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Evolution of cooperation under social pressure in multiplex networks

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In this work, we aim to contribute to the understanding of human prosocial behavior by studying the influence that a particular form of social pressure, "being watched," has on the evolution of cooperative behavior. We study how cooperation emerges in multiplex complex topologies by analyzing a particular bidirectionally coupled dynamics on top of a two-layer multiplex network (duplex). The coupled dynamics appears between the prisoner's dilemma game in a network and a threshold cascade model in the other. The threshold model is intended to abstract the behavior of a network of vigilant nodes that impose the pressure of being observed altering hence the temptation to defect of the dilemma. Cooperation or defection in the game also affects the state of a node of being vigilant. We analyze these processes on different duplex networks structures and assess the influence of the topology, average degree and correlated multiplexity, on the outcome of cooperation. Interestingly, we find that the social pressure of vigilance may impact cooperation positively or negatively, depending on the duplex structure, specifically the degree correlations between layers is determinant. Our results give further quantitative insights in the promotion of cooperation under social pressure.

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I. INTRODUCTION

Human cooperation is a ubiquitous yet not fully-understood phenomenon. Explaining how cooperation emerges and withstands selfish behaviors is one of the biggest challenges in natural and social sciences. Multiple mechanisms have been proposed to explain under which conditions cooperation emerges and is sustained: direct reciprocity (repetition), indirect reciprocity (reputation), spatial selection, multilevel (group) selection, and kin selection [1–3].

Evolutionary game theory [4–6] is the arena to analyze the evolution of cooperation. In the past several years, many experimental studies with humans facing game-theoretical dilemmas have been conducted [7–10]. Interestingly, these experiments have challenged the way we understand human cooperation, and more work on the consequences of these experiments have to follow.

Another way to approach the understanding of the evolution of cooperation in human societies consists of deciphering from historical records the cooperative behavior in ancient communities. In a previous work [11] we studied cooperation in the Yamana society who inhabited the Beagle Channel in Argentina, with respect to sharing beached whales (a scarce, unpredictable, and valuable resource). In that work we observed that the emergence of an informal network of vigilance promoted cooperation.

Historically, ancient societies have exploited the power that images of watchful eyes have on people. We can find examples in totem monuments decorated with eyes to enhance charitable behaviors in tribes [12]; different religions use this power to promote honesty [12], which is coherent with the *Supernatural Monitoring Hypothesis*, which states that the perception of being watched promotes prosocial behavior [13,14], "They remind us that our actions have consequences" [12].

The essential idea is that being watched can play an important role in promoting prosocial cooperative behavior. Several field studies have found evidence of humans exposing a prosocial behavior when being observed by others (recently confirmed in a field experiment with 2000 individuals [15]) and also under the presence of subtle cues of being watched. Although there are also some studies that could not find such evidence. A review on the topic can be found in Refs. [16,17]. A possible reason for the failure of previous studies in eye cue influence is proposed in Ref. [17], where the authors found that people with weak public self-awareness, i.e., people not concerned about how they appear in the eyes of others, are not affected by the watching eyes phenomenon. The observability effect (the increase of cooperation under vigilance) seems to be driven by our reputational concerns, bringing the indirect reciprocity mechanism into play.

This work is aimed to shed light, from a complex networks perspective, on the phenomenon mentioned above, i.e., the emergence of cooperation in a networked society interacting with a network of vigilance. The effect of the structure of interactions on different social dilemmas has been largely studied within the scope of network theory over the past few years, from topology influence [18] to spatial and temporal effects [19]. Recently, a new perspective for the representation of multiple types of social interactions has been proposed under the name of multiplex networks. Different kinds of interactions are modeled by different interconnected layers [20,21]. This approach has been successfully applied to the study of the prisoner's dilemma (PD) game [22] and also to the understanding of cooperation in coupled networks [23].

We adopt a similar approach here, modeling our problem in the scope of a multiplex network. Specifically, we investigate the interplay between two dynamical processes, an evolutionary game (a prisoner's dilemma) and dynamical social pressure (a vigilance network evolving according to a threshold dynamics), and the duplex structure of these interactions.

