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ORIGINAL PAPER

Coordination in the network minimum game

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Abstract
Motivated by the problem of organizational design, we study coordination in the *network minimum game*: a version of the minimum-effort game where players are connected by a directed network. We show experimentally that acyclic networks such as hierarchies are most conducive to successful coordination. Introducing a single link to complete a network cycle may drastically inhibit coordination. Furthermore, acyclic networks enable resilient coordination: initial coordination failure is often overcome (exacerbated) after repeated play in acyclic (cyclic) networks.

Keywords: coordination failure; equilibrium; minimum-effort game; organizational design; quantal response; weak-link game

JEL Codes: C72; C92; D85

1. Introduction

Organizations generate coherent, intricate patterns of coordinated activity. This is no mean feat. Van Huyck et al. (1990) famously documented a consistent pattern of coordination failure in large groups playing the minimum-effort game, where the group members stand to benefit if they successfully coordinate on high actions, but each player is incentivized to match the lowest action in the group.

The classic minimum-effort game captures a stylized organization where incentives are coarse and untargeted: each individual is rewarded based on the entire group's performance, and thus is held responsible for coordinating with everyone else. In practice, the scope and complexity of task interdependencies within most organizations are limited – by design. Production may be organized so that workers on an assembly line coordinate amongst themselves but operate almost independently of the rest of the organization. Incentives may be tailored so that a team member is responsible only for completing his own assignments while the manager is responsible for the team's overall performance.

A particularly salient feature of many real organizations is that task and incentive interdependencies are predominantly *acyclic*. Work often flows along a chain of responsibility, from upstream tasks to downstream ones, without substantial feedback in the opposite direction. A production line typically imposes a strict order of operations: the quality of a downstream worker's output depends on the care taken upstream, but upstream workers are not directly penalized for mistakes made further down the line.

Hierarchical reporting structures provide another example of acyclic interdependencies. An entry-level worker may be tasked with mechanically following procedures and instructions, so that his

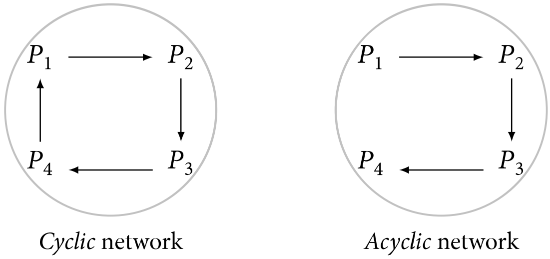

Fig. 1. Cyclic vs. acyclic networks (examples)

Table 1. Mean final-round action, by network structure

	Acyclic	Cyclic
Sparse	6.52	4.90
	[.81]	[2.02]
Dense	6.72	2.08
	[.63]	[1.33]

Mean [st. dev.] action for each network structure, averaged over groups of size $n = 6$. Action set $= \{1, 2, \ldots, 7\}$.

payoff is independent of others' actions. In contrast, a senior manager is often held accountable for coordination failures even when her subordinates are at fault. In such environments, responsibility and exposure to coordination failures flow upward through the hierarchy, forming directed chains rather than reciprocal loops.

Suppose we represent the set of interdependencies in an organization's task and incentive design as a network across agents. Put loosely, if agent 2's payoff depends on agent 1's actions, we draw a link from $1 \to 2$. Given a network representation of organizational structure, we seek to understand how organization-wide coordination emerges from the ensemble of network interactions.

To do so, we study a generalization of the minimum-effort game where players are linked by a directed network, and each player is incentivized to match the lowest action amongst their direct links. We refer to this setting as the *network minimum game*.

The classic minimum-effort game corresponds to the special case of a complete network. In contrast, our analysis allows for incomplete networks, thus capturing the notion of limited within-organization interdependencies. Furthermore, by considering directed networks, we allow for asymmetric interdependencies between players: player i's payoff may depend on player j's actions, but not vice versa. Such asymmetries allow us to capture acyclic task dependencies within organizations, as discussed above.

Our experimental setting represents repeated interactions within long-lived organizations with persistent structure: participants play in fixed groups, with fixed network structure, for ten rounds. The treatments vary two aspects of network structure: network *cyclicity* (the existence of cycles of dependencies in the network; see Figure 1) and network *density* (the number of links per player).

We find that network cycles inhibit coordination. Table 1 summarizes our key findings. On acyclic networks of all densities, players coordinate on almost-maximal actions (the maximum action being 7). Cyclic networks perform worse than acyclic networks. Dense cyclic networks perform worst: they generate almost-minimal actions (the minimum action being 1). That is, cycles matter, especially for dense networks.

Our experiment's acyclic networks are hierarchical: they take the form of a chain of command where higher-indexed participants depend on lower-indexed participants. This construction captures the essence of an organizational hierarchy, where supervisors are held responsible for their subordinates' activities, and each worker has a unique chain of command leading to the CEO. Some

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papers study the efficiency of hierarchical structures from the perspective of organizational design (e.g.,Harris & Raviv, 2014; Radner, 1993; Sah & Stiglitz, 1986). The same network structure can also be interpreted as a stylized sequential production technology: directed paths represent production lines or process flows in which intermediate outputs move from upstream to downstream stages, so that a downstream stage's payoff depends on the care taken upstream but not on actions further down the line. Our results highlight that acyclic structures – including hierarchies and sequential production lines – are particularly effective at fostering coordination.[1]

What mechanisms underlie our results? We have in mind that dependency cycles create feedback loops that allow 'seeds' of strategic uncertainty to circulate and amplify, potentially leading to coordination failure: eventually, each player selects a low action simply because he anticipates that the next player in the cycle may do the same, ad infinitum. In contrast, destructive feedback loops do not arise in acyclic networks, thus enabling successful coordination.

This logic may be starkly interpreted in terms of the Nash equilibrium. For acyclic networks, the unique Nash equilibrium is for all players to take a maximum action. Whereas, for our cyclic networks, every common action level is a Nash equilibrium – that is, the strategic uncertainty associated with network cycles translates to equilibrium multiplicity. Such multiplicity, however, also means that the Nash equilibrium is silent about why sparse cyclic networks coordinate more successfully than dense cyclic networks. (Indeed, the set of pure-strategy Nash equilibria for cyclic networks is independent of network density.) Nor does it speak to some of our other experimental findings. We find, for instance, that in cyclic networks, the level of coordination is independent of cycle length. We also find that in acyclic networks, participants who are higher in the pecking order – that is, participants whose payoffs depend more on others' actions – take lower actions.

To address these experimental findings and to enrich our intuitions about how network structure amplifies or dampens strategic uncertainty, we analyse logit (quantal-response) equilibria of the network minimum game (in Appendix A). In logit equilibrium, seeds of strategic uncertainty are introduced by assuming that each player inevitably makes small mistakes when choosing actions (Anderson et al., 2001; Goeree et al., 2016; McKelvey & Palfrey, 1995). This modelling device allows us to tractably capture the feedback-loop mechanisms discussed above. Furthermore, logit equilibrium produces sharp comparative static predictions that match our experimental findings.

We also examine how participants learn to coordinate over time. We find that coordination is more resilient in acyclic networks. In initial rounds, play is noisy, and average actions are intermediate for both cyclic and acyclic networks. Participants in acyclic networks tend to overcome such initial miscoordination: average actions increase towards the maximum level over time. In contrast, in cyclic networks, initial miscoordination is exacerbated: average actions decrease over time. We interpret our results as being largely consistent with a notion of 'learning to coordinate' where participants gradually improve at predicting others' actions and at making optimal decisions. Viewed in this light, acyclic networks empower players to develop and maintain coordinated outcomes.

1.1. Related literature

Our paper builds on a large experimental literature on weakest-link/minimum-effort games and on coordination games played on networks.

