among peripheral players when the core player is active versus inactive. Specifically, peripheral players invest, on average, at a much lower level when the core player in their group is active in the contest than when the core player is inactive.[33] This is consistent with a preference among the peripheral players for a more socially efficient outcome in which the core player wins the contest and all peripheral players benefit from the positive externality flows. When the core player is inactive, peripheral players' investments are, on average, well above the NE prediction across all rounds, consistent with the impact that joy of winning appears to have in the Baseline condition.

In CP2-P, average investments by peripheral players in groups with active cores appear to be converging to a slightly lower level in later rounds compared to those groups with inactive cores. However, the disparity is not nearly as stark as in the Star network. This is not especially surprising, since there remains some conflict between the two sides of the CP2 network. Specifically, unlike in the Star network, the peripheral players are not guaranteed to benefit when an active core player wins the contest. Only when the prize is allocated to the core player to whom the peripheral player is linked does the player enjoy the positive externality.

[32] Figure B.8 in Appendix B provides boxplots for each individual core player in the Star-P and CP2-P conditions, using all rounds.

[33] Furthermore, their mean investment is also below the NE prediction for most of the final 10 rounds.



(a) Star-P **(b)** CP2-P

Figure 12. Average investment level among peripheral players in Star-P and CP2-P, separated by whether the core player(s) are *active* or *inactive*.

Examining the data at the group-level provides some additional clarity regarding the patterns of behavior that influence the observed levels of over-investment. Figure 13 plots the average investments of individuals by type in the final six rounds of the Star-N condition, for each independent group. For half of the groups, the core player consistently invests more than the average of the peripheral players' investments (see group IDs 14, 16, 21, 22, 23, 29, 30, and 38), in line with the equilibrium profile. However, there are also groups in which the core player is inactive, while the peripheral players average significantly positive investments (e.g., see group IDs 13, 24, and 39, and to a lesser degree, group IDs 15, 17, and 18, where the core player invests less than both the NE prediction and the average of the peripheral players).

Similarly, in the CP2 network (see Figure 14), there are several groups in which the core players invest (on average) more than the peripheral players (for example, group IDs 43, 44, 46, 53, and 59). Yet, in most other groups, mean investment by the peripheral players is comparable to, or even slightly above, the mean investment by the core players. Indeed, for six of the groups, the average core player investment is below the NE prediction over the final six rounds.

Altogether, the heterogeneity among groups in the Star and CP2 networks serves to illustrate that the different patterns of mean over-investment for core and peripheral players in the Negative externality condition may be driven by the differential impact of social efficiency concerns in several groups.

Figure 15 plots the average investments of individuals by type in the final six rounds of the Star-P condition, for each independent group. First, we observe

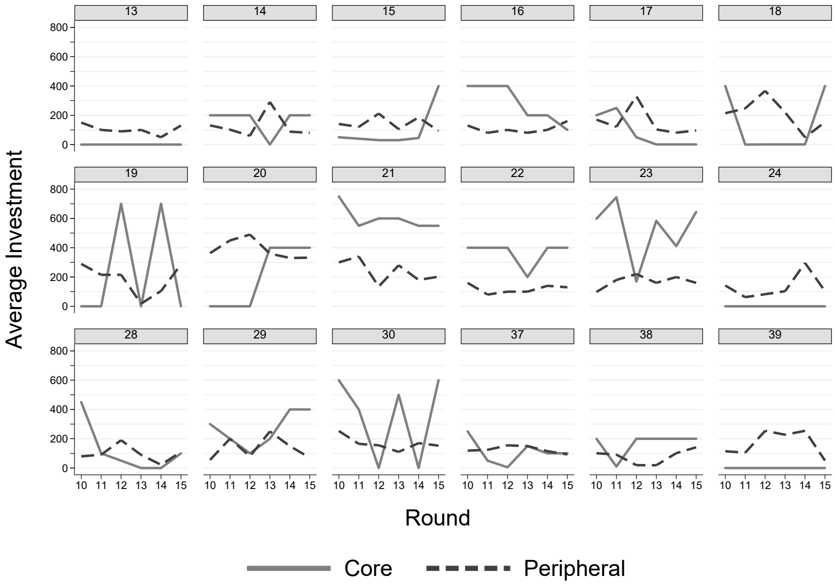


Figure 13. Average investment by player type over the final six rounds in the STAR-N condition. Each cell represents one independent group.

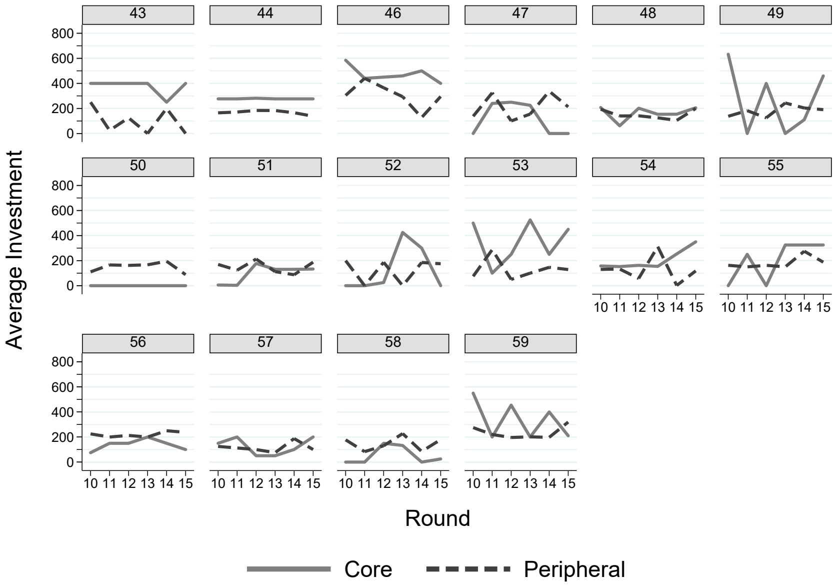


Figure 14. Average investment by player type over the final six rounds in the CP2-N condition. Each cell represents one independent group.