The paper is organized as follows. We present the definition of the model in Sec. II. Results obtained by means of simulation are analyzed in Sec. III. First, we focus our analysis on the influence of these coupled dynamics on cooperation under different monoplex network structures (Sec. III A) and the

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impact that different costs of vigilance have on the outcome of cooperation (Sec. III B). Second, in Sec. III C, the analysis moves to a duplex structure of networks, where we study how the topologies and average degrees of the different layers affect cooperation and also how the layer-degree correlations can promote or hinder cooperation. Last, a modification is introduced on the vigilance dynamics, where a vigilance actor can stop being vigilant. The influence of this dynamics is studied in Sec. III D. Finally, we conclude with Sec. IV by summarizing what insights are offered by our work.

II. MODEL DYNAMICS

A. Description of the model

The abstracted framework for our analysis is a networked system of agents (nodes) playing a theoretical game under vigilance pressures. In particular, our agents play an evolutionary PD game. The links define the neighborhood of the players and with whom they are playing. The same players involved in the game are also endowed with a state that defines them as vigilant or not. The whole dynamics is composed by an interaction between the spreading of the vigilant behavior and the game. The game is divided into two phases: (1) payoff recollection and (2) strategy update.

In phase 1, at each round, node i can choose to play one of the two strategies, cooperation (C) or defection (D). The PD game can be defined according to its payoff matrix (entries correspond to the row player's payoffs):

$$\begin{array}{cc} & \begin{array}{cc} C & D \end{array} \\ \begin{array}{c} C \\ D \end{array} & \begin{pmatrix} R & S \\ T & P \end{pmatrix} \end{array}, \tag{1}$$

where R represents the reward obtained by a cooperator playing against another cooperator; S is the sucker payoff obtained by a cooperator when she plays against a defector; the temptation payoff, T, is the payoff received by a defector when his opponent is a cooperator; and, finally, P represents the payoff obtained by a defector which engages with another defector. In the PD [24], $T > R > P > S$. We rescale the game so it depends on only one parameter, as is done traditionally [25]. We define b as the advantage of defectors over cooperators, being $T = b > 1$. The values of R and P are fixed to $R = 1$ and $P = 0$ in order to provide a fixed scale for the game payoffs. Applying this constraint, it turns out that the selection of the remaining parameters b and S enables the definition of several games according to their evolutionary stability. We will focus on the PD with $S = 0$ (weak PD [25]) then being the only parameter of the game the advantage of defectors over cooperators b.

For the spreading of the vigilance behavior, we will assume a cascade-of-imitation effect. Players activate (become vigilant) ($V_i^{0\to 1} = 1$) following a Watt's threshold model [26]:

$$V_i^{0\to 1}(m_i,k_i) = \begin{cases} 1 & \text{if } m_i/k_i > \theta_i, \\ 0 & \text{if } m_i/k_i \leqslant \theta_i, \end{cases} \tag{2}$$

where m_i is the number of neighbors of the node i that are already vigilant, k_i is the degree of node i, and θ_i the personal threshold of node i above which she becomes vigilant.

Players are affected by the pressure of being watched by their neighborhood, which modifies their temptation to defect, decreasing it as the pressure (percentage of vigilant neighbors) increases. The individual temptation T_i of node i is

$$T_i = R + (T - R)(1 - m_i/k_i), \tag{3}$$

where again m_i is the number of neighbors of the node i that are already vigilant, and k_i is the degree of node i. The fitness of an individual is the accumulated payoff after playing k_i PD games with her neighbors.

The second phase of the game is the update of individual strategies, which is performed each generation. Darwinian dynamics are introduced to promote the fittest strategy. The replicator dynamics [27] is the traditional approach for well-mixed populations (populations with no structure where individuals play with each other). For evolutionary models, finite populations and discrete time, the equivalent classic approach is the use of the proportional imitation rule [28,29]. The update of strategies is performed as follows. Let N be the number of individuals in the population, s_i the strategy the individual i is playing, and π_i her payoff. With the proportional imitation rule, each individual i randomly choose one from her k_i neighbors (individual j) and adopts her strategy with probability:

$$p_{ij}^t \equiv P\{s_j^t \to s_i^{t+1}\} = \begin{cases} (\pi_j^t - \pi_i^t)/\Phi & \text{if } \pi_j^t > \pi_i^t, \\ 0 & \text{if } \pi_j^t \leqslant \pi_i^t, \end{cases} \tag{4}$$

where $\Phi = max(k_i,k_j)[max(1,T) - min(0,S)]$ so $p_{ij}^t \in [0,1]$.