1.1.1. Minimum-Effort/Weakest-Link Games

The classic minimum-effort game of Van Huyck et al. (1990) has been used extensively to study coordination with Pareto-ranked equilibria and strategic uncertainty. Early experiments by Van Huyck

[1] Less commonly, some organizations are structured in matrix form, which is also acyclic. In a matrix organization, a subordinate may have multiple superiors, and there may be multiple chains of command from each employee to the top, but no 'cycles of responsibility'. We view our findings as applying to matrices and other acyclic structures as well.

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et al. (1990), Knez and Camerer (1994), and Camerer and Knez (2000) documented robust coordination failure in baseline designs: in large fixed groups without communication, play typically converges to the lowest-effort equilibrium, whereas small fixed pairs often reach the efficient equilibrium.[2] These findings have motivated a vast literature that examines how structural, cognitive, and behavioural factors influence coordination outcomes.[3]

A first strand asks when and why coordination failure can be overcome. Weber (2005); Weber (2006) show that efficient coordination in large weakest-link groups can be achieved by gradual growth: start with a small, efficiently coordinated group, then add new members who observe the group's history. Brandts and Cooper (2006) demonstrate that temporarily increasing the payoff from high-effort coordination can move groups to efficient outcomes that persist even after incentives are scaled back. Weber et al. (2004) study a 'virtual observability' treatment in which players move sequentially in the minimum-effort game but cannot observe predecessors; although the information and payoff structure is unchanged, such timing reduces uncertainty and modestly improves coordination. Chen and Chen (2011) show that inducing a salient group identity among participants increases effort in weakest-link games, even in relatively large groups.

More recent work continues to refine our understanding of how design and environment shape coordination in weakest-link games. Leng et al. (2018) and Gärtner et al. (2023) study long-horizon and continuous-time versions of the weak-link game and find that longer horizons or continuous time do not by themselves resolve coordination failure. Feri et al. (2022) use belief elicitation and structural modelling in a repeated minimum-effort game to show that some agents systematically play above their stated beliefs about others' effort, effectively acting as 'leaders' trying to pull the group towards more efficient outcomes. Szkup and Trevino (2025) study costly information acquisition in coordination games and find that higher-precision information choices lead to more coordination attempts and higher success rates, pointing to information design as another lever for mitigating strategic uncertainty. Caparrós Gass et al. (2025) investigate endogenously formed institutions in weakest-link games with fixed neighbourhoods and show that even weak unanimous institutions can substantially raise effort, while also providing a quantal-response-equilibrium interpretation of their data.

A second, closely related strand examines dynamic and intergenerational aspects of coordination in minimum-effort settings. Cooper et al. (1992), Charness (2000), and Blume and Ortmann (2007) show that pre-play cheap-talk communication – including intergenerational advice – can greatly improve coordination in weakest-link games, although not all groups manage to sustain high effort. Van Huyck et al. (1992), Brandts and MacLeod (1995), and Weber et al. (2001) model leadership by allowing one participant to send a pre-play message; such leadership can help, but is no panacea. Weber (2006) demonstrate that efficient coordination can be 'built' through gradual organizational growth, while Brandts and Cooper (2006) show that once high-effort profiles are reached under favourable incentives, they may persist even when incentives are later weakened. Avoyan and Ramos (2023) show that partially binding communication – which falls between cheap talk and full commitment – can further improve coordination. Relative to this work, our contribution is to show that even in the absence of communication, leadership, or institutional change, appropriately designed acyclic network structures can deliver coordination levels in large groups of size 6 or 12 that are comparable to those achieved with these richer institutions.[4]

[2] See also Dufwenberg and Gneezy (2005) and the detailed survey by Devetag and Ortmann (2007).

[3] Devetag and Ortmann (2007) and Cooper and Weber (2020) provide recent surveys.

[4] As a quick comparison, the gradual growth treatment of Weber (2006) induced and sustained successful coordination (median action of 7) in two of nine groups of size $n = 12$; in Blume and Ortmann (2007), with the addition of pre-play cheap-talk messages, groups of size $n = 9$ play (on average) actions of around 6 out of 7. In comparison, in our paper, the dense acyclic network treatment eventually induced and sustained full coordination at the maximum level of 7 out of 7 in two of two $n = 12$ groups.

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1.1.2. Coordination on Networks

A growing experimental literature studies coordination games played on fixed networks. Keser et al. (1998) and Berninghaus et al. (2002) show that 'circle' and 'lattice' networks can sustain higher coordination than small complete networks in certain threshold and coordination games. Cassar (2007) compares local, random, and small-world networks and finds that small-world networks – which combine short path length with some clustering – achieve better coordination than purely local or purely random networks. Charness et al. (2014) study a class of network games with strategic complementarities and show that networks with greater clustering tend to coordinate more successfully. Gallo and Yan (2015) implement a network game with a unique but inefficient Nash equilibrium and find that simple, symmetric networks facilitate informal cooperation to improve on the equilibrium outcome. Relatedly, Choi et al. (2016) and Calford and Chakraborty (2020); Calford and Chakraborty (2021) study network dilemmas with public goods and higher-order beliefs embedded in network formation.

Our paper is particularly close to work that combines weakest-link technologies with endogenous or rich network structure. Riedl et al. (2016) introduce endogenous (undirected) network formation in a weakest-link game and show that efficient coordination can emerge because subjects are motivated to take high actions by the threat of exclusion by others. Riyanto and Teh (2020) study weak-link games on networks with adjustable neighbourhoods and find that greater flexibility in choosing whom to interact with substantially improves coordination efficiency. Caparrós Gass et al. (2025) consider weakest-link games with fixed neighbourhoods but allow subjects to form 'institutions' endogenously to coordinate their choices. Relative to this literature, we work with *exogenously* fixed networks but vary the presence of directed cycles and the density of dependencies, focusing on how the architecture of a given network – rather than the ability to choose partners or institutions – affects the emergence and robustness of efficient coordination. A key difference is that the networks studied in the papers just cited are undirected, so any link creates a two-player dependency cycle. By contrast, we work with directed networks and can cleanly separate acyclic (hierarchical or sequential) structures from those containing cycles.

1.1.3. Network Design as an Organizational Tool

Finally, from the perspective of organizational design, our results complement theoretical work on hierarchies, polyarchies, and the processing of information in organizations.[5] The network minimum game highlights a downside of dense interdependencies: additional links strictly reduce performance in logit equilibrium, and closing a single directed cycle in an otherwise hierarchical structure can dramatically undermine coordination. At the same time, our experiment shows that acyclic structures – including hierarchies, sequential production lines, and other directed acyclic graphs – are particularly effective at fostering and sustaining high-effort coordination, even without communication or explicit leadership. Relative to the many other devices that have been shown to improve coordination in weakest-link games (communication, leadership, identity, dynamic growth, institutional design), network design is simple and robust: merely avoiding cycles of responsibility can substantially reduce the scope for destructive feedback loops of strategic uncertainty.

2. Framework

2.1. Background: the (classic) minimum-effort game

The classic *Minimum-Effort Game* models coordination amongst an n-player group under a 'weakest-link' production technology where output is determined by the group's worst performer. Each player P_i in the group $\{P_1, \dots, P_n\}$ simultaneously chooses an action x_i from a compact action set $X \subset \mathbb{R}$,

[5] See, for example, Sah and Stiglitz (1986), Radner (1993), and Harris and Raviv (2014).

