Large-scale network analysis reveals cheating spreads through victimization and observation

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Abstract

Antisocial behavior such as negative gossip, cheating, or bullying can be contagious, spreading from individual to individual and rippling through social networks. Previous experimental research has suggested that individuals who either experience or observe antisocial behavior become more likely to behave antisocially. Here, we distinguish between victimization and observation using an observational study. We apply temporal network analysis on large-scale digital trace data to study the spread of cheating in online gaming. We analyze 1,146,941 matches of the multiplayer online game PlayerUnknown’s Battlegrounds, in which up to 100 players compete individually or in teams against strangers. We identify temporal motifs in which a player who is killed by or observes cheaters starts cheating, and evaluate the extent to which these motifs would appear if we preserve the team and interaction structure but assume an alternative sequence of events. The results suggest that social contagion is only likely to exist for those who both experience and observe cheating multiple times. The findings point to strategies for targeted interventions to stem the spread of cheating and antisocial behavior in online communities, schools, organizations, and sports.
Introduction

Previous research has shown that social behavior can spread from one individual to another, even among strangers. Social behavior refers to our actions towards other people. Prosocial behavior confers a benefit to others that comes at a personal cost, while antisocial behavior imposes costs on others often for one’s own personal gain. Prosocial behavior is contagious, such that if you help a stranger, you not only increase the likelihood that they help others [1, 2, 3, 4] but possibly those they help will also help others, and so on, out to three steps [5]. But unfortunately, socially irresponsible behavior such as littering, stealing, verbal aggression, and cheating spreads in a similar manner.

The idea that antisocial behavior is contagious among strangers underlies the “broken windows” hypothesis [6]. The theory posits that minor infractions such as graffiti, litter, or vandalism can signal the absence of monitoring, enforcement, and public support of laws and social norms, encouraging such behavior, and leading to a self-reinforcing downward spiral. Field experiments have revealed that if people witness minor norm and law violations, they become more likely to litter, trespass, and steal [7, 8]. In the lab, participants who observe other group members steal or cheat become more likely to steal and cheat too [9, 10]. In schools, the presence and awareness of cheaters are associated with higher rates of academic cheating [11, 12, 13]. And in online forums, incidents of trolling and swearing cause others to exhibit verbal aggression [14, 15].

Most of this prior research investigates the contagion of antisocial behavior through observation. The idea is that when witnessing antisocial behavior by others, the observer may change their estimation of the likelihood of being caught or change their understanding of the social norms related to that behavior [7, 10]. However, antisocial behavior may also spread through victimization [16]. In this case, the expectation is that those who are victims of antisocial behavior may “pay it forward” by “retaliating” not against the perpetrator but against innocent others. This mechanism is evident in the context of negative dyadic interactions such as theft, physical assault, or verbal abuse but it is also plausible for competitive environments, in which individuals may incorrectly approach situations as zero-sum [17] and perceive others’ unethical behavior as unfair and personally damaging.

In this paper, we use temporal network data to isolate victimization and observation as distinct
pathways for the social contagion of antisocial behavior. We employ temporal motif analysis to find evidence for the two mechanisms in the spread of cheating in a massive multiplayer online game. Cheating in this context involves the use of unauthorized software or hardware to modify certain in-game elements in order to help the user outperform other players. We analyze data from 1,146,941 matches from PlayerUnknown’s Battlegrounds (PUBG), a popular online multiplayer first-person shooter game (Fig. S1). In a typical match of the game, up to 100 players, either individually or in teams of up to four, compete to remain the last one standing by avoiding obstacles and killing others. To find evidence for contagion, we use the fact that players are randomly assigned as opponents in the matches, focus on the temporal proximity between experiencing/observing cheating and adopting cheating, and control for the confounding effects of friend homophily and influence within teams.

The virtual world we study serves as a simulation of actual social and economic transactions [18]. Our proof-of-principle findings can transfer to antisocial behavior in other contexts such as negative gossip in the office, academic cheating, bullying, illegal drug use by athletes, and employee theft. The contagion of antisocial behavior implies that a single act of misbehavior has the potential to trigger a chain reaction that reaches far beyond the original initiator. To prevent this from happening, we need to understand when to intervene, whom to target, and how. This knowledge will aid policy makers, managers, administrators, and educators develop effective strategies to reduce the incidence and normative acceptance of antisocial behavior and ensure functional and sustainable organizations and communities.

Two mechanisms for contagion

Social behavior can spread among strangers through two distinct mechanisms: generalized reciprocity and third-party influence [1] [16]. Under generalized reciprocity, a recipient of social behavior is more likely to pay it forward and under third-party influence, an observer of social behavior is more likely to emulate it. The first mechanism characterizes a displaced response triggered by normative obligation or affect [19] [20] and the second—social learning by imitating, or rejecting, others’ behavior [7] [10]. It is obvious that to experience social behavior also means to observe it but one can observe social behavior without experiencing it. Thus, although we cannot in practice completely isolate generalized reciprocity from third-party influence, comparing the response to
experiencing, observing, and both experiencing and observing could provide evidence for either 
mechanism and their relative prominence and strength.