The strategies of the individuals are updated synchronously. Note that we identify vigilance as a prosocial engagement activity, and then we assume that noncooperative individuals will not be willing to engage this costly action, i.e., defectors will loose their be vigilant state when acquiring the defection strategy, although they could gain again the vigilant state by social pressure the next step of the vigilance dynamics.

The dynamics are sequenced as follows. First, players update their temptation to defect [Eq. (3)] and then their vigilance status [Eq. (2)]. Then the game dynamics takes place and players play k_i PDs with their neighbors (phase 1), and afterwards strategies are updated (phase 2). The two dynamics (vigilance and game) are advanced iteratively (one step of vigilance, one step of game dynamics) until the stop condition (as shown afterwards at Sec. II B) is reached.

B. Simulations

All simulations presented hereafter have been carried out for networks of 1000 nodes and results are averaged over at least 100 different realizations of the initial conditions.

Players are randomly initialized as cooperators or defectors with equal probability. The cooperators are also equiprobably chosen to be either vigilant or nonvigilant, while defectors are always nonvigilant. So, on average, we start with half of the population as cooperators, half as defectors, and a quarter as both cooperators and vigilant. All players have the same personal threshold θ_i in each simulation run, so for the sake of simplicity, it will appear as θ thereafter.

Statistics are measured after a transient of 100 000 generations and averaged over a time window of 100 generations if the system has reached a stationary state defined by the slope of the average fraction of cooperators $\langle\rho\rangle$ being inferior to 10^{-2}; if not, then we let the system evolve subsequent time windows of 100 generations.

III. INTERPLAY BETWEEN STRUCTURE AND DYNAMICS

A. Cooperation dynamics over a monoplex structure

First, we focus on the aforementioned two biderectionally coupled dynamics over a monoplex network. We show that cooperation is significantly enhanced when players feel the pressure of being watched, independently of the topology and the average degree of the network (Fig. 1). Cooperation promotion is affected by the personal threshold θ, as Fig. 1(a) shows.

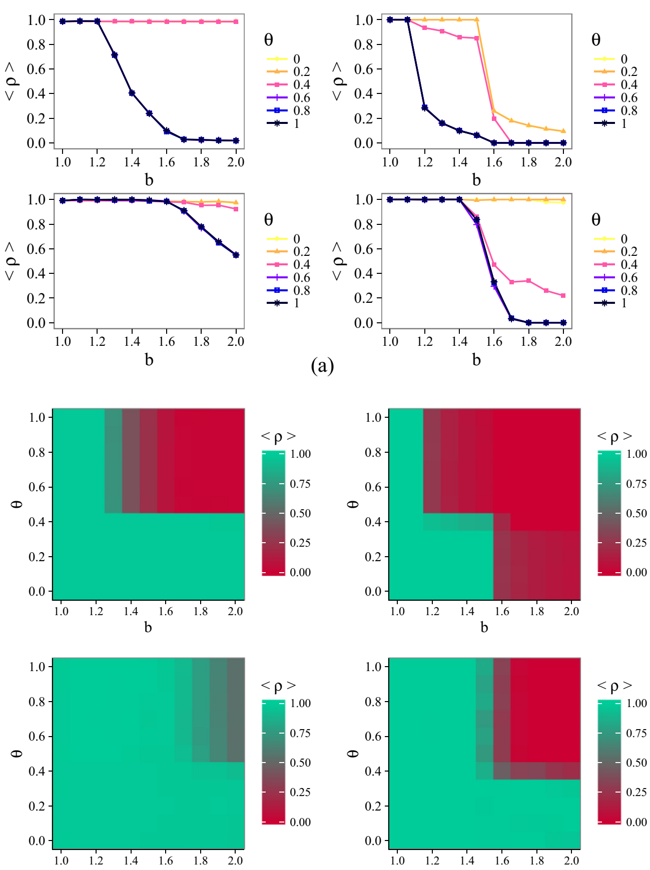


FIG. 1. Simulation results for an Erdös-Rényi network (upper panels of both subfigures) and Barabási-Albert network (bottom panels of both subfigures) with average degrees $z = 4$ (left) and $z = 16$ (right). Panel (a) shows the average fraction of cooperators $\langle\rho\rangle$ as functions of the advantage of defectors b, and (b) shows the average fraction of cooperators $\langle\rho\rangle$ as functions of the personal threshold θ of the nodes (horizontal axis) and as functions of the advantage of defectors b (vertical axis). The maximum standard error (SE) of all $\langle\rho\rangle$ values in the figure is 0.048.