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Table 2. Average final-round actions in classic minimum-effort games, by group size n

Study	$n = 2$	$n = 3$	$n = 6$	$n = 9$	$n = 14–16$
Van Huyck et al. (1990)	6.39				1.74
Knez and Camerer (1994)		4.05	1.52		
Cachon and Camerer (1996)				2.06	
Camerer and Knez (2000)	6.85	3.48			

Mean action out of action set $\{1, 2, \ldots, 7\}$, averaged over groups. List of papers is from Table 2 of Weber (2006), excl. Chaudhuri et al. (2009) where data for final-round average actions was unavailable.

and receives the minimum group action less a private action cost:

$$\pi_i\left(x_1, \ldots, x_n\right) = \min\left\{x_1, \ldots, x_n\right\} - cx_i \text{with } c < 1.$$

In most existing experimental implementations, the action set X is discrete: each participant chooses an integer action between 1 and 7. We follow this convention in the laboratory, but impose a continuous action set in our theoretical analysis (Appendix A).

With at least two (self-interested) players, any symmetric action profile $(x, \ldots, x)$ is a Nash equilibrium. These equilibria are Pareto-ranked, with higher-action equilibria being more efficient. The natural interpretation is that low-action equilibria represent coordination failure.

Table 2 reports existing experimental results from papers to highlight one of the most consistent findings about the classic minimum-effort game (absent communication or network structure): coordination deteriorates dramatically with group size, and failure (in the form of almost-minimal actions) is almost inevitable in groups with four or more players.

2.2. The network minimum game

Let's augment the classic minimum game with a (connected) directed network $\mathbf{g}$ over the group $\{P_1, \ldots, P_n\}$. If there is a link $P_j \to P_i$, then we say that P_i *depends on* P_j. We require that players always depend on themselves: $P_i \to P_i$ for all P_i. Each player P_i's *neighbourhood* S_i is the subset of players that P_i depends on.[6]

The network minimum game differs from the classic minimum game in just one respect: each player P_i's payoff depends only on actions of those in P_i's neighbourhood,

$$\pi_i\left(x_1, \ldots, x_n\right) = \min\left\{x_j : j \in S_i\right\} - cx_i \text{with} c < 1. \tag{1}$$

Notice that the classic minimum-effort game is a special case of the network minimum game where $\mathbf{g}$ is the complete network: $P_i \to P_j$ for all $i, j \in \{1, \ldots, n\}$.

Some terminology: a network *path* is a sequence of players where each player depends on, and is distinct from, his predecessor. A network *cycle* is a network path that starts and ends with the same player. A network without network cycles is *acyclic*.

In any acyclic network, the unique Nash equilibrium is for everyone to play the maximum action, $x_i \equiv \max X$. Network cycles introduce equilibrium multiplicity: for any network cycle, any common action $x_i \equiv x \in X$ is a Nash equilibrium. Taken together, these observations hint at the central point of our paper: network cycles introduce strategic uncertainty, potentially leading to coordination failure. However, this multiplicity also implies that the Nash equilibrium is silent about how coordination varies across different cyclic networks. Instead, we appeal to an alternative solution concept.

In Appendix A, we analyse logit equilibria of the (one-shot) network minimum game. Logit equilibrium introduces seeds of strategic uncertainty into the interactions between players. Each player

[6]Within organizations, it is natural to interpret a worker's neighbourhood as representing their span of responsibility: the set of coworkers whose efforts affect one's task outcomes. So, in our game, each player's own effort always affects their task outcomes, and (depending on the network structure) those outcomes may also depend on the efforts of others.

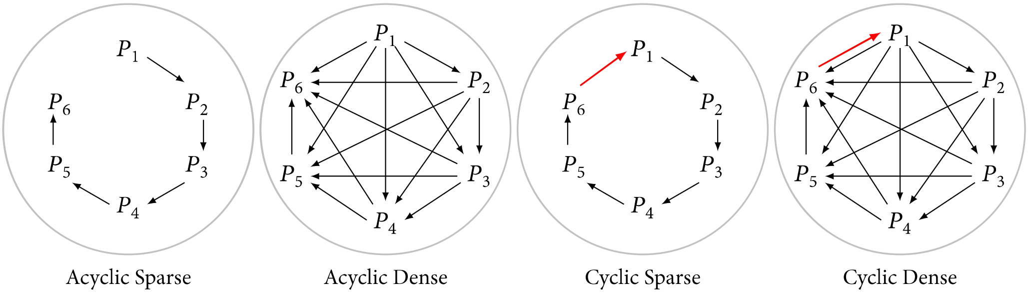

Fig. 2. Six-player networks
Cyclic networks are constructed by adding a single (red) link to the corresponding acyclic networks.

best-responds 'noisily' – by playing a distribution over actions where higher-payoff actions are chosen (exponentially) more frequently – to the similarly noisy play of others. Such noise captures the strategic uncertainty inherent in our coordination-game setting. Furthermore, as in Anderson et al. (2001)'s logit-equilibrium analysis of the classic minimum-effort game, the introduction of noise shrinks the set of equilibria relative to the Nash case, and thus serves as an effective equilibrium-selection device. Consequently, logit equilibria produce intuitive predictions about the circumstances under which coordination failure occurs. When discussing the intuitions underlying our experimental results in Section 4, we will often refer the interested reader to theoretical results in Appendix A.

3. Experimental design

3.1. Network treatments

In the experiment, groups of participants played a version of the network minimum game where actions are integers between one and seven, i.e., $X = \{1, 2, \ldots, 7\}$.

The experiment adopted a between-subject design: each participant in each session was assigned to a specific network position within a group of fixed size and network structure, and each group played ten rounds of the network minimum game. Groups differed in size: $n \in \{2, 3, 4, 6, 12\}$. Modulo size, network structure took one of four ($= 2 \times 2$) forms, which differed along two dimensions: density and cyclicity. Each treatment thus corresponded to some combination of group size $\times$ network density $\times$ network cyclicity. This taxonomy is illustrated in Figure 2 for groups of size $n = 6$.

Consider our acyclic networks. Both the sparse and dense acyclic networks are hierarchical: participant P_i depends on participant P_j only if $i \geq j$, so higher-indexed participants depend (directly or indirectly) on lower-indexed participants. The sparse acyclic network is minimally connected, in the sense that removing any link will partition the group into two distinct components. The dense acyclic network is maximally connected, in the sense that adding any link will introduce a network cycle. So, our sparse and dense networks represent extremes in density amongst the set of connected acyclic networks.

Our cyclic networks are defined in relation to our acyclic networks. To create the sparse/dense cyclic network of size n, we add a single link – chosen judiciously to complete a network cycle – to the sparse/dense acyclic network of size n. Each cyclic network is thus ostensibly identical to its acyclic counterpart, except for the single additional link.

Some combinations of group size $\times$ network density $\times$ network cyclicity were not implemented. Table 3 summarizes which, and how many, network treatments were run; Appendix E illustrates each such treatment.[7]

[7]Broadly speaking, we chose network treatments to isolate comparative statics in (i) cyclicity, (ii) density, and (iii) group size n. As a benchmark, we implemented $n = 6$ sparse cyclic and acyclic networks. To study density, we added $n = 6$ dense

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Table 3. Experimental design

	Acyclic		*Cyclic*	
	Sparse	*Dense*	*Sparse*	*Dense*
$n = 2$				$\checkmark_{[10]}$
$n = 3$	$\checkmark_{[9]}$		$\checkmark_{[10]}$	
$n = 4$	$\checkmark_{[10]}$		$\checkmark_{[10]}$	
$n = 6$	$\checkmark_{[10]}$	$\checkmark_{[10]}$	$\checkmark_{[10]}$	$\checkmark_{[10]}$
$n = 12$		$\checkmark_{[2]}$		

$\checkmark_{[m]}$ = treatment was run; $[m]$ = number of groups.