Most of previous empirical research on the contagion of antisocial behavior among strangers 
uses field experiments to test the effects of observation only. This research offers ample evidence 
for the third-party influence mechanism, showing that observing instances of antisocial behavior 
makes individuals more likely to behave antisocially [7, 8, 10, 21]. One experimental study compares 
all three scenarios and finds support for generalized reciprocity but not for third-party influence, 
nor an interaction between the two [16]. Other experimental studies likewise find evidence for the 
contagion of antisocial behavior but since they use setups with both victimization and observation, 
they cannot help determine which of the two mechanisms drive the results [9, 22].

Isolating generalized reciprocity from third-party influence is particularly difficult with observa-
tional data for a number of reasons. First, in most social settings, researchers need to isolate social 
contagion from homophily and common external causes, which are inherently confounded in social 
networks [23, 24]. Second, a person’s social activity and the level of antisocial behavior in their 
social environment drive both victimization and observation, so they are not independent of each 
other either. Third, measuring victimization and observation could be challenging without detailed 
information on interactions over time and such data are often difficult to obtain in practice.

Here, we overcome these challenges by studying the contagion of cheating in an online multi-
player game. Gamers use cheating tools to enhance their abilities and increase their chances of 
winning, thus harming the game performance and experience of other players. Cheating in online 
gaming is analogous to using performance-enhancing drugs in professional sports or cheating on a 
test in school. It presents game companies with serious problems, including damaged reputations 
and loss of revenue and hence, many game companies attempt to detect cheaters and punish them 
by suspending or permanently banning their accounts [25, 26].

One explanation for why cheating is prevalent in online gaming is because it is socially con-
tagious. Researchers have found that players who have many cheating friends are likely to start 
cheating as well [27, 25, 28] and this effect could be attributed to social influence, not just ho-
umphily [29, 30]. Further, players who are randomly matched with more cheaters are more likely 
to adopt cheating [26]. However, this previous study does not account for the fact that players who 
play more and are hence more likely to experience and observe cheaters may be also more likely to
adopt cheating for entirely different reasons.

Figure 1: (Top) We create temporal networks in which an edge points from the killer to the victim (black or pink) and from the cheater to the observer (turquoise). For clarity, the visualization shows that an observation occurred when the cheater killed at least five times while the player was in the game (this corresponds to the strict definition of observation we use in Figure 4). Cheaters and their killings are outlined in pink. Thicker edges show killing events that occur later in the match. The winner of this example squad match is the team composed of nodes 4, 5, and 6. The self-loop for player 91 indicates that they either killed themselves or were killed in an accident. (Bottom) We analyze \((n_v, n_o)\) temporal motifs in the killing networks, according to which player \(i\) is killed by \(n_v\) cheaters and observes \(n_o\) cheaters before \(i\) starts cheating within a period \(\delta = 7\) days.

Distinguishing between mechanisms with temporal motif analysis

To provide a stricter test for the social contagion of cheating, we approach the gaming interactions as a temporal network. The game we analyze groups players with strangers as competitors for each match but players can pick their team members when playing a team version of the game. Thus, the exposure to a cheating teammate is not random and could be due to homophily. What is more, even though the presence of a cheating opponent is random, observing or being killed by them, i.e. the treatments, are not. The interactions in a match follow particular temporal and structural patterns due to the fact that players can get killed once only and the killed can neither kill nor observe (Fig. 4). Moreover, cheaters are likely to kill more (Fig. S2A).

To account for the temporal and structural features of the gaming interactions, we apply motif
analysis to the temporal networks of killings and observations in the game. Network motifs are subgraph patterns with a fixed topology that occur more frequently in the real network than in random networks \[31\]. In temporal networks, temporal motifs are topologically equivalent patterns that additionally include the same order of events and are defined to occur within a specified period of time \[32, 33, 34, 35\]. In our case, we look for \((n_v, n_o)\) temporal motifs, whereby player \(i\) is killed by \(n_v\) cheaters and observes \(n_o\) cheaters before \(i\) starts cheating within time \(\delta\), with \(\delta = 7\) days (Fig. 1).

![Original and Randomized Networks](image)

Figure 2: To simulate alternative sequence of events, we permute the nodes in the killing networks by match. Permutation is constrained within cheater-type and within teams to account for the fact that cheaters tend to kill more and that team members tend to move together and avoid killing each other. In this example of permuting a squad match, nodes with the same color belong to the same team. Cheaters (nodes 54, 64, and 91) and their killings are outlined in pink.

If cheating does not spread through contact with cheating opponents, the count of motifs in the empirical network should be similar to that in a suitably randomized network. When randomizing the networks, we preserve the match and team structure and composition but simulate alternative sequences of events to use as counterfactuals (Fig. 2). We then estimate the probability of observing a motif count as large as the empirical one under the null hypothesis that the sequence of events is random. Since we hypothesize that both victimization and observation increase the adoption of cheating, we expect that the counts for the \((n_v, 0)\) and \((0, n_o)\) motifs in the empirical data will be
much higher than those in the randomized networks. In addition, we hypothesize that victimization and observation interact positively and hence, we expect that the \((n_v, n_o)\) motifs with \(n_v, n_o > 0\) will be particularly overrepresented compared to the null model. Finally, we hypothesize the contagion effect to be stronger when the treatment is stronger, i.e. when players suffer from or observe more cheaters. Consequently, we expect the results will be stronger for motifs with larger \(n_v\), larger \(n_o\), and particularly with both larger \(n_v\) and larger \(n_o\).