that the most common pattern is a core player investing at or near zero in every round, accompanied by positive average investment levels among the peripheral players. We see this type of behavior, which most resembles the equilibrium predictions in 12 of the 18 groups (those with group IDs 13, 16, 17, 18, 19, 20, 23,

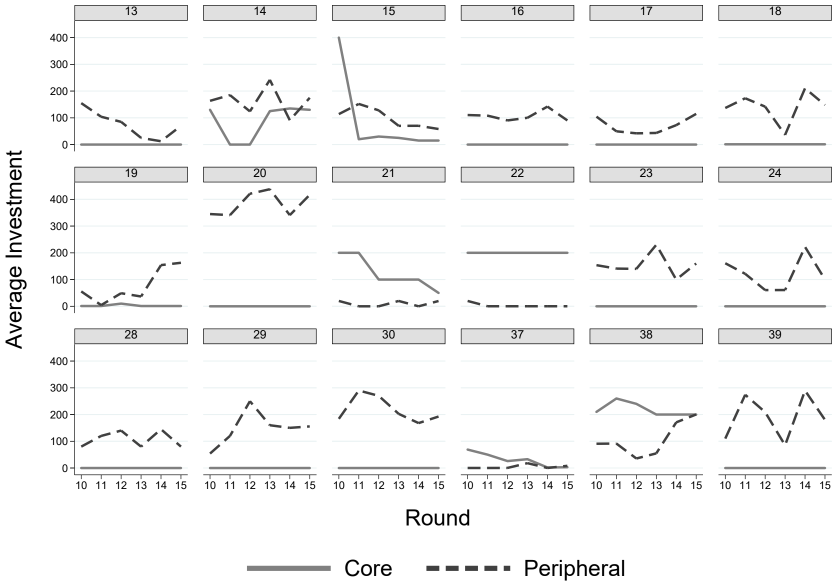


Figure 15. Average investment by player type over the final six rounds in the Star-P condition. Each cell represents one independent group.

24, 28, 29, 30, and 39). However, another pattern that emerges is the one in which the core player is active (investing strictly positive amounts) while the peripheral players average at or near zero investment. This type of pattern, which is more consistent with coordination on a more socially efficient outcome, can be clearly seen in groups 21 and 22, and to a lesser degree, in group 37.

Similarly, Figure 16 plots the average investments of individuals by type in the final six rounds of the CP2-P condition, for each independent group. As in the Star network, one of the prominent patterns is, consistent with the NE prediction, for the core players to invest nothing while the peripheral players compete against each other. These groups are characterized by zero (or near-zero) core investments and positive peripheral players' investments (for instance, see groups with IDs 47, 50, 53, 55, 58, and 59). Another pattern involves relatively higher (average) investment by the core players, and lower investment by the peripheral players, as in groups 43 and 51. However, several other groups display a mixture of behavior, with both core and peripheral players competing actively even over the final six rounds. As discussed above, this is not especially surprising, since it may correspond to groups in which the peripheral players on one side of the CP2 network and the core player on the other side of the CP2 network compete against each other.

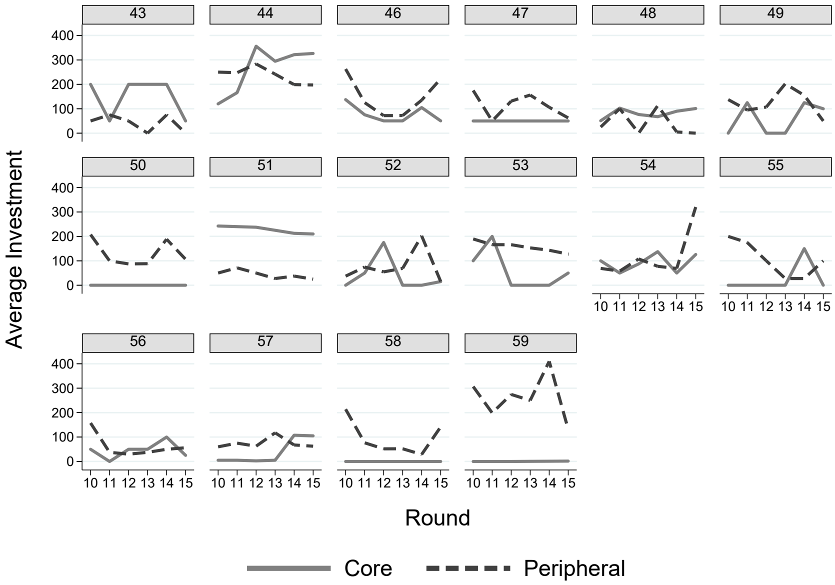


Figure 16. Average investment by player type over the final six rounds in the CP2-P condition. Each cell represents one independent group.