Table 4. Network minimum game payoffs

	Minimum action in neighbourhood						
Your action	7	6	5	4	3	2	1
7	13.00	10.00	7.00	4.00	1.00	-2.00	-5.00
6	—	12.00	9.00	6.00	3.00	0.00	-3.00
5	—	—	11.00	8.00	5.00	2.00	-1.00
4	—	—	—	10.00	7.00	4.00	1.00
3	—	—	—	—	9.00	6.00	3.00
2	—	—	—	—	—	8.00	5.00
1	—	—	—	—	—	—	7.00

3.2. Procedural details

Experimental sessions ran from April to August 2017 at UNSW Sydney's BizLab. Participants were recruited from the university's subject pool and administered via ORSEE (Greiner, 2015); the experiment was programmed in zTree (Fischbacher, 2007). Overall, 421 participants participated in 33 sessions plus a pilot study, with 12 to 30 participants per session. Each treatment was played by ten groups of participants.[8] Groups were fixed throughout.

Participants faced a version of the payoff function from Equation (1). Specifically,

$$\pi_i(x_1, \ldots, x_n) = 6 + 3\min\{x_j : j \in S_i\} - 2x_i,$$

where payoffs were denominated in AUD. Payoff information was presented to participants in the form of Table 4. Participants were paid their experimental earnings from one randomly selected round plus a show-up fee of AUD 5. No participant was allowed to participate in more than one session. On average, each session lasted about 50 minutes, and each participant earned AUD 16.27.

The experimental design corresponds to a complete-information setting. At the start of the experiment and at the start of each round, each participant was reminded about the network structure and their position within the network. At the end of each round, each participant was informed about every participant's action within their group and every participant's neighbourhood's minimum action in that round. Each participant only participated in one session and was only exposed to one network structure and one position within that network.

cyclic and acyclic networks, comparable to the sparse $n = 6$ benchmark. To study group size, we added $n = 3$ and $n = 4$ sparse cyclic and acyclic networks, varying only n relative to the $n = 6$ benchmark.

[8]There were two exceptions to this ten-group-per-treatment rule: the cyclic sparse network with $n = 3$ (nine groups) and the acyclic dense network with $n = 12$ (two groups). Each session consisted of multiple groups. In some sessions, groups corresponding to different treatments were run in the same session; this was done to optimize the use of participants given room-size constraints. Table 3 in the Appendix summarizes the experimental design.

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Table 5. Mean actions by network structure (final round)

	$n = 2$ *Dense*	$n = 3$ *Sparse*	$n = 4$ *Sparse*	$n = 6$ *Sparse*	$n = 6$ *Dense*	$n = 12$ *Dense*
Acyclic		6.52 [.53]	6.70 [.50]	6.52 [.81]	6.72 [.63]	7.00 [.00]
Cyclic	4.50 [2.60]	4.13 [2.22]	4.13 [1.93]	4.90 [2.02]	2.08 [1.33]	
Mean-difference tests: p-values						
Wilcoxon		0.021	0.003	0.057	0.001	
OLS (clustered)		0.004	0.001	0.027	0.001	

Notes: Mean action in the final round, averaged across groups. Standard deviations in brackets below means. Each column corresponds to a distinct treatment (group size and network density). p-values from two-sided tests comparing mean actions between acyclic and cyclic networks: (i) Wilcoxon rank-sum test (non-parametric), and (ii) OLS regression with robust standard errors clustered at the group level. There were 10 groups per treatment, with the exception of sparse acyclic $n = 3$, and acyclic dense $n = 12$.

Participants received written instructions and were then shown a 5-minute video which explained each step of the experiment.[9] Before the start of the experiment, participants had to pass two on-screen comprehension tests, after which all participants in the session started the experiment simultaneously.

4. Experimental findings

This section studies how network density and network cyclicity affect coordination. Here, the analysis is static: we report mean final-round actions for each treatment, averaged over groups. In contrast, Section 5 will study dynamics: that is, how mean actions evolve over the ten rounds. Throughout our analysis, the mean action for one group is treated as a single observation. The approach controls for potential within-group correlations in a conservative fashion.

4.1. Acyclic Networks

Our first experimental finding is that groups coordinate well in acyclic networks regardless of group size or network density.

Table 5 lists average final-round actions for sparse and dense acyclic networks of various group sizes. Participants achieved close to the maximum action in the final round of each treatment. Across the various acyclic networks, the final-round average action ranged from 6.52 to 6.72 out of 7.[10]

To highlight the point that high density does not hinder coordination in acyclic networks, we collected data for two 'super-dense' acyclic networks with $n = 12$ (Figure 3). These networks coordinated remarkably successfully. In the final round, all participants played the maximum action 7.

To sum up, neither group size nor network density made a substantial dent on coordination in acyclic networks. Such insensitivity is in stark contrast with the fact that coordination deteriorates rapidly with group size (and thus with network density) in the classic minimum-effort game (see Table 2). But the same insensitivity is consistent with the Nash equilibrium prediction that participants in

[9]These written instructions are reproduced in the Online Appendix. The videos are available at www.johanneshoelzemann.com.

[10]In every acyclic treatment, most participants played the maximum action: the number of such participants in the sparse $n = 3, 4, 6$ and the dense $n = 6$ treatments is 18 of 27, 32 of 40, 46 of 60, and 56 of 60, respectively.

Differences in average final-round actions between sparse acyclic treatments of different group sizes are not significant: (two-sided) Wilcoxon rank-sum tests produce p-values of $p_{34} = 0.3412$, $p_{36} = 0.4888$, and $p_{46} = 0.7980$ (where $p_{n_1 n_2}$ is the p-value from comparing group sizes n_1 vs. n_2). The difference in average final actions between the sparse vs. dense $n = 6$ acyclic treatments is not significant either: $p = 0.4016$.

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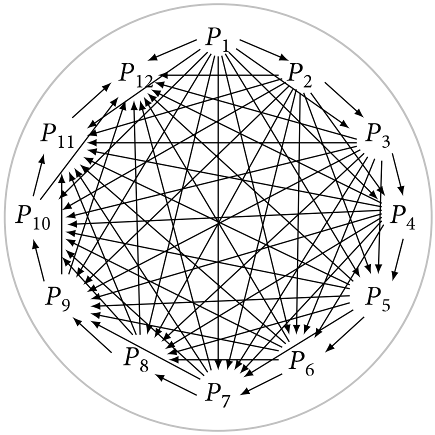

Fig. 3. Large dense acyclic network

any acyclic network will coordinate well. Pushing this point further, we find in Proposition A.1 of Appendix A that under logit equilibrium, participants in any acyclic network will choose close-to-maximal actions *as long as players' mistakes are not too large*. We will elaborate on this point shortly, when we compare our experimental results for cyclic versus acyclic networks.

4.2. Cyclic (vs. Acyclic) Networks

Our second experimental finding is that coordination weakens when cycles are introduced into a network, especially when the existing network is dense. Recall that in our experimental design, the only difference between each acyclic network and its cyclic counterpart is the addition of a single link.

Table 5 also shows the mean final-round action in sparse and dense cyclic networks of various group sizes. Sparse cyclic networks produce intermediate levels of coordination, but perform substantially worse than sparse acyclic networks. Average final-round actions are significantly lower in each size-n sparse cyclic network than in the corresponding size-n sparse acyclic network: Wilcoxon rank-sum tests produce p-values of 0.0208, 0.0033, and 0.0571 for $n = 3, 4$, and 6, respectively.