**Results**

Our data cover 1,146,941 matches played by 1,975,877 unique players on a South Korean server in the period March 1-31, 2019. The matches involve 98,319,451 killings between players. Only a small portion of the players played the game regularly every day; 30% of the players accessed the game just on a single day, with a median participation period of three days (Fig. S4B). Over our observation period, 6,161 of the players, equivalent to 0.3%, were banned for cheating, 287,342 players were killed by a cheater at least once, and 1,185,279 players played in at least one game with a cheater. Cheaters represent a small proportion of all players but thousands of teams have two or more cheating members (Table S2), providing evidence for homophily and influence among friends regarding cheating. Further, since teams with more cheating members are more successful (Table S2), players likely aim to team up with cheaters. We need to account for these competing mechanisms when identifying the contagion of cheating among strangers.

Our definition of victimization and observation relies on the ability of players to identify who is a cheater but this is not guaranteed since cheaters are not flagged in the game. Cheaters often exhibit abnormal kill patterns which can give them away. In addition, PUBG offers an in-game system that allows players to watch replay recordings or watch the rest of the game from the perspective of their killers and the game company actively encourages players to use this system and report cheaters. To affirm the robustness of the effects we study to measurement errors, we use two different definitions of victimization and observation. We begin with a simple, more relaxed definition, according to which victimization occurs any time a player is killed by a cheater, while observation occurs when the cheater has killed at least two other players before the observer is killed.
Figure 3: Cheating is contagious only for those who both suffer from and observe it, and especially so in the case of multiple instances of victimization and observation. The analysis uses a simple definition of victimization and observation, whereby victimization occurs every time a player is killed by a cheater and observation occurs when a cheater kills at least two others while the player is still in the game. Cell numbers and colors show the probability to observe motif counts as large as the empirical ones in a randomized killing network, estimated over 200 randomizations.

First, we test for the overall effects by counting the motifs (1, 0), (0, 1), and (1, 1), regardless of whether they involve the same nodes. For example, if a player was never killed by a cheater but observed 2 cheaters, we count this as two (0, 1) motifs; if a player was killed by 3 cheaters and observed 4 cheaters, we count this as three (1, 1) motifs. We find that the probabilities to observe motif counts as large as the ones we have in the empirical networks compared to what we would expect in networks with randomized events are sufficiently small only for the (1, 1) motif (Fig. 3). This suggests that although we do not find evidence for direct effect from victimization and observation alone, their co-presence appears to be associated with adopting cheating more than expected by chance.

To establish whether the observed effect is driven by a large number of individuals with few instances of victimization and observation or by a small number of individuals with many instances, we next identify motifs with all combinations \((n_v, n_o)\) that occur frequently enough in the data (Fig. S5). In this case, if a player was never killed by a cheater but observed 2 cheaters, we count this as one (0, 2) motif; if a player was killed by 3 cheaters and observed 4 cheaters, we count this as one (3, 4) motif. Put differently, one (0, 1) motif now corresponds to a player who was never killed by a cheater but observed exactly one cheater. If the contagion effect is stronger with higher intensity of victimization and observation, then motifs with higher values for \(n_v\) and \(n_o\) will be the ones that are the most overrepresented.
Indeed, we observe that motifs with larger sum $n_v + n_o$ are the ones that are less likely to occur by chance (Fig. 3). On the one hand, this confirms the finding from the more general analysis that observation and victimization have an additive effect. On the other hand, it also suggests a complex contagion phenomenon whereby the contagion is more likely as the individual encounters a higher number of others who have already adopted the behavior.

Finally, we replicate the analyses with a stricter definition for victimization and observation. This time, we assume that only players who are among the 30% remaining in the game and are killed by a cheater are victimized, while only players who die after a cheater has killed at least five other players observe the cheater. Thus, the strict definition posits that a player would identify a cheater only if the levels of harm and observation are salient enough for them to pay attention and investigate. Alternatively, the strict definition implies that social contagion only occurs when the stimuli are sufficiently strong. Put differently, the stricter definition provides more reliable measurements of the phenomena, but also restricts the analysis to more impactful events.

The results are confirmed and appear even stronger when we use the stricter definition (Fig. 4). This suggests that the results are not driven by measurement errors and are robust to the operationalization decisions.

Figure 4: Using stricter definitions for victimization and observation confirms that cheating is contagious only for those who both suffer from and observe it and particularly for those with multiple instances of victimization and observation. According to the strict definition, victimization occurs if a player is killed by a cheater when the player is among the last 30% of survivors and observation occurs when a cheater kills at least five others while the player is still in the game. Cell numbers and colors show the probability to observe motif counts as large as the empirical ones in a randomized killing network, estimated over 200 randomizations.
Discussion

In this study, we aimed to find evidence for two different social mechanisms that enable the contagion of antisocial behavior. Most notably, we searched for this evidence in an actual social setting, outside of the lab. To do this, we made use of large-scale digital records of player interactions and activity in online gaming. Analyzing temporal motifs in the network of game interactions between players, we showed that the tendency to have players who suffer from and observe cheaters start cheating themselves cannot be fully explained with the composition, temporal patterns, and structure inherent to the system. This provides evidence that cheating is contagious. Specifically, we found evidence that cheating spreads when both victimization and observation are present. In addition, we discovered strongest evidence for contagion among those who both suffer from and observe a large number of cheaters, suggesting a complex contagion phenomenon [36].