The following result summarizes our findings regarding the impact of social efficiency concerns on over-investment patterns in the core-periphery networks.

Result 12. *In the core-periphery networks, the aggregate patterns of mean over-investment are driven by a mixture of group-level patterns: some groups converge to investment profiles consistent with NE predictions, while others exhibit behavior consistent with a concern for social efficiency. For negative (positive) externalities, this heterogeneity combines to decrease (increase) the mean investment of core players and increase (decrease) the mean investment of peripheral players.*

6 Conclusion

In this paper, we report the results of a controlled laboratory experiment designed to examine the impact of identity-dependent externalities on investment behavior in an all-pay contest environment. We test the theoretical predictions of a simple version of the model introduced in Boosey and Brown (2022), by systematically varying both the network structure and externalities. Our experimental findings lend considerable support to the comparative static predictions. For instance, in regular network structures like the Complete network or the Circle network, mean investment is substantially higher in the presence of negative externalities, where the stakes of losing are heightened, and substantially lower with positive externalities, which introduce free-riding incentives. Moreover, the comparison between the CIRCLE network and the COMPLETE network confirms that the impacts of the externalities increase with the density of the network. The effects are similar in our two core-periphery networks, where the well-connected core players respond more strongly to both negative and positive externalities than the peripheral players.

Despite broad confirmation of the comparative statics predictions, we also observe mean over-investment in most treatment conditions, consistent with the existing experimental literature on contests. However, the particular patterns of over-investment depend on the network, the externality condition, and, in the core-periphery structures, the player's position within the network. We provide supporting evidence for the influence of two behavioral phenomena—joy of winning and social efficiency concerns—that appear to play an important role in the resulting network contest games. One important takeaway from the experimental data is that, in the core-periphery networks, where the equilibrium outcomes are especially inefficient, some groups behave in ways that are consistent with efforts to improve the efficiency of the contest outcome. For instance, when externalities are negative, we observe much stronger over-investment by peripheral players who have a collective incentive to mitigate the chances of widespread harm that occurs if the core players win. When externalities are positive, some core players remain active (even when the equilibrium prescribes that they should free-ride on others' investments) while the peripheral players are more restrained in their investment activity, recognizing that there may be widespread efficiency improvements if the prize is allocated to a core player.

Although our experiment was not designed to test for these social efficiency concerns, our results ought to motivate additional work aimed at better understanding the importance of social efficiency and joy of winning for competitive behavior in the presence of externalities. It would also be interesting and important to explore the impact of such externalities in other, potentially larger, network structures than those considered here. Additionally, in the current study, we restrict attention to the case of homogeneous link weights, which is appealing for its tractability and stark comparative statics. However, there may be many interesting patterns of behavior to explore in contests with heterogeneous weighted links, including structures that involve a mixture of positive and negative externalities. Finally, given the expanding interest in games played on endogenous networks, future research could also direct attention to the emergence or evolution of network-based externalities over time, particularly in settings where competitors interact repeatedly.

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A Equilibrium Results for Homogenous Link Weights

This appendix reproduces the closed-form results of Boosey and Brown (2022) for equilibrium investment in regular networks—covering the Complete and Circle networks—and a subclass of core-periphery networks—covering the Star and CP-2 networks.

The first result concerns the existence of a symmetric equilibrium in any regular network with homogenous links.

Proposition (Boosey and Brown (2022), Proposition 3.)**.** *Consider the network contest game in which the network* $\mathbf{G}$ *has homogenous links, such that* $g_{ij} \in \{0, \bar{g}\}$ *where either* $\bar{g} = 1$ *or* $\bar{g} = -1$.

Suppose $\mathbf{G}$ *is regular of degree* $d \in \{0, \ldots, n-1\}$. *Then for any* $\alpha \in [0, 1)$, *there exists a symmetric, pure strategy Nash equilibrium,* $\mathbf{x}^* = (x^*, \ldots, x^*)$, *where*

$$x^* = \frac{n - 1 - \alpha\bar{g}d}{n^2}. \qquad [7]$$

The next result characterizes the semi-symmetric equilibrium in *core-to-periphery* networks, which consist of a set of core players and a set of peripheral players that satisfy the following conditions: (i) each peripheral player is connected to exactly one core player (and no other peripheral players), (ii) each core player is connected to m peripheral players, and (iii) each core player is connected to every other core player.

Proposition (Boosey and Brown (2022), Proposition 4.)**.** *Consider the game defined by* $\alpha \in [0, 1)$ *and the network* $\mathbf{G}$, *for which links are homogenous, such that* $g_{ij} \in \{0, \bar{g}\}$ *(where* $\bar{g}$ *is either* 1 *or* -1*).*

Suppose $\mathbf{G}$ *is a core-to-periphery network with* n_c *core players, each connected to* m *peripheral players. Then there exists a semi-symmetric, pure strategy Nash equilibrium in which every core player chooses the same investment* x_c^*, *and every peripheral player chooses the same investment* x_p^*, *where*

(i) *if* $\alpha\bar{g} < \frac{1}{m}$, *then* $x_c^* = [1 - \alpha\bar{g}m]\Delta$ *and* $x_p^* = [1 + \alpha\bar{g}(n_c - 2)]\Delta$, *where*

$$\Delta = \frac{n_c[1 + m + \alpha\bar{g}m(n_c - 3)] - [1 + \alpha\bar{g}(n_c - 1 - \alpha\bar{g}m)]}{n_c^2[1 + m + \alpha\bar{g}m(n_c - 3)]^2} \geqslant 0.$$

(ii) *if* $\alpha\bar{g} \geqslant \frac{1}{m}$, *then* $x_c^* = 0$ *and* $x_p^* = \frac{n_c m - 1}{(n_c m)^2}$.