Comparing the reported results in Table 5, the difference in final-round actions between the dense acyclic treatment and the dense cyclic treatment is particularly dramatic. With $n = 6$, the mean final-round action in the dense cyclic network is 2.08 [s.d. 1.33], compared to 6.72 [s.d. .63] in the dense acyclic network ($p < 0.0001$). That is, the addition of a single link – to a dense network – that completes network cycles has devastating effects on coordination.[11]

Relatedly, actions decrease with network density in cyclic networks. With $n = 6$, the mean final-round action in the sparse cyclic network is 4.90 [s.d. 2.02], versus 2.08 [s.d. 1.33] in the dense cyclic network ($p = 0.0035$).

Moving beyond point estimates, Figure 4 shows the empirical distribution of action distributions by network treatment for $n = 6$. Action distributions are significantly higher in stochastic dominance in each acyclic treatment than in its cyclic counterpart: two-sample Kolmogorov-Smirnov (KS) tests and two-sample Epps-Singleton (ES) tests both produce $p < 0.001$ for final-round actions.[12]

What forces underlie coordination failure in cyclic networks, and why are these forces muted in acyclic networks? We have in mind that small seeds of strategic uncertainty are amplified by strategic interactions in cyclic networks, but not in acyclic networks. We formalize this intuition in

[11] We obtain similar – indeed, even more pronounced – differences across acyclic and cyclic treatments when we consider each player's neighbourhood's minimum action rather than each player's action.

[12] Empirical distributions for networks with $n = 2, 3, 4$ can be found in Figure B.2 of Appendix B.

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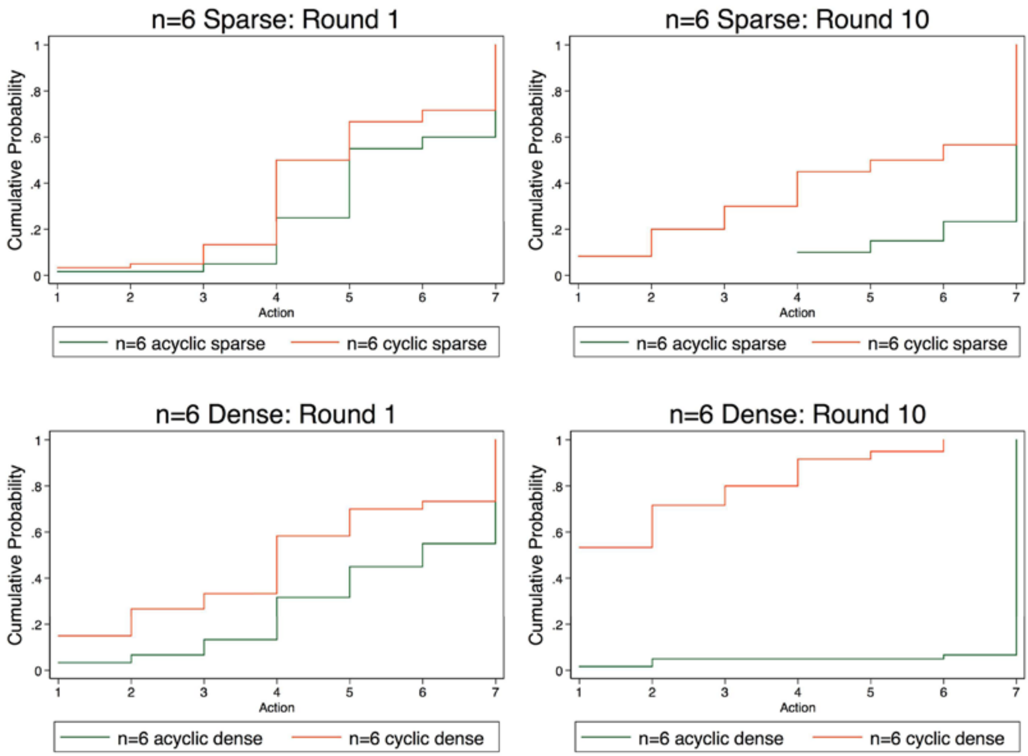

Fig. 4. Empirical distributions of acyclic vs. cyclic networks with $n = 6$

Propositions A.1 and A.2 of Appendix A. We have in mind that as best-response dynamics play out over time, doubt unfolds – and potentially reverberates – across the network. Suppose players on a network cycle all (initially) play the maximum action. Inject a small 'seed' of noise by adding noise to perturbing some player P_i's action downward. In the subsequent best-response dynamic, each player who depends on P_i best-responds by lowering his action; in this way, the negative shock propagates along network paths from P_i. In fact, this negative shock will circle back to i along the network cycle, potentially inducing P_i to further lower their action. In other words, the network cycle serves as a feedback loop for the initial seed of strategic uncertainty. Indeed, players may be embedded in multiple network cycles, in which case the feedback effect is multiplied. In dense cyclic networks where many players are embedded in many cycles, the feedback effect is sufficiently strong that any small shock becomes self-reinforcing and eventually leads to coordination failure, where everyone involved plays almost-minimal actions. In contrast, seeds of strategic uncertainty may propagate across acyclic networks but are eventually damped due to the absence of feedback loops, and thus do not substantially damage coordination.[13]

4.3. Cycle Length

Our third experimental finding is that cycle length has little, if any, effect on coordination. Consider the sparse cyclic networks. In a sparse cyclic network of size n (Figure 5), there is a single cycle of length n and every neighbourhood has size $|S_i| \equiv 2$. To wit: we can study how cycle length affects

[13]Although the logit quantal response equilibrium we analyse in Appendix A is a static solution concept, it admits a dynamic interpretation – as the steady-state outcome of a gradual, noisy best-response dynamic – that neatly captures our intuition here. We provide more details in Appendix A.

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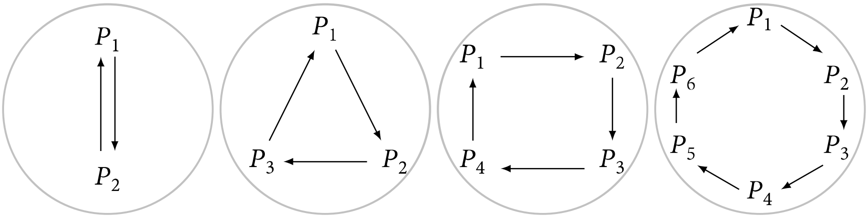

Fig. 5. Sparse cyclic networks

coordination, keeping density fixed at $\ell = 2$, by comparing the sparse cyclic networks with different group sizes.

Table 5 also shows average final-round actions in each of the sparse cyclic treatments. Average final-round actions in the various sparse cyclic networks are not significantly different: testing for differences between pairs of treatments, we get p-values of $p_{23} = 0.7596$, $p_{24} = 0.6212$, $p_{26} = 0.7010$, $p_{34} = 0.9095$, $p_{36} = 0.4452$, and $p_{46} = 0.3620$ (where $p_{n_1 n_2}$ is the p-value from comparing group sizes n_1 vs. n_2).[14]

This experimental result is consistent with Proposition A.2 in Appendix A, which implies that logit equilibrium action distributions are independent of cycle length for sparse cyclic networks.[15]

These findings may shed some light on the mechanisms leading to coordination failure in large groups in the classic minimum-effort game, which (as we recall) corresponds to the complete network. Given a complete network, an increase in group size corresponds to both (i) an increase in network density and (ii) the introduction of longer cycles into the network. What role does each of these factors play in inducing coordination failure in the classic minimum-effort game? Our finding that cycle length has little effect on coordination suggests that (ii) is not a major factor; and thus that coordination failure in large groups in the classic minimum-effort game is due to high network density.

4.4. Pecking Order

We also find tentative evidence for a fourth regularity: within each group with an acyclic network structure, participants in ‘higher’ positions (higher index i) choose lower actions. We refer to this as the *pecking-order* hypothesis. Our acyclic network structures are hierarchical in the sense that there is a strict ordering of players, with higher-indexed participants depending on lower-indexed participants but not vice versa (see Appendix E). Thus, the pecking-order hypothesis states that higher-indexed players in the hierarchy, who bear greater responsibility for coordination, take lower actions than lower-indexed players.