Our unique social context and data allowed us to study population dynamics in ways that were impossible until recently. Online gaming systems represent a useful research tool for social scientists to investigate people’s behavior and its spread. The online gaming world can be considered a proxy for large social systems in general. But as always, generalizations to other social contexts should be made with caution. People in different social settings may have different attitudes or susceptibilities to peer influence and antisocial behavior. In addition, different kinds of antisocial behavior vary in the extent to which they are personally beneficial or damaging to others. Both of these characteristics could affect the contagion process.

Our work extends existing research on the contagion of social behavior in two different ways. First, we differentiate between the victimization and observation mechanisms in the spread of antisocial behavior, the former of which has received little attention in the literature so far. Most notably, we do this using observational data, which is notoriously difficult to accomplish given that selection and influence are confounded in social interaction networks. Studying the contagion of antisocial behavior in an actual social setting allows us to contextualize the mechanisms and their impact, as well as think more concretely about possible strategies to fight the spread of bad influence. Our study proves that cheating is a social phenomenon rather than a psychological trait. Since individuals’ interactions with cheaters affect the spread and prevalence of cheating, interventions should target interactions, rather than individuals.
Further, our work contributes to social research methodology by demonstrating the power of temporal motif analysis to differentiate between social mechanisms in large-scale data. The method allowed us to control for the compositional, temporal, and structural patterns in our data driven by the low incidence of the phenomenon we study, the peculiar nature of interactions, and the confounding effect of exogenous friendship relations. Both traditional statistical methods, such as logistic regression, and other advanced network approaches, such as exponential random graph models [37] and stochastic actor-oriented models [38], would struggle with the amount of data we analyzed. Alongside other previous studies that have used temporal motifs to distinguish between social mechanisms [39], we demonstrate the underused potential of this approach for gaining behavioral and sociological insights from large-scale temporal network data.

Nevertheless, we also recognize that our study has certain limitations. Our measures may not be precise enough since we had to use a number of assumptions and heuristics to estimate when identified cheaters start cheating and define when players experience and observe cheaters. In particular, we do not know whether victims of cheaters were fully aware that they were harmed by or observed cheaters because it is sometimes difficult to distinguish between cheaters and very skillful players. However, the fact that our results are relatively robust to different operationalizations of victimization and observation gives us confidence in the findings.

Further, our findings do not align with previous experimental research, which found an effect for victimization but not for a positive interaction between victimization and observation [16]. However, this discrepancy could easily be explained with the strength of the observed effects. It is possible that we cannot detect social contagion for those who only observe and those who only experience because the effects are simply too weak to detect in our data. Thus, at the very least, our results imply that social contagion is strongest and most detectable for those who both experience and observe.

Rather than providing a definitive answer to the problem of the contagion of antisocial behavior, we hope that our work inspires further research. There is need both for replications in the lab and generalizations to other social contexts and settings. For instance, our study can easily be repeated to investigate the spread of offensive language in online forums. In cases where detailed data on interactions are not readily available, instead of testing for the mechanisms directly, one can instead test for their macro-level implications. For example, the finding that victimization
positively interacts with observation would imply that there would be higher incidence of antisocial behavior in settings where it is directly and personally damaging. For instance, academic cheating is considered anti-social behavior but its negative effects are usually diffused. However, when grading happens “on the curve”, a cheater’s unfair advantage directly affects everyone else’s grades. Thus, we would expect that academic cheating would be more widespread in schools or courses that grade “on the curve” than those that do not and this hypothesis can be tested with observational studies and field experiments.

In terms of practical applications, our findings point to a number of ways to regulate cheating and antisocial behavior in online games specifically, but also in any social environment more generally. One strategy would be to micro-target individuals who both experience and observe antisocial behavior since they may be at a high risk to adopt it. For example, athletes who have in the past narrowly lost to a newly uncovered cheater may be more susceptible to doping or cheating. A complementary strategy would be to control the interactions of antisocial individuals and information about their activity in order to minimize the possibility that any individual would both experience and observe multiple instances of antisocial behavior. Finally, situations and settings that increase the personal costs from others’ antisocial behavior should be avoided. Thus, for example, schools and organizations could reduce the spread of cheating by abolishing practices such as grading students “on the curve” or evaluating employees with “forced ranking”, since, with them, one person’s cheating has direct effect on another person’s performance.

Materials and Methods

The data comprise gameplay logs and lists of players banned for cheating obtained between March 1 and March 31, 2019 from the South Korean PUBG server operated by Kakao Games. To estimate when banned players actually start cheating, we use a rule-based algorithm that considers the ban date, the average kill ratio per game, and the average time difference between consecutive kills (see SI).