There is a phase transition in $\langle\rho\rangle$ as functions of θ. The critical point happens around $0.5 < \theta < 0.8$. Values of θ below this point promote cooperation for both network configurations, as Fig. 1(a) shows, and values of θ above the critical point make no difference in the outcome of cooperation with respect to the case with no vigilance network. It can be observed that values of $\theta < 0.5$ are sufficient to promote cooperation and, more importantly, it can be quantified. The higher the threshold, the more vigilant neighbors a player need to become vigilant, too, and the more difficult is to promote cooperation based on vigilance.

The average fraction of cooperators $\langle\rho\rangle$ as functions of the personal threshold θ of the nodes and as functions of the advantage of defectors b is shown in Fig. 1(b), where the bottom-left (green) areas represent cooperation ($\langle\rho\rangle$ greater than 0.5) and the top-right (red) areas represent defection ($\langle\rho\rangle$ lower than 0.5).

The influence of the vigilance network on cooperation is far more pronounced for the Barabási-Albert networks. In the case of $z = 4$ [Fig. 1(b), bottom-left panel], cooperation is fully achieved in almost all regions of the parameter space. For $z = 16$ cooperation emerges for $b < 1.5$ independently of the θ value, which does not hold for the Erdös-Rényi network, where cooperation is fully achieved ($\langle\rho\rangle = 1$) in a 70% of the parameter space ($b < 1.5$, all θ values; and $b \geqslant 1.5$, $\theta < 0.4$).

Until now, we have studied a population with the same personal threshold θ. A more realistic approach is to have a heterogeneous population, i.e., to initialize the population with random θ_i values. If we initialize the θ_i of the population with values drawn from a uniform distribution U[0,1], then the expected $\langle\theta\rangle = 0.5$ and indeed the results for the average fraction of cooperators $\langle\rho\rangle$ are undistinguishable from the ones obtained when $\theta_i = 0.5$. This also holds for the duplex network case in Fig. 3.

B. Influence of cost of the vigilance action

So far our analysis of the interplay between vigilance and cooperation assumed no cost for the vigilance action. However, a more realistic hypothesis is that vigilance comes at a certain cost for the action. We have introduced this cost in the following way: we consider that every agent has to afford a vigilance cost each generation, which is a fraction (Cv) of her reward in the game R. Figure 2 shows the influence of Cv in the outcome of cooperation for the Barabási-Albert network.

When the cost of vigilance is high ($0.5R$ and $0.75R$, middle and left panels of Fig. 2), the vigilance network can promote cooperation and defection depending on the value of the temptation parameter b. Note that the percentage of vigilant nodes in the population $\langle V\rangle$ corresponds to the critical point in b (not the same for all θ) from which full cooperation is dismantled. This critical point in b where $\langle V\rangle$ starts to be inferior to 1 can be used as a predictor for the critical point in b above which full cooperation disappears, as the dashed vertical gray lines in Fig. 2 exemplify for several arbitrary θ values. As the cost of vigilance Cv increases, the critical point (above which full cooperation is dismantled) is shifted to lower values of b.

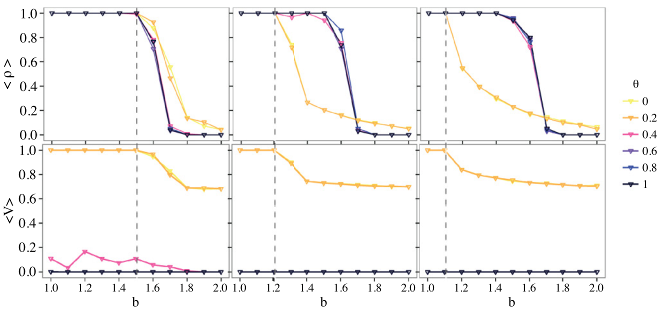


FIG. 2. Average fraction of cooperators $\langle\rho\rangle$ (top panels) and average fraction of vigilant players $\langle V\rangle$ (down panels) for Barabási-Albert networks with $z = 16$ and cost of vigilance Cv 0.25R (left), 0.5R (middle), and 0.75R (right). The higher the cost of vigilance, the lower the average fraction of cooperators $\langle\rho\rangle$ in the regions of b where the population is not fully vigilant. The maximum SE of all $\langle\rho\rangle$ values in the figure is 0.023.