Table 6 reports mean final-round actions by participant position for each treatment. In every acyclic treatment, mean actions generally decline with position. The differences across positions are modest: in each acyclic treatment, the highest-indexed participants still choose higher actions, on average, than the average participant (at any position) in the corresponding cyclic treatment.

We test the pecking-order hypothesis in two ways. First, for each network structure, we regress participants’ final-round action ranks on network position, clustering standard errors by group. Second, for each group, we run a J-T test of the hypothesis that higher-indexed participants take lower actions,

[14] Two-sample Kolmogorov-Smirnov (two-sample Epps-Singleton) tests produce p-values of $p_{23} = 0.976$ (0.628), $p_{24} = 0.660$ (0.528), $p_{26} = 0.660$ (0.277), $p_{34} = 0.660$ (0.842), $p_{36} = 0.976$ (0.771), and $p_{46} = 0.294$ (0.957) for final-round actions for networks with $n = 2, 3, 4$ and $n = 6$, respectively.

[15] More generally, action distributions are independent of cycle length for networks where all participants have the same neighbourhood size ℓ. Sparse cyclic networks correspond to the special case $\ell = 2$.

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Table 6. Mean actions by network position (final round)

Network structure		P_1	P_2	P_3	P_4	P_5	P_6	β	*J-T*
Acyclic	$n = 3$ *sparse*	6.78	6.56	6.22				-0.23	0.083
		[.44]	[.73]	[.97]				(p=0.11)	
	$n = 4$ *sparse*	6.90	6.70	6.90	6.30			-0.17	0.028
		[.32]	[.67]	[.32]	[1.06]			(p=0.05)	
	$n = 6$ *sparse*	6.80	6.80	6.80	6.40	6.30	6.00	-0.13	0.001
		[.63]	[.42]	[.42]	[1.26]	[1.16]	[1.41]	(p=0.03)	
	$n = 6$ *dense*	7.00	6.90	6.40	7.00	6.50	6.50	-0.05	0.188
		[0]	[.32]	[1.90]	[0]	[1.58]	[1.58]	(p=0.23)	
	All of the above								< 0.001
Cyclic	$n = 3$ *sparse*	3.80	4.20	4.40				0.11	0.995
		[2.35]	[2.35]	[2.22]				(p=0.08)	
	$n = 4$ *sparse*	4.50	3.90	4.30	3.80			-0.10	0.314
		[2.01]	[2.18]	[2.11]	[2.10]			(p=0.08)	
	$n = 6$ *sparse*	4.90	5.40	4.60	4.30	4.90	5.30	-0.01	0.435
		[2.38]	[2.17]	[2.50]	[2.31]	[1.97]	[2.16]	(p=0.39)	
	$n = 6$ *dense*	1.90	2.80	2.60	1.80	1.80	1.60	-0.06	0.017
		[1.73]	[1.81]	[1.84]	[1.03]	[1.14]	[1.07]	(p=0.01)	
	All of the above								0.148

Notes: Mean [st. dev.] final-round action. The β column reports the slope estimate (p-value) from a linear regression of ranked actions on ranked network position, with standard errors clustered by group; one-sided p-values in parentheses correspond to the hypothesis that higher positions take lower actions. The *J-T* column reports p-values from Jonckheere–Terpstra (J-T) tests of the hypothesis that, within each group, final-round actions are weakly decreasing in network position. Group-level J-T p-values are aggregated by network structure using Fisher's combined probability test. Network positions for each P_i are given in Appendix E.

then use Fisher's method to combine the group p-values within each network structure.[16] The β and J-T columns of Table 6 report these statistics.

The acyclic-network results are broadly consistent with the pecking-order hypothesis. The slope estimates β are negative for every network structure, with significance at the 5% level for the $n = 4$ sparse and $n = 6$ sparse networks. Similarly, the Fisher J-T p-values point in the same direction, with significance at the 5% level for the $n = 4$ sparse and $n = 6$ sparse networks. Combined across all acyclic-network groups, the Fisher J-T p-value is below 0.001.

The pecking-order hypothesis relates only to acyclic networks; for comparison, we report the same tests for the cyclic treatments. The cyclic-network slope estimates β are mixed in sign and generally smaller in magnitude, with only one slope estimate (for the $n = 6$ dense cyclic network) being significant at the 5% level. The J-T results for cyclic networks are similarly mixed: only the $n = 6$ dense cyclic network is individually significant ($p = 0.017$), and the Fisher J-T p-value combined across the four cyclic networks is not significant ($p = 0.148$).

Intuitively, in acyclic networks, higher-indexed players find high actions more costly. Their neighbours are themselves relatively high-indexed and therefore choose lower actions than the neighbours of lower-indexed players. In dense acyclic networks, higher-indexed players also have larger neighbourhoods and thus face a greater risk of at least one low action in their neighbourhood. More

[16]Groups in which all participants chose the same final-round action are excluded, since the J-T statistic is then uninformative.

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Table 7. Mean actions in cyclic networks with additional anchor player (final round)

	$n = 6$ *unanchored*		$n = 6$ *connected*		$n = 6$ *isolated*	
	Sparse	*Dense*	*Sparse*	*Dense*	*Sparse*	*Dense*
Action	4.90	2.08	3.86	1.69	4.54	1.08
	[2.02]	[1.33]	[2.01]	[.87]	[1.81]	[.17]

Mean [st. dev.] action, averaged across groups. The first two columns ($n = 6$ unanchored) reproduce the mean final-round actions from our original $n = 6$ sparse and dense cyclic networks (Table 5). The next two columns ($n = 6$ connected) report, for the sparse and dense cyclic networks with a connected anchor player, the mean final-round actions of the non-anchor players (P_1 to P_6) in each group. The last two columns report the analogous figures for the sparse and dense cyclic networks with an isolated anchor player.

generally, within a hierarchy higher-ups bear more of the coordination risk, which induces them to choose lower actions.[17] We formalize these points in Proposition A.3 of Appendix A.

4.5. *Additional Tests*

We conducted three robustness tests on this section's results. Our first test excludes participant P_1 from the analysis of acyclic networks. Unlike the other participants, in acyclic networks, P_1's neighbourhood contains nobody else, so P_1 faces no strategic uncertainty – thus their dominant strategy is always to play the maximum action, $x_{i,t} = 7$. Excluding P_1 from the analysis of acyclic networks thus serves, in a sense, to 'level the playing field' between cyclic and acyclic networks. Table B.5 reports mean actions for acyclic networks without P_1, and Table B.6 tests for differences between cyclic and acyclic treatments after excluding P_1. Our results remain qualitatively unchanged.

Our second test is to consider, instead of the mean action, the mean neighbourhood-minimum action; i.e., the minimum action in each participant's neighbourhood, averaged over participants. Each participant's neighbourhood-minimum action captures the extent to which coordination failure affects the participant. Table C.4 compares cyclic versus acyclic treatments and shows that the differences in such mean neighbourhood-minimum actions are, if anything, even more pronounced than the differences in mean actions.

Our third robustness test examines an alternative 'anchor' hypothesis. Notice that in our acyclic networks, player P_1's neighbourhood consists only of themself, and thus has a strictly dominant strategy: play 7. Indeed, we observe in the laboratory that P_1 consistently and quickly arrive at a stable choice of 7 in almost all sessions. The anchor hypothesis is that acyclic networks coordinate successfully because the anchor player serves as a focal point for coordination on the highest action 7 by other players. On the other hand, cyclic networks have no anchor position, so successful coordination on high actions is less likely.