We use temporal networks to represent interactions between players in matches. In the killing network, a time-stamped directed edge from node $i$ to node $j$ means that $i$ killed $j$ at a certain time during the match. Nodes have a property that describes whether they are currently cheating
or not. We use this information to create and overlay the cheater observation network, in which a
time-stamped directed edge from node $i$ to node $j$ indicates that $j$ just observed cheater $i$ cheat.
In PUBG, all players can see who killed whom in real-time through “kill feeds” that appear on
the upper right corner of the screen during the match (Fig. S1). Some players have recognized the
presence of cheaters by viewing the kill feeds that display killers and their victims on a real-time
basis, as these logs may reveal bot-like behavioral patterns of cheaters. For example, a player who
kills many other players consecutively in a very short time interval is more likely to be suspected
a cheater.

We use $(n+1)$-node, $n$-edge, $\delta$-temporal motifs to identify cases in which a player has observed
$n_o$ cheaters and has been killed by $n_v$ cheaters before starting to cheat within time $\delta$ of the first
event. Given the typical weekly cycle of gameplay activity in our data (Fig. S4A), we assume a
time window for influence of seven days ($\delta = 7$ days). We count the number of times the possible
$(n_v, n_o)$ motifs occur in the data and then measure the extent to which we would expect frequencies
of this magnitude given the complex structure of interactions the game entails and the behavioral
patterns players exhibit. This approach essentially tells us whether the temporal dependency we
hypothesize, e.g. if you suffer from or observe a cheater you adopt cheating, could occur simply
due to chance.

We randomize the interaction network to simulate alternative scenarios. We use the node-label
 permutation approach, which preserves the network and event structure but reshuffles the node
labels [40]. We permute cheaters in a match separately from non-cheaters in order to account
for the fact that cheaters kill more opponents than non-cheaters and thus exhibit higher node
outdegrees. Since 87.3% of the 107,139 matches with at least one cheater have exactly one cheater,
in most cases, cheaters remain in the same position as in the original network. In addition, if the
match is played in team mode, we permute players within teams only (Fig. 2). This accounts for
social influence or homophily from friends since cheaters are unlikely to kill their teammates but
more likely to be observed by them as teams typically move together.

We repeat the network randomization process 200 times and count the motifs in each instance.
We then estimate the proportion of randomized networks that produce a motif count that is equal
to or larger than the one in the empirical network. This gives us the estimated probability to obtain
the counts we observe in the empirical network by chance. In essence, we measure the extent to
which the transitions to cheating due to cheater victimization and observation could be occurring even when we randomly reassign who the victims and observers are. All analyses were carried out using Spark, Python, and R.

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References

[1] Tsvetkova, M. & Macy, M. W. The social contagion of generosity. *PLoS ONE* **9**, e87275 (2014).

[2] Kizilcec, R. F., Bakshy, E., Eckles, D. & Burke, M. Social influence and reciprocity in online gift giving. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, CHI ’18, 1–11 (Association for Computing Machinery, Montreal QC, Canada, 2018).

[3] Norbutas, L. & Corten, R. Sustainability of generalized exchange in the sharing economy: The case of the freecycling Facebook groups. *International Journal of the Commons* **12**, 111–133 (2018).

[4] Simpson, B., Harrell, A., Melamed, D., Heiserman, N. & Negraia, D. V. The roots of reciprocity: Gratitude and reputation in generalized exchange systems. *American Sociological Review* **83**, 88–110 (2018).

[5] Fowler, J. H. & Christakis, N. A. Cooperative behavior cascades in human social networks. *Proceedings of the National Academy of Sciences* **107**, 5334–5338 (2010).

[6] Wilson, J. Q. & Kelling, G. L. Broken windows. *Atlantic Monthly* **249**, 29–38 (1982).

[7] Cialdini, R. B., Reno, R. R. & Kallgren, C. A. A focus theory of normative conduct: Recycling the concept of norms to reduce littering in public places. *Journal of Personality and Social Psychology* **58**, 1015–1026 (1990).
[8] Keizer, K., Lindenberg, S. & Steg, L. The spreading of disorder. *Science* **322**, 1681–1685 (2008).

[9] Falk, A. & Fischbacher, U. Crime in the lab-detecting social interaction. *European Economic Review* **46**, 859–869 (2002).

[10] Gino, F., Ayal, S. & Ariely, D. Contagion and differentiation in unethical behavior: The effect of one bad apple on the barrel. *Psychological Science* **20**, 393–398 (2009).

[11] McCabe, D. L., Trevino, L. K. & Butterfield, K. D. Cheating in academic institutions: A decade of research. *Ethics & Behavior* **11**, 219–232 (2001).

[12] Carrell, S. E., Malmstrom, F. V. & West, J. E. Peer effects in academic cheating. *Journal of Human Resources* **43**, 173–207 (2008).

[13] Rettinger, D. A. & Kramer, Y. Situational and personal causes of student cheating. *Research in Higher Education* **50**, 293–313 (2009).

[14] Cheng, J., Bernstein, M., Danescu-Niculescu-Mizil, C. & Leskovec, J. Anyone can become a troll: Causes of trolling behavior in online discussions. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*, 1217–1230 (ACM, 2017).

[15] Kwon, K. H. & Gruzd, A. Is offensive commenting contagious online? Examining public vs interpersonal swearing in response to Donald Trumps YouTube campaign videos. *Internet Research* **27**, 991–1010 (2017).