B Additional figures

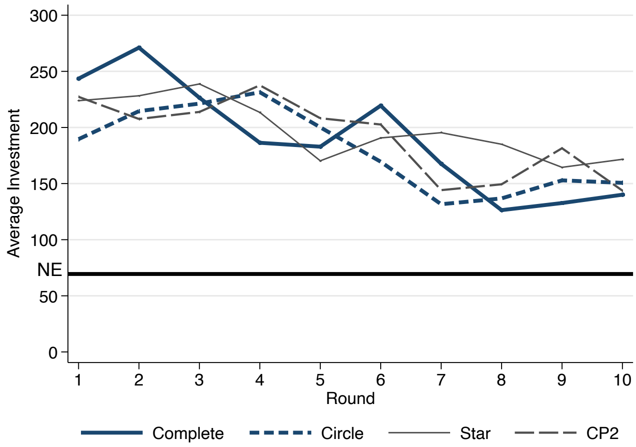


Figure B.1. Mean investment levels in the Baseline condition ($\alpha\bar{g} = 0$) from Block 1, by network and across rounds. The solid reference line indicates the NE point prediction (69.44).

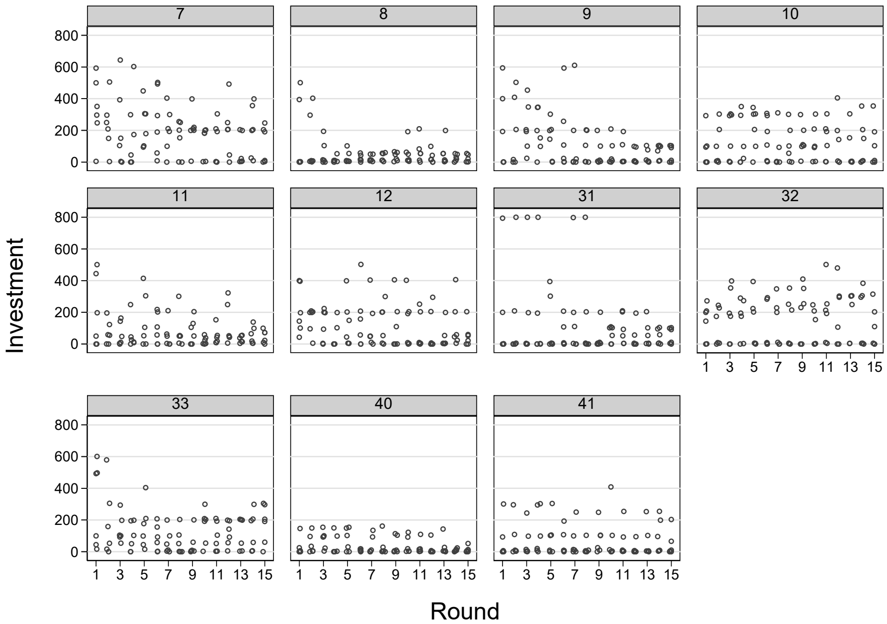


Figure B.2. Scatter plot of investments in all rounds by group in the CIRCLE-P condition.

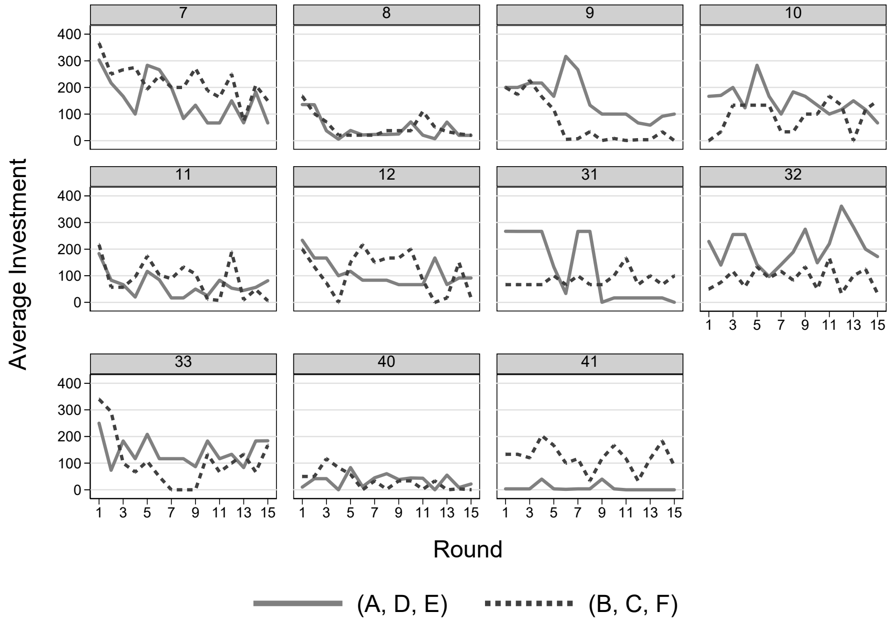


Figure B.3. Average investment by maximal independent sets $M_A = \{A, D, E\}$ and $M_B = \{B, C, F\}$ over all 15 rounds in the Circle-P condition. Each cell represents one independent group.