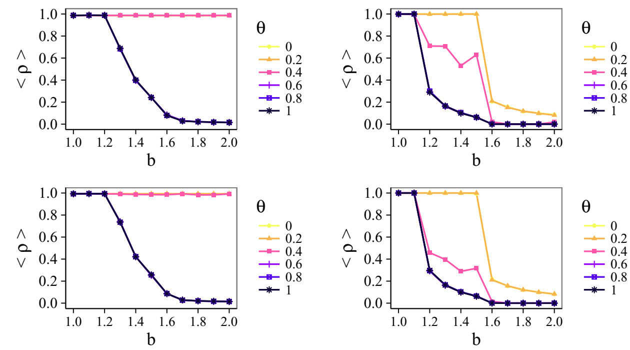
C. Cooperation dynamics over a duplex structure

We extend the analysis to a duplex structure of networks: a network for the game dynamics and a network for the vigilance dynamics. We study the bidirectional coupling of both layers. From now on, we will not assume a cost for the vigilance action.

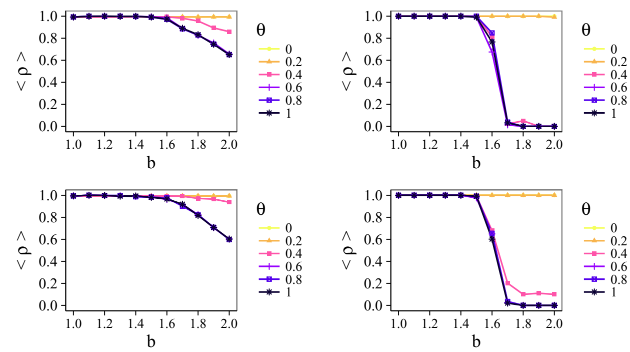
First, we will consider that both layers have the same average degree and we will study the influence of network topology. For a vigilance network with a given average degree and topology, we study the influence of vigilance layer for different game networks topologies. For example, for a vigilance Barabási-Albert network with $z = 16$ [Fig. 3(b), right panels], the average fraction of cooperators $\langle\rho\rangle$ is shown for the case where the game network is a Barabási-Albert network (upper panel) and an Erdös-Rényi network (bottom panel). For the four vigilance network configurations studied, the vigilance network has a significant influence on the dynamics of cooperation so there is no significant difference in the stationary average fraction of cooperators $\langle\rho\rangle$ for different game network topologies, as can be seen in Fig. 3. The outcome of cooperation is led by the vigilance network.

Now, let us focus on the case where vigilance and game layers do not have equal average degree. As Fig. 4 shows, the average degree of the vigilance layer dominates the dynamics of cooperation. Indeed, there is no significant difference in the average fraction of cooperators $\langle\rho\rangle$ obtained where the game layer has the same average degree of the vigilance network or it does differ and when the topology of the game layer differs. It can be seen that each panel in Fig. 4 shows the same average fraction of cooperators $\langle\rho\rangle$ as the one in Fig. 3. For example, the top-left panel in Fig. 4 corresponds to the Fig. 1(a) left panels, and it also holds for the other panels in Fig. 4 and its correspondence in Fig. 3. Vigilance networks with higher average degree hinder cooperation, since it is more difficult for an agent to fulfill her threshold to become vigilant, and, therefore, the diffusion of the vigilance dynamics is more costly.

Now we study the impact of correlated multiplexity, i.e., layer-degree correlations, since in real-world complex systems the degree of nodes in the different layers of the multiplex



(a)Vigilance networks as Erdös-Rényi. Game networks as Erdös-Rényi (top) and Barabási-Albert (bottom). Both layers with the same degree, z=4 (left) or z=16 (right).



(b)Vigilance networks as Barabási-Albert. Game networks as Erdös-Rényi (top) and Barabási-Albert (bottom). Both layers with the same degree, z=4 (left) or z=16 (right).

FIG. 3. Average fraction of cooperators $\langle\rho\rangle$ for a duplex structure of networks. The combination of network topologies (Erdös-Rényi and Barabási-Albert networks) and average degrees (both layers with the same degree, $z = 4$ or $z = 16$) are explored. The vigilance network drives the cooperative outcome of the game dynamics. The vigilance network promotes cooperation as in the monoplex scenario (Fig. 1). The maximum SE of all $\langle\rho\rangle$ values in the figure is 0.05.