[16] Tsvetkova, M. & Macy, M. The social contagion of antisocial behavior. *Sociological Science* **2**, 36–49 (2015).

[17] Meegan, D. V. Zero-sum bias: Perceived competition despite unlimited resources. *Frontiers in Psychology* **1**, 1–7 (2010).

[18] Bainbridge, W. S. The scientific research potential of virtual worlds. *Science* **317**, 472–476 (2007).
[19] Bartlett, M. Y. & DeSteno, D. Gratitude and prosocial behavior. *Psychological Science* **17**, 319–325 (2006).

[20] Hoobler, J. M. & Brass, D. J. Abusive supervision and family undermining as displaced aggression. *Journal of Applied Psychology* **91**, 1125–1133 (2006).

[21] Dimant, E. Contagion of pro- and anti-social behavior among peers and the role of social proximity. *Journal of Economic Psychology* **73**, 66–88 (2019).

[22] Jordan, J. J., Rand, D. G., Arbesman, S., Fowler, J. H. & Christakis, N. A. Contagion of cooperation in static and fluid social networks. *PLoS ONE* **8**, e66199 (2013).

[23] Aral, S., Muchnik, L. & Sundararajan, A. Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks. *Proceedings of the National Academy of Sciences* **106**, 21544–21549 (2009).

[24] Shalizi, C. R. & Thomas, A. C. Homophily and contagion are generically confounded in observational social network studies. *Sociological Methods & Research* **40**, 211–239 (2011).

[25] Blackburn, J., Kourtellis, N., Skvoretz, J., Ripeanu, M. & Iamnitchi, A. Cheating in online games: A social network perspective. *ACM Transactions on Internet Technology (TOIT)* (2014).

[26] Zuo, X., Gandy, C., Skvoretz, J. & Iamnitchi, A. Bad apples spoil the fun: Quantifying cheating in online gaming. In *Tenth International AAAI Conference on Web and Social Media* (2016).

[27] Wu, Y. & Chen, V. H. H. A social-cognitive approach to online game cheating. *Computers in Human Behavior* **29**, 2557–2567 (2013).

[28] Chen, V. H. H. & Ong, J. The rationalization process of online game cheating behaviors. *Information, Communication & Society* **21**, 273–287 (2018).

[29] Anagnostopoulos, A., Kumar, R. & Mahdian, M. Influence and correlation in social networks. In *Proceedings of the 14th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 7–15 (2008).
[30] Woo, J., Kang, S. W., Kim, H. K. & Park, J. Contagion of cheating behaviors in online social networks. *IEEE Access* **6**, 29098–29108 (2018).

[31] Milo, R. *et al.* Network motifs: Simple building blocks of complex networks. *Science* **298**, 824–827 (2002).

[32] Kovanen, L., Karsai, M., Kaski, K., Kertsz, J. & Saramki, J. Temporal motifs in time-dependent networks. *Journal of Statistical Mechanics: Theory and Experiment* **11**, 11005 (2011).

[33] Holme, P. & Saramki, J. Temporal networks. *Physics Reports* **519**, 97–125 (2012).

[34] Kovanen, L., Kaski, K., Kertsz, J. & Saramki, J. Temporal motifs reveal homophily, gender-specific patterns, and group talk in call sequences. *Proceedings of the National Academy of Sciences* **110**, 18070–18075 (2013).

[35] Paranjape, A., Benson, A. R. & Leskovec, J. Motifs in temporal networks. In *Proceedings of the Tenth ACM International Conference on Web Search and Data Mining*, 601–610 (ACM, 2017).

[36] Centola, D. & Macy, M. Complex contagions and the weakness of long ties. *American Journal of Sociology* **113**, 702–734 (2007).

[37] Lusher, D., Koskinen, J. & Robins, G. *Exponential Random Graph Models for Social Networks: Theory, Methods, and Applications* (Cambridge University Press, 2013).

[38] Snijders, T. A. B., van de Bunt, G. G. & Steglich, C. E. G. Introduction to stochastic actor-based models for network dynamics. *Social Networks* **32**, 44–60 (2010).

[39] Tsvetkova, M., Garca-Gavilanes, R. & Yasseri, T. Dynamics of disagreement: Large-scale temporal network analysis reveals negative interactions in online collaboration. *Scientific Reports* **6**, 36333 (2016).

[40] Croft, D. P., Madden, J. R., Franks, D. W. & James, R. Hypothesis testing in animal social networks. *Trends in Ecology & Evolution* **26**, 502–507 (2011).
[41] Alayed, H., Frangoudes, F. & Neuman, C. Behavioral-based cheating detection in online first person shooters using machine learning techniques. In 2013 IEEE Conference on Computational Intelligence in Games (CIG), 1–8 (2013).
Supporting Information for:

Large-scale network analysis reveals cheating spreads through victimization and observation

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Background information

PlayerUnknown’s Battlegrounds (PUBG) is a popular online multiplayer first-person shooter game (Fig. S5). First-person shooter is a game genre in which players use weapons to kill other players’ characters in the first-person point of view. A PUBG match involves up to 100 players. There are three different play modes depending on whether players cooperate with each other: solo, duo, and squad. In a solo match, players are on their own and in duo and squad matches, players can invite their friends to form a team of up to two or four, respectively. Players who do not have friends to invite are matched with random teammates. Players tend to play more duo or squad matches than solo matches, showing a preference for team play (Table S1).