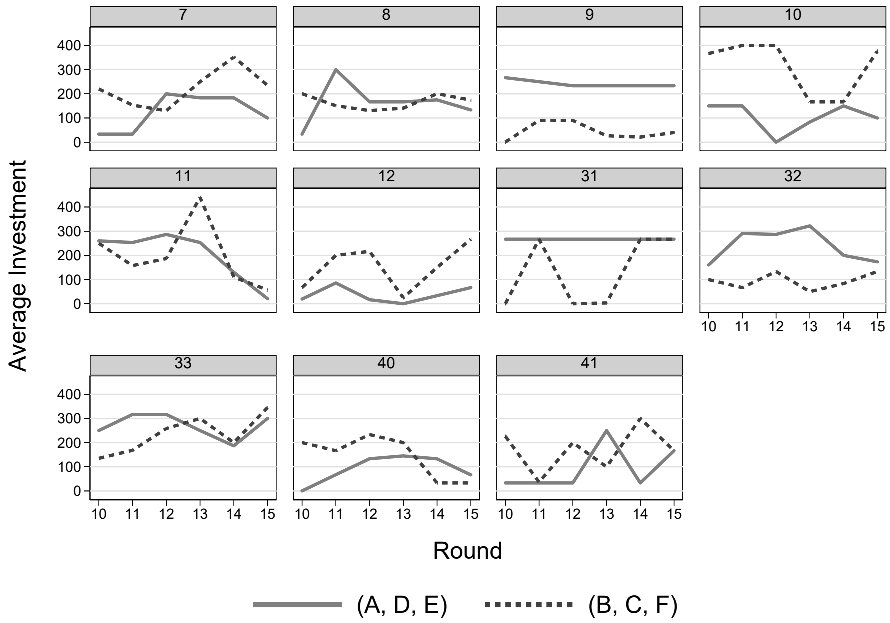


Figure B.4. Average investment by maximal independent sets $M_A = \{A, D, E\}$ and $M_B = \{B, C, F\}$ over the last rounds in the Circle-N condition. Each cell represents one independent group.

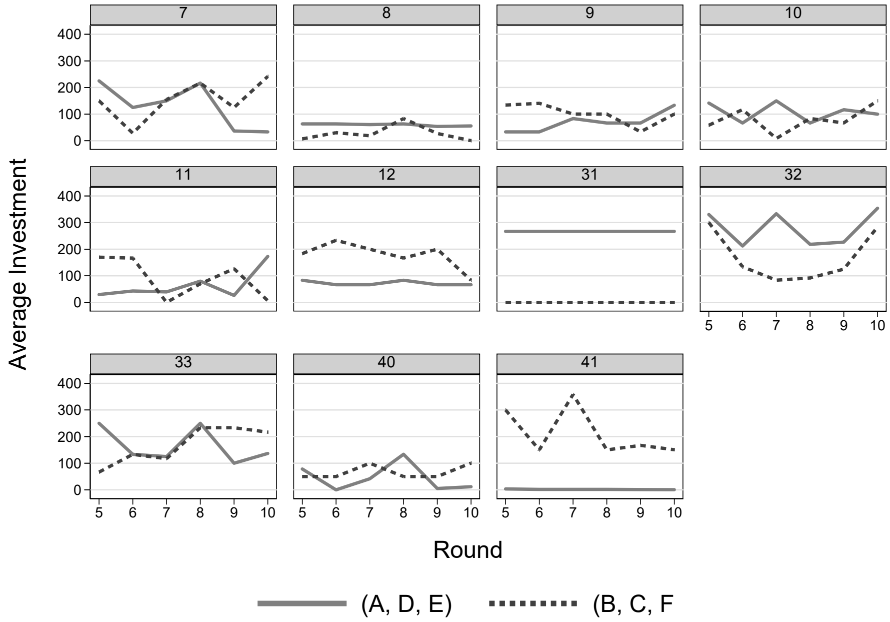


Figure B.5. Average investment by maximal independent sets $M_A = \{A, D, E\}$ and $M_B = \{B, C, F\}$ over the last rounds in the CIRCLE-B condition. Each cell represents one independent group.