We test this hypothesis by introducing *anchored* cyclic networks. Each anchored cyclic network is constructed by adding an additional anchor position P_0 to either the six-player sparse cyclic or the six-player dense cyclic network. Figure 6 illustrates. For each of the two anchored cyclic networks, we consider two variants. In the first variant, the anchor is *isolated*, i.e., does not belong to anyone else's neighbourhood. In the second variant, the anchor is *connected* in the sense that they are in P_1's neighbourhood (and nobody else's).[18]

Table 7 shows average final-round actions from unanchored cyclic treatments (reproduced from Table 5) as well as average final-round actions from their anchored counterparts.

[17]In practice, various countervailing forces not captured by our model may mitigate or reverse this effect: for example, organizations may assign more highly motivated personnel to higher positions and offer them stronger incentives to take high actions.

[18]We ran additional sessions in August and September 2025 for these anchored networks. In total, we collected data from 7, 6, 4 and 4 groups (of seven participants) for the connected dense, connected sparse, isolated dense, and isolated sparse network treatments, respectively.

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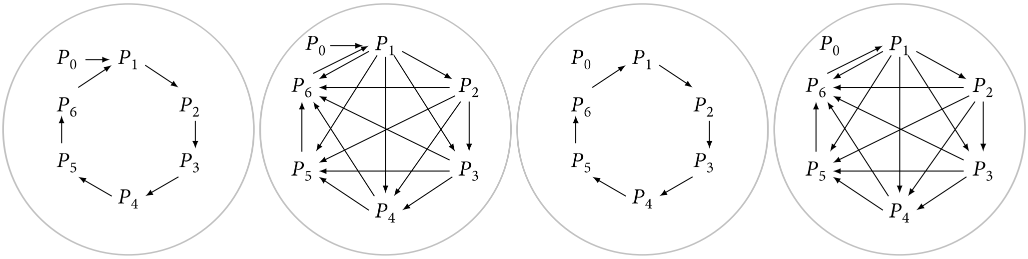

Cyclic Sparse (connected anchor) | Cyclic Dense (connected anchor) | Cyclic Sparse (isolated anchor) | Cyclic Dense (isolated anchor)

Fig. 6. Anchored cyclic networks

We find that the addition of anchor players to our cyclic networks does not significantly improve coordination amongst the remaining players, and may even worsen coordination. In one case, the anchor player may have *significantly* worsened coordination: the cyclic dense network with an additional isolated anchor player produced average final-round actions (1.08) that were significantly worse compared to those from the anchor-less dense cyclic network (2.08). Overall, we have neither a sufficiently strong signal nor a plausible mechanism to infer with confidence that anchor players worsen coordination in our cyclic networks.[19] We view our findings as relatively strong evidence *against* the hypothesis that 'anchor' players improve coordination.

5. Experimental findings: dynamics

Section 4's analysis was static: it focused on final-round actions. Complementarily, Appendix A studies logit equilibria of the one-shot minimum effort game. In this section, we step away from the static setting and discuss how coordination evolved over the ten rounds of play in our experiment.

5.1. Coordination Levels

Table 8 shows average action choice by treatment, for round 1; rounds 1–5; rounds 6–10; and round 10.[20] A clear pattern emerges: actions increase over time (culminating in relatively high actions) in acyclic networks, but decrease over time (culminating in relatively low actions) in cyclic networks.[21]

Figure 7 paints a richer picture – showing means and 25th to 75th percentiles of action distributions round-by-round.[22] In the acyclic networks, actions generally increased over time. In contrast, in cyclic networks, action distributions decrease over time. This is especially so in dense networks.[23]

[19]One speculative hypothesis, though, is the following: as the game proceeds, the presence of an anchor P_0 who plays the maximum action early in the game may have a *discouraging* effect on the remaining participants P_1 - P_6 by making their coordination failure more salient than it would be in the absence of P_0.

[20]Tables B.1 and B.2 report statistical tests for differences between cyclic and acyclic treatments. Furthermore, Table 6 omits the cyclic dense $n = 2$ and acyclic dense $n = 12$ treatments; these are relegated to Table B.4.

[21]These trends are statistically significant. For acyclic networks, Jonckheere-Terpstra tests for ascending order produce p-values of 0.0008, 0.0007, 0.0001, and 0.0001 for sparse $n = 3, 4, 6$ and dense 6, respectively. In contrast, testing for descending order in cyclic networks yields p-values of 0.1288, 0.0554, 0.9877, and 0.0001 for sparse $n = 3, 4, 6$ and dense $n = 6$, respectively.

[22]A more detailed figure (B.1) can be found in Appendix B, where means and 25th to 75th percentiles of action distributions round-by-round *and by participant position* are shown.

[23]As Figure B.1 shows, in the acyclic networks, actions at each position generally increased over time, especially 'higher-up' (higher-indexed) participants. Furthermore, consistent with the patterns recorded in Table 6, higher-indexed participants play lower actions than lower-indexed participants. In contrast, in cyclic networks, action distributions at each position generally decrease over time, and there is no consistent trend across positions in action distributions.

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Table 8. Time trends in mean actions – acyclic vs. cyclic networks

	$n = 3$ *sparse*		$n = 4$ *sparse*		$n = 6$ *sparse*		$n = 6$ *dense*	
	Acyclic	*Cyclic*	*Acyclic*	*Cyclic*	*Acyclic*	*Cyclic*	*Acyclic*	*Cyclic*
$Action_1$	5.81	4.47	5.80	4.90	5.52	4.90	5.45	4.23
	[.44]	[1.33]	[.73]	[.77]	[.80]	[.62]	[.53]	[.52]
$Action_{1-5}$	5.99	4.43	6.18	5.08	5.92	5.11	5.70	3.32
	[.91]	[1.68]	[.68]	[.98]	[.89]	[.98]	[.88]	[1.23]
$Action_{6-10}$	6.41	3.98	6.45	4.56	6.43	5.14	6.52	2.29
	[.88]	[2.05]	[.63]	[1.66]	[.85]	[1.64]	[.98]	[1.23]
$Action_{10}$	6.52	4.13	6.70	4.13	6.52	4.90	6.72	2.08
	[.53]	[2.22]	[.50]	[1.93]	[.81]	[2.02]	[.63]	[1.33]
Round	.09***	-.08*	.07*	-.09	.11***	.01	.16***	-.21***
	(.02)	(.04)	(.03)	(.07)	(.03)	(.07)	(.03)	(.04)
Constant	5.72***	4.63***	5.93***	5.33***	5.59***	5.08***	5.25***	3.94***
	(.31)	(.46)	(.21)	(.29)	(.28)	(.23)	(.26)	(.31)
Clusters	9	10	10	10	10	10	10	10
Observations	270	300	400	400	600	600	600	600

Mean [st. dev.] action, averaged across groups. Each cell reports the estimated coefficient on *Period* from an OLS regression of x on *Round* for the specified treatment (network structure and size). Standard errors (clustered by group) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. There were 10 groups per treatment with the exception of sparse acyclic $n = 3$.