At the beginning of a match, the players start from different spots on the virtual battlefield. They scavenge for weapons, which can be found all over the playing field, and kill other players they encounter to survive and win. Players can make a car or boat trip to move from one place to another. To prevent players from deliberately avoiding combat or hiding for a long time, the game constantly reduces the size of the battlefield over time. If players do not move to the safe area, they are harmed by a player-damaging barrier or bombs and eventually get killed. Thus, players ultimately end up in one place at the game’s conclusion after moving constantly to avoid danger zones. The last surviving player or team becomes the winner of the match.

As in most games, PUBG players become skillful by playing many matches and learning from experience. However, players can also use cheating tools that unfairly enhance their abilities and increase their chances of winning. These tools can be purchased from online providers or downloaded
for free. Many different types of cheating tools exist: for example, “aimbots” automatically aim a gun at other players and “wallhacks” make walls transparent to allow players to see or attack competitors hiding behind a wall.

**Data collection**

We gathered data from two different online sources between March 1 and March 31, 2019. First, we used the PUBG API to obtain gameplay logs from the Kakao Games server. Kakao Games is one of the two gaming platforms that distribute PUBG in South Korea (the other being Steam). Second, we downloaded the lists of banned cheaters that Kakao Games uploads daily on its website. The company defines cheating as any use of third-party software that violates its policies.

Due to restricted data access, we employed breadth-first search sampling for the gameplay logs. We started with a set of random matches returned by the API and retrieved all players in them. We then retrieved the game logs for all matches these players played in. For the new players in these matches, we also retrieved the game logs for all their matches, and so on. We repeated the process until we did not discover any new players. Since the out-of-date game logs on the platform expire after a retention period of 14 days, we revisited the logs of all players repeatedly in order to obtain longitudinal data during the month-long observation period. The Kakao Games server has a relatively small population compared to the servers maintained by Steam and randomly assigns players to matches, so we have confidence that we practically have a census of all matches played on the server in March 2019.

Initially, we collected data on a total of 1,291,441 matches. Each match is described with a link to a telemetry file, which contains a list of events that happened during the match and detailed logs. Due to technical issues with the API, it was impossible to decode about 9% of the telemetry files, leaving us with a dataset of 1,179,537 matches. Finally, we also removed 32,596 matches that were played in special modes such that players could revive multiple times. Thus, the final dataset we analyze consists of 1,146,941 matches.
**Estimating the time of cheating adoption**

Because the game company only provides the date when a ban is applied to a cheater, we need to estimate the time when identified cheaters actually start cheating. It is in the game company’s interest to detect cheaters as soon as possible but some cheaters may be reported or detected quickly, whereas others may go undetected for longer time periods. In some cases, the game company needs additional time for a thorough inspection before banning cheaters. For these reasons, it is likely that cheaters began cheating at different times even if they were banned on the same day.

To compensate for this missing information, we employ a data-driven approach and use the gameplay logs to estimate when a cheater starts to cheat. We employ a player behavior analysis approach, which is based on the idea that cheaters behave differently from non-cheaters [11]. To distinguish cheaters from non-cheaters, we assume that the features that are related to kill scores are most informative. We use two features: the average kill ratio per day and the average time difference between consecutive kills per day.

The average kill ratio per day is calculated by dividing the number of kills by the sum of the number of kills and deaths in a day. The average time difference between consecutive kills is measured if a player killed at least two other players during the match. This measure serves as an important feature for cheating detection. In general, cheaters tend to show abnormal and noticeable kill patterns with the help of cheating tools.

We note that there may be some cheaters who perform poorly even if they use cheating tools. In these cases, it is difficult to detect the timing of cheating adoption with the player behavior analysis we use. Nevertheless, we assume that non-cheaters are tempted to cheat when they observe that cheating tools are effective. In other words, we assume that the more successful cheaters are in killing other players, the more influential they are. Put differently, we regard performance as a proxy for the level of influence a cheater can exert on non-cheaters.

To confirm that cheaters and non-cheaters are fundamentally different in terms of performance, we first calculate the average kill ratio to compare the two groups. We tentatively suppose that cheaters who were banned between March 1 and March 3 were cheating during those three days and use them as a baseline for the estimation. The number of cheaters who were identified and banned during this period is 651, while the number of non-cheaters who played at least one match then is
854,153. As expected, we find that cheaters perform better than other players as they show a higher average kill ratio (Fig. S6A). The mean values of cheaters and non-cheaters are 0.77 and 0.40 and the median—0.82 and 0.44, respectively. Using Welch’s two-independent-samples t-test to compare the two groups, we obtain \( t(651.26 \text{ df}) = -48.64, p < 0.01 \), which is statistically significant.

Further, as expected, the average time difference between kills is shorter for cheaters than non-cheaters (Fig. S6B). The mean values for cheaters and non-cheaters are 139.67 and 194.11 seconds, respectively and the median—123.93 and 172.63. The difference between the two is statistically significant: Welch’s \( t(632.74 \text{ df}) = -18.24, p < 0.01 \).