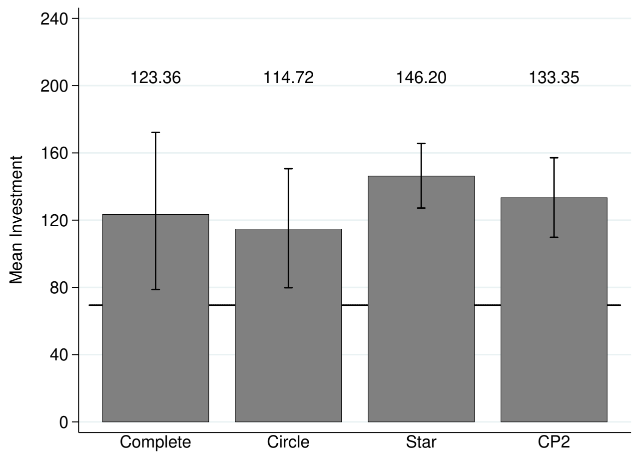
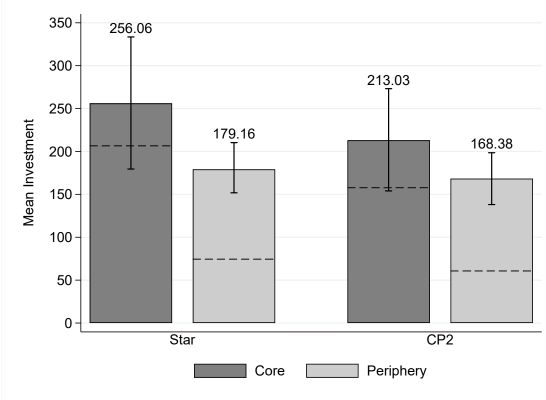
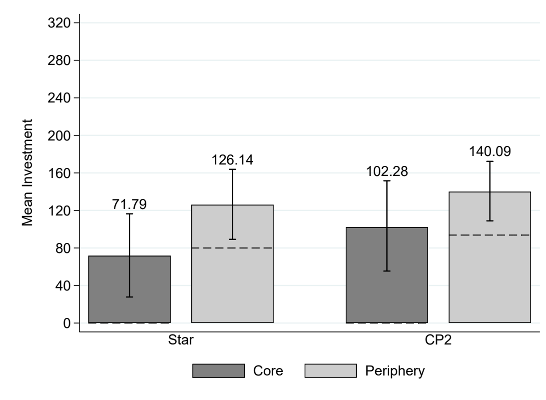


Figure B.6. Mean investment levels in the Baseline condition ($\alpha = 0$) from Blocks 2 and 4, by network. The solid reference line indicates the NE point prediction (69.44). Error bars indicate 95% wild cluster bootstrap confidence intervals.

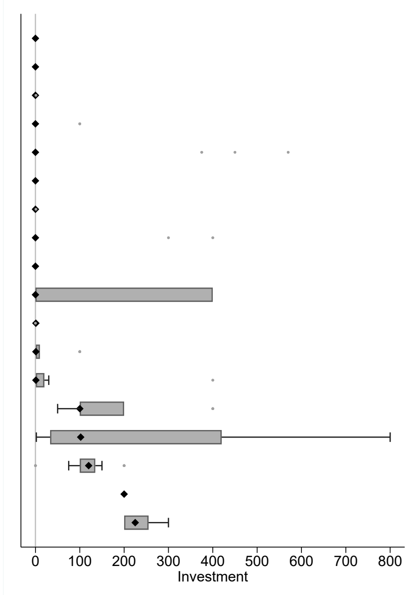


(a) Negative

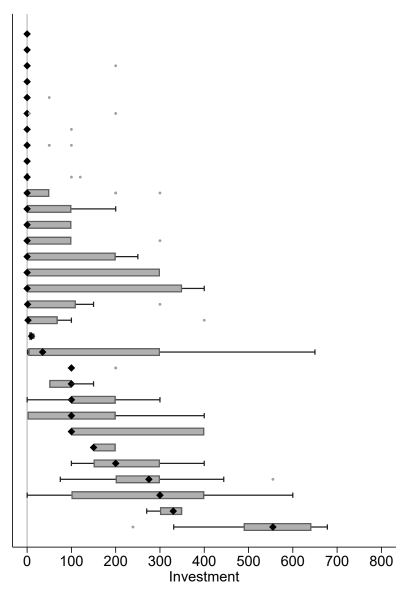


(b) Positive

Figure B.7. Mean investment levels in all rounds of the Negative ($\alpha = -0.8$) and Positive ($\alpha = 0.8$) conditions, by network. Dashed lines indicate NE point predictions. Error bars indicate 95% wild cluster bootstrap confidence intervals.



(a) STAR



(b) CP2

Figure B.8. Boxplots of investment choices by core players in the positive externality rounds. Subjects are sorted by median investment (indicated by a black diamond). The vertical line at zero indicates the baseline Nash equilibrium prediction.

C Experimental instructions

Thank you for participating in today's experiment. I will read through the script so that everyone receives the same information. Please remain quiet and do not communicate with other participants during the experiment. Raise your hand if you have any questions and an experimenter will come to you to answer the question privately.

For your participation in today's experiment, you will receive the show-up fee of $7. In addition, during the experiment, you will have the opportunity to earn more money. Your additional earnings will depend on the decisions you make and on the decisions made by other participants. At the end of the experiment, you will be paid anonymously by check. No other participant will be informed about your payment.

The experiment consists of multiple parts. The instructions for subsequent parts will be given only after each previous part is completed. Below you will find the instructions for Part 1.

Part 1 Instructions

In this part, you will be asked to make three decisions. **One** of these three decisions will be randomly chosen at the end of the experiment and that decision will be used to calculate your actual earnings for Part 1.

The basic setups for the three decisions are similar. In each case, you will see a list of 20 choices between lotteries and sure amounts of money. Lotteries will always be on the left, and sure amounts of money on the right. The lists will be ordered such that you will prefer the lottery to the sure amount of money in the choice at the top of the list. As you go down the list, you will tend to like the lotteries less and less as compared to the sure amounts. At some point, you will be willing to switch from preferring a lottery to preferring the corresponding sure amount of money. At the point where you are willing to switch, please click on the SWITCH HERE button.

When you click on a SWITCH HERE button, lotteries will be your choice everywhere above that line, and sure amounts of money will be your choice everywhere below that line. All of the 20 choices that you generate will be highlighted. If you want to change your decision, simply click on another SWITCH HERE button. When you are ready to finalize your decision, click SUBMIT.