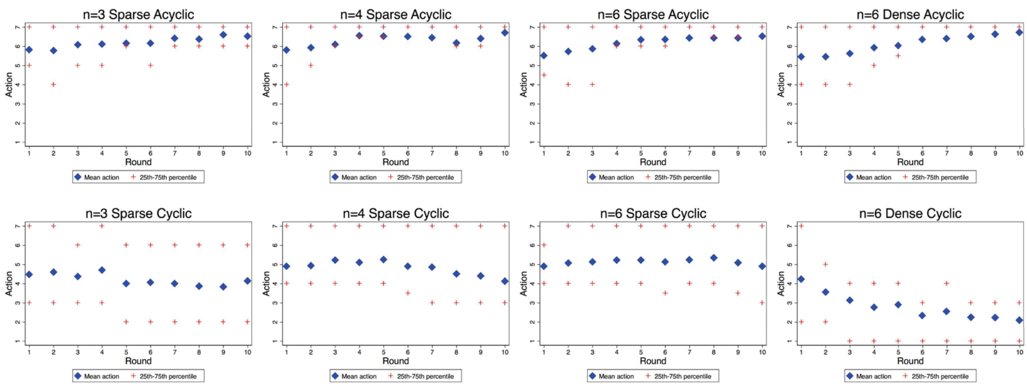

Fig. 7. Evolution of mean actions in acyclic & cyclic networks
Mean actions averaged across treatment are displayed on the vertical axis and rounds are depicted on the horizontal axis. The 25^{th}-75^{th} percentiles of the empirical distributions are highlighted in red. The first (second) column from the left illustrates sparse networks of size n=3 (4). The two columns on the centre-right show networks of size n=6, differing in density with sparse and dense. The top (bottom) row always shows acyclic (cyclic) networks.

Overall, these time trends suggest that participants may be playing adaptively, adjusting their actions over time in response to recent play. Next, we consider whether such adaptive play reduces the uncertainty that participants face.

5.2. Learning

We provide suggestive evidence that participants in both cyclic and acyclic networks learn to coordinate over time, in the sense that they improve their predictions of others' actions. Note that a participant P_i who perfectly anticipates the play of other group members should optimally match

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Table 9. Time trends in prediction errors – acyclic vs. cyclic networks

	n = 3 *sparse*		*n* = 4 *sparse*		*n* = 6 *sparse*		*n* = 6 *dense*	
	Acyclic	*Cyclic*	*Acyclic*	*Cyclic*	*Acyclic*	*Cyclic*	*Acyclic*	*Cyclic*
$Error_1$	1.44	2.07	1.15	1.90	1.28	1.77	1.90	2.70
	[.87]	[1.19]	[.72]	[.57]	[.51]	[.47]	[.76]	[.68]
$Error_{1-5}$	1.02	1.31	.80	1.70	.96	1.53	1.34	1.78
	[.84]	[1.10]	[.68]	[.85]	[.59]	[.62]	[.91]	[1.03]
$Error_{6-10}$	.44	.72	.66	1.16	.41	1.09	.41	.77
	[.51]	[.83]	[.87]	[.92]	[.62]	[.88]	[.85]	[.74]
$Error_{10}$	.41	.40	.28	.90	.23	.83	.52	.43
	[.33]	[.84]	[.55]	[.91]	[.35]	[.74]	[1.28]	[.48]
Round	-.12***	-.13**	-.04	-.10***	-.11***	-.08**	-.17***	-.21***
	(.02)	(.05)	(.03)	(.03)	(.02)	(.04)	(.03)	(.04)
Constant	1.39***	1.72***	.97***	1.99***	1.31***	1.75***	1.78***	2.45***
	(.31)	(.46)	(.20)	(.25)	(.20)	(.14)	(.30)	(.24)
Clusters	9	10	10	10	10	10	10	10
Observations	270	300	400	400	600	600	600	600

Mean [st. dev.] prediction error, averaged across groups. In the $n = 6$ dense acyclic network, eliminating a single outlier reduces final-round mean prediction error to 0.13 [0.39]. Each cell reports the estimated coefficient on *Period* from an OLS regression of x on *Round* for the specified treatment (network structure and size). Standard errors (clustered by group) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. There were 10 groups per treatment with the exception of sparse acyclic $n = 3$.

the minimum action elsewhere in his neighbourhood by choosing period-t action

$$x^*_{i,t} = \begin{cases} \min\{x_{j,t} : P_j \in S_i \setminus P_i\} & \text{if } |S_i \setminus P_i| \geq 1, \\ 7 & \text{if } |S_i \setminus P_i| = 0. \end{cases}$$

Accordingly, call the difference between the participant P_i's optimal action and realized action, $|x_{i,t} - x^*_{i,t}|$, the participant's *prediction error*.

Table 9 shows time trends in average prediction errors by treatment.[24] Two patterns emerge.

First, prediction errors are generally substantially larger in cyclic treatments than in the corresponding acyclic treatments.[25] Using two-sided Wilcoxon rank-sum tests to compare prediction errors between acyclic and cyclic treatments – where each observation is the average prediction error in one treatment over a specific time range – we find that, for most network structures and most time ranges, prediction error is significantly higher in a given cyclic treatment than the corresponding acyclic treatment.[26]

[24] In acyclic networks, participant P_1 has a particularly easy prediction problem: $x^*_{1,t} = 7$. We obtain similar results if we drop participant P_1 from all (acyclic and cyclic) treatments.

[25] We can further disaggregate mean prediction errors *by participant position*. Table B.7 lists prediction error by participant position, averaged over all ten rounds. As with Table 9, prediction errors are generally larger in cyclic networks than in the corresponding acyclic networks and at the corresponding network positions. Analogous to our discussion of Table 5, we find in acyclic networks that prediction errors generally increase as we move higher up the hierarchy (i.e., as participant index increases).

[26] See Table B.8 for details. We find that the differences between acyclic and cyclic treatments are statistically significant for the sparse $n = 4$ and $n = 6$. For the dense $n = 6$ treatments, the differences are statistically significant for all time ranges – except that, in the final round, the acyclic treatment has a higher mean prediction error than the cyclic treatment (due to a single outlier in the acyclic treatment). For the sparse $n = 3$ treatments, differences for some time ranges for the sparse $n = 3$ treatment are not significant.

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Second, prediction error decreases over time in both cyclic and acyclic networks: the average prediction error over the last five rounds is lower than over the first five rounds in every treatment.[27] For acyclic networks, such improvements in prediction go hand-in-hand with improvements in actions, in the sense that actions increase over time (Table 6) – but not for cyclic networks, where actions decrease over time.

We prefer to interpret prediction error as arising from a combination of strategic uncertainty and noisy decision-making: participants make smaller prediction errors when they face less strategic uncertainty about actions in their neighbourhood, and when they understand better how to make optimal choices given others' actions. That is, our experimental findings from Table 9 suggest that over repeated play, participants improve their decision-making and strategic uncertainty diminishes. In this context, it is not surprising that our results from Section 4 – which focus on final-round play – are consistent with the predictions of low-μ logit equilibrium (Appendix A), which posits that agents optimize with a small amount of noise.

6. Conclusion

This paper argues that introducing cycles of interdependencies into an organization's design may trigger coordination failure. In this sense, the network minimum game provides a perspective that highlights the downsides of interdependencies within organizations; indeed, Lemma A.2 states that performance decreases monotonically whenever interdependencies are introduced. This stark result arises because the network minimum game framework essentially assumes that interdependencies produce no benefits for organizations. While this assumption is clearly unrealistic, we prefer not to take a stand on how to model such benefits (see, e.g., Becker & Murphy, 1992; Dessein & Santos, 2006 for some options). Instead, we show that the disadvantages of additional interdependencies may be mitigated by avoiding network cycles. In other words, if interdependencies are necessary, an acyclic structure is preferable to a cyclic structure. Where cycles are technologically unavoidable, our results point to the value of complementary mechanisms studied in the minimum-effort literature – such as communication, endogenous neighbourhood choice, and targeted group incentives – that can help organizations sustain high-effort outcomes even in the presence of feedback loops.

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[27] Specifically, Jonckheere-Terpstra tests for descending order produce p-values of 0.0001 (0.0001), 0.0022 (0.0003), 0.0001 (0.0006), and 0.0001 (0.0001) for sparse $n = 3, 4, 6$ and dense $n = 6$ acyclic (cyclic) networks, respectively.

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