On the basis of these observations, we came up with a rule-based algorithm to estimate the starting date of cheating. We assume that cheaters start cheating on the day when they meet the following two conditions: 1) average kill ratio greater than or equal to 0.8 and 2) average time difference between consecutive kills equal to or shorter than 140 seconds.

Among the 6,161 identified cheaters, complete performance information was available for 2,980. For these, the average duration of cheating before the ban was five days, with a modal value of two days (Fig. S7). For the 3,181 cheaters who had at least one missing value on performance or did not meet the conditions above, the modal value of two days was applied as the period of cheating. In the end, around 71% of all cheaters (4,387 players) were estimated to have cheated for two days.

**Statistical tests for motif counts**

Previous research typically uses z-scores to evaluate the deviation of the empirical motif counts from the null model \[34, 39\]. However, since the events we investigate are rare, the motif counts are relatively small (Fig. S9) and their expected value cannot always be described with a normal distribution defined by a mean and a standard deviation. For counts with a low expected mean, the Poisson distribution is more appropriate. We tested whether either of the two distributions fit the counts obtained in the randomized networks but there are important deviations in both cases, particularly salient for the motifs involving observation (Fig. S10 and S11). Consequently, we use neither of these statistical approximations and instead, we directly estimate the proportion of motif counts in the 200 randomizations that are as large or larger than the empirical motif counts. This gives us an estimation of the probability to observe motif counts as large as the empirical ones by
chance. One drawback of this approach, however, is that it prevents us from estimating an effect size. Thus, the method allows us to find evidence for the mechanisms but not to quantify their strength.
Figure S5: Screenshot from a match of PlayerUnknown’s Battlegrounds. Kill feeds (upper right corner) display killers and their victims in real time. Image source: https://www.reddit.com/r/PUBATTLEGROUNDS/comments/7cu7lz/is_this_kill_feed_new_found_a_setting_for_it_in/
Figure S6: A) Histogram of the average kill ratio for cheating and non-cheating players. B) Histogram of the average time difference between consecutive kills for cheating and non-cheating players (outliers are excluded).

Figure S7: Histogram of the period of cheating for the 2,980 cheaters with full information on performance.
Figure S8: A) Number of matches played by day for the period March 1–31, 2019. The sudden dip in the last trough is due to the game server being down between 9:30 am and 4:30 pm on March 28th as part of routine maintenance. B) Histogram of the number of days players accessed the game during the month-long data collection period.
Figure S9: The frequency of \((n_v, n_o)\) motifs in the empirical data for A) simple and B) strict definition of experience and observation. Under the simple definition, victimization occurs every time a player is killed by a cheater and observation occurs when a cheater kills at least two others while the player is still in the game. Under the strict definition, victimization occurs if a player is killed by a cheater when the player is among the last 30% of survivors and observation occurs when a cheater kills at least five others while the player is still in the game. The plots exclude the outliers with more than 20 observations.
Figure S10: $\chi^2$ goodness-of-fit tests for whether the motif counts from the 200 network randomizations follow a normal distribution with the same mean and standard deviation. Cell numbers and colors show the $p$-value for testing the null hypothesis that the two distributions are identical; a small $p$-value ($p < 0.05$) means that the null hypothesis can be rejected and the two distributions are sufficiently different.
Figure S11: $\chi^2$ goodness-of-fit tests for whether the motif counts from the 200 network randomizations follow a Poisson distribution with the same mean rate. Cell numbers and colors show the $p$-value for testing the null hypothesis that the two distributions are identical; a small $p$-value ($p < 0.05$) means that the null hypothesis can be rejected and the two distributions are sufficiently different.
Table S1: Number of matches and number of matches with cheaters by game mode.

| Game mode | Num. matches | Num. cheaters |
|------------|--------------|---------------|
|            |              | 1  | 2   | 3   | 4   | 5   | 6   |
| Solo       | 124,421 (10.8%) | 10,265 | 951 | 77  | 3   | 0   | 0   |
| Duo        | 359,870 (31.4%) | 19,195 | 1,730 | 135 | 11  | 0   | 0   |
| Squad      | 662,650 (57.8%) | 64,095 | 9,079 | 1,355 | 212 | 27  | 4   |
| Total      | 1,146,941 (100.0%) | 93,555 | 11,760 | 1,567 | 226 | 27  | 4   |

Table S2: Rate of success for cheating solo players and for teams with cheating teammates.

| Num. cheaters | Num. players | Prop. who win | Prop. in top 30% |
|---------------|--------------|---------------|------------------|
| Solo matches  |              |               |                  |
| 0             | 1,049,113    | 0.01          | 0.28             |
| 1             | 12,410       | 0.13          | 0.42             |
| Duo and squad matches | 143,791 | 0.00          | 0.19             |
| 1 (single-player team) | 4,889 | 0.08          | 0.30             |
| 0             | 2,807,526    | 0.03          | 0.38             |
| 1             | 96,747       | 0.15          | 0.55             |
| 2             | 4,094        | 0.26          | 0.60             |
| 3             | 187          | 0.39          | 0.69             |
| 4             | 11           | 0.82          | 0.91             |

Note: The statistics are calculated over the 107,139 matches with at least one cheater.