After you have made your decision, one of the 20 choices will be selected randomly. If your decision for that choice is a sure amount of money, you will earn that amount of money. If your decision for that choice is the lottery, then the outcome of the lottery will be determined according to the listed probabilities and your earnings will be equal to that outcome.

You will not be informed about your earnings from this part of the experiment until the very end of the session today, after you have completed all parts of the experiment.

Are there any questions before you begin making your decisions?

Part 2 Instructions

All amounts in this part of the experiment are expressed in **tokens**. The exchange rate is 400 tokens = \$1.

This part of the experiment consists of a sequence of 10 decision rounds. At the beginning of round 1, you will be randomly assigned to a group consisting of 6 participants, including you. You will remain in this group for the duration of this part. That is, you will interact with the same 5 other participants in all 10 rounds.

Your group

Before round 1, you and the 5 other participants in your group will be randomly assigned to positions in the network graph shown in Figure **??** below. One person will be assigned to each position. Each position is labeled with a letter ID, from A to F. Positions, and therefore also the letter IDs, will remain fixed for the duration of this part. In the network graph, a straight line between two positions indicates that players at those positions are "connected".

During the decision rounds, the network graph will be shown on the screen. Your own position will be highlighted in red. The players you are connected to will be highlighted in yellow, while those you are not connected to (if there are any) will be shown in black.

For example, Figure C.1 shows the network graph from player A's perspective. Thus, player A's position will be displayed in red, while the positions for player B and player C will be displayed in yellow. All of the other players' positions will be displayed in black, since only player B and player C are connected by an edge to player A in this network graph.

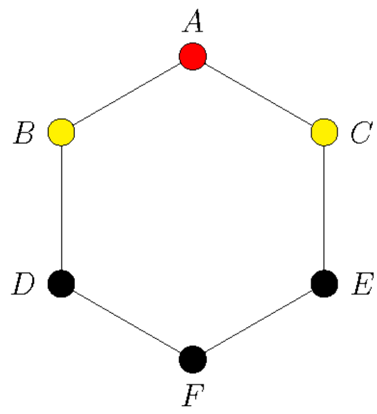


Figure C.1. The network graph - as viewed by player A

Your decision

In each round, you will be given an endowment of 800 tokens. You may use these tokens to make decisions in the round. Specifically, during the round, you can invest any integer number of tokens, from 0 to 800, into a project. Other participants in your group will face the same decision, with the same endowment of 800 tokens. After everyone has chosen a project investment, one participant in the group will be declared **the winner**, based on the following procedure. The probability that you are the winner is given by:

$$\frac{\text{Number of tokens you invested in your project}}{\text{Sum of the tokens invested in projects by all participants in your group}}$$

The computer program will determine the winner according to the probabilities calculated in this way.
Consider the following two examples.

Example 1: Suppose you invested 100 tokens in your project, while the other five participants in your group invested 150 tokens, 80 tokens, 100 tokens, 120 tokens, and 250 tokens, respectively. Then, the sum of the tokens invested in projects by all participants in your group will be $(100+150+80+100+120+250) = 800$ tokens. The probability you are the winner is then

$$\frac{100}{800} = \frac{1}{8} = 0.125 = 12.50\%$$

Example 2: For this example, suppose you invested 300 tokens in your project, while the other five participants in your group invested 20 tokens, 30 tokens, 0

If you are the winner:

$$\begin{array}{l} +800 \quad \text{(endowment)} \\ +500 \quad \text{(prize)} \\ - \text{(tokens you invested)} \\ \hline 1300 - \textbf{(tokens you invested)} \end{array}$$

If you are not the winner:

but are connected to the winner:	and are not connected to the winner:
+800 (endowment)	+800 (endowment)
+0 (no prize)	+0 (no prize)
$+X$ (change in earnings)	+0 (no change in earnings)
− (tokens you invested)	− (tokens you invested)
$800 + X -$ **(tokens you invested)**	$800 -$ **(tokens you invested)**

tokens, 200 tokens, and 50 tokens, respectively. Then, the sum of the tokens invested in projects by all participants in your group will be $(300 + 20 + 30 + 0 + 200 + 50) = 600$ tokens. The probability you are the winner is then

$$\frac{300}{600} = \frac{1}{2} = 0.5 = 50.00\%$$

Your earnings

In each decision round, the winner will receive a prize of **500 tokens**. All participants (including the winner) must pay their project investments.
In addition, the earnings for each participant who is **connected to the winner** will be changed by X tokens. In general, X can be positive, negative, or zero.
Thus, your earnings in a given round are determined as follows:

Example 3: Suppose you are the winner and your project investment was 100 tokens. Then your earnings for the round will be $1300 - 100 = 1200$ tokens.
Alternatively, suppose you are not the winner, and you **ARE NOT** connected to the winner. If your project investment was 100 tokens, then your earnings for the round will be $800 - 100 = 700$ tokens.
Finally, suppose you are not the winner, but that you **ARE** connected to the winner. Moreover, suppose $X = +200$. That is, the earnings of each player connected to the winner are **<u>increased</u>** by 200 tokens. If your project investment was 100 tokens, then your earnings for the round will be $800 + 200 - 100 = 900$ tokens.

If, instead, $X = -200$, the earnings of each player connected to the winner are **decreased** by 200 tokens. Thus, if your project investment was 100 tokens, your earnings for the round will be $800 - 200 - 100 = 500$ tokens.

Control Questions

In a moment, you will be asked to complete some control questions shown on the screen. These questions are only to help you understand the instructions - they will not affect your earnings. After several minutes, we will walk through the answers together, then move on to the next set of questions. After these are completed, we will continue with the instructions.

Feedback

After all participants have made their decisions, you will be shown the individual project investments for each participant in your group, the sum of all tokens invested in projects by participants in your group, and your probability of winning. Then, after the program determines the winner, the screen will display the position of the winner, whether or not you are connected to the winner, and a calculation of your earnings for the round.

Summary

Part 2 will consist of 10 decision rounds. In each round, you and the other participants in your group will choose project investments. The probability that your project wins depends on the share of your own project investment out of the total number of tokens invested by all participants in your group. Only one participant can be the winner in a given round. All participants must pay their project investments out of the endowment (800 tokens). The winner will receive a prize of 500 tokens. For any participant who does not win, but is connected to the winner, earnings will be changed by X tokens.

As a reminder, in the network graph shown on the screen, your position will be shown in red. The positions of the players with whom you are connected will be shown in yellow (in addition to being linked with your position by an edge). The positions of players who you are not connected to (if there are any) will be shown in black.

In Part 2, $X = 0$ for all 10 decision rounds. That is, the earnings for a

participant who does not win, but is connected to the winner will not be adjusted.

To make this clear, your earnings in any decision round will be given by:

1300 – (tokens you invested)	if you are the winner,
800 – (tokens you invested)	if you are not the winner, but are connected to the winner
800 – (tokens you invested)	if you are not the winner, and are not connected to the winner

At the end of the experiment, you will be paid for **one** randomly chosen decision round from Part 2. Each of the 10 decision rounds in this part is equally likely to be selected.

Part 3 Instructions

The instructions for Part 3 are almost identical to the instructions for Part 2. However, Part 3 will consist of a sequence of 15 decision rounds. Your group, the network graph, and your position will be the same as in Part 2.

In Part 3, $X = -400$ **for all 15 decision rounds. That is, the earnings for a participant who does not win, but is connected to the winner will be decreased by 400 tokens.**

To make this clear, your earnings in any decision round will be given by:

1300 – (tokens you invested)	if you are the winner,
400 – (tokens you invested)	if you are not the winner, but are connected to the winner
800 – (tokens you invested)	if you are not the winner, and are not connected to the winner

At the end of the experiment, you will be paid for **one** randomly chosen decision round from Part 3. Each of the 15 decision rounds in this part is equally likely to be selected.

Part 4 Instructions

The instructions for Part 4 are almost identical to the instructions for Part 3. Part 4 will also consist of a sequence of 15 decision rounds. Your group, the network graph, and your position will be the same as in Parts 2 and 3.

In Part 4, $X = +400$ for all 15 decision rounds. That is, the earnings for a participant who does not win, but is connected to the winner will be <u>increased</u> by 400 tokens.

To make this clear, your earnings in any decision round will be given by:

1300 – (tokens you invested)	if you are the winner,
1200 – (tokens you invested)	if you are not the winner, but are connected to the winner
800 – (tokens you invested)	if you are not the winner, and are not connected to the winner

At the end of the experiment, you will be paid for **one** randomly chosen decision round from Part 4. Each of the 15 decision rounds in this part is equally likely to be selected.

Part 5 Instructions

The instructions for Part 5 are **exactly** identical to the instructions for Part 2. Thus, it will consist of a sequence of 10 decision rounds. Your group, the network graph, and your position will be the same as in Parts 2, 3, and 4.

In Part 5, as in Part 2, $X = 0$ for all 10 decision rounds. That is, the earnings for a participant who does not win, but is connected to the winner will not be adjusted.

To make this clear, your earnings in any decision round will be given by:

1300 – (tokens you invested)	if you are the winner,
800 – (tokens you invested)	if you are not the winner, but are connected to the winner
800 – (tokens you invested)	if you are not the winner, and are not connected to the winner

At the end of the experiment, you will be paid for **one** randomly chosen decision round from Part 5. Each of the 10 decision rounds in this part is equally likely to be selected.

Part 6 Instructions

This part of the experiment consists of a single decision round. The basic setup is similar to the setup for Parts 2, 3, 4, and 5.

Before the round begins, you will be randomly rematched into a new group of 6 participants. In addition, there is no network graph connecting the participants for this part. However, you will still be randomly assigned a letter ID from A to F.

You and the other participants in your group will be given an endowment of 800 tokens each and asked to choose project investments. As in previous parts, the probability that your project wins depends on the share of your own project investment out of the total number of tokens invested by all participants in your group. All participants must pay their project investments out of the endowment.

There are two main differences from previous parts. The first is that **in this part, the winner will receive a prize of 0 tokens.** The second is that, since there is no network graph connecting participants, **there is no adjustment** X to be made to the earnings of participants who are connected to the winner.

To make this clear, your earnings for this part (1 decision round only) will be given by:

800 − (tokens you invested)	if you are the winner,
800 − (tokens you invested)	if you are not the winner

After all participants have made their decisions, you will be shown the individual project investments for each participant in your group, the sum of all tokens invested in projects by participants in your group, and your probability of winning. Then, after the program determines the winner, the screen will display the letter ID of the winner, whether or not that is you, and a calculation of your earnings.