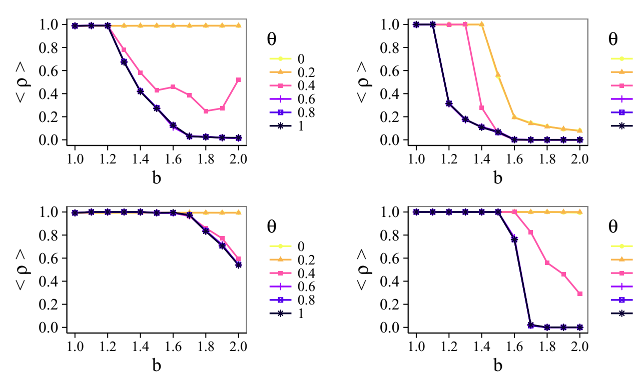
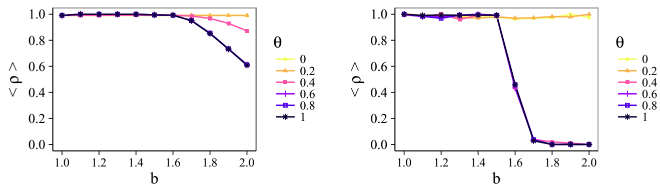
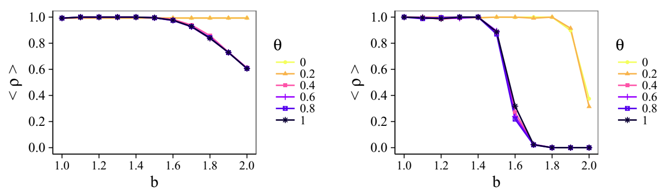


FIG. 4. Average fraction of cooperators $\langle\rho\rangle$ for a duplex structure of networks, where layers have different average degrees. Vigilance and game networks both as Erdös-Rényi (top panels), and vigilance and game networks both as Barabási-Albert (bottom panels). Vigilance networks with $z = 4$ and game networks with $z = 16$ (left panels), and vigilance networks with $z = 16$ and game networks with $z = 4$ (right panels). The maximum SE of all $\langle\rho\rangle$ values in the figure is 0.05.



(a)Maximally positive correlated multiplexity.



(b)Maximally negative correlated multiplexity.

FIG. 5. Average fraction of cooperators $\langle\rho\rangle$ for a duplex structure of Barabási-Albert networks. The degree distributions of the layers are maximally positive correlated (a) and maximally negative correlated (b). The average degree of both layers of the duplex is the same and takes the values $z = 4$ (left) and $z = 16$ (right). The maximum SE of all $\langle\rho\rangle$ values in the figure is 0.044.

structure are not randomly distributed but correlated. We focus this study on a duplex structure where both layers are Barabási-Albert networks, as the majority of real-world social networks present scale free degree distributions with exponent between 2 and 3.

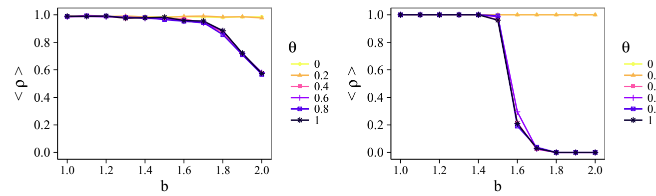
Maximally positive and negative correlations between the duplex layers are constructed as explained in Ref. [30].

Results for layers with average degree distribution $z = 4$ (Fig. 5, left panels) do not show to be influenced significantly by the correlated multiplexity of their layers. It is not the same for higher average degrees (Fig. 5, right panels). When the degree distribution of game and vigilance layers are maximally positive correlated [Fig. 5(a)], cooperation is fairly promoted ($\theta \leqslant 0.3$ end up with $\langle\rho\rangle = 1$) compared to the uncorrelated scenario [Fig. 1(a), bottom panels]. In the opposite case, where layers are maximally negative correlated [Fig. 5(b)], cooperation is drastically hindered. The critical point where cooperation is dismantled is shifted to lower b values for all θ values. In fact, for values of b larger than 1.8 full cooperation in not achieved for any θ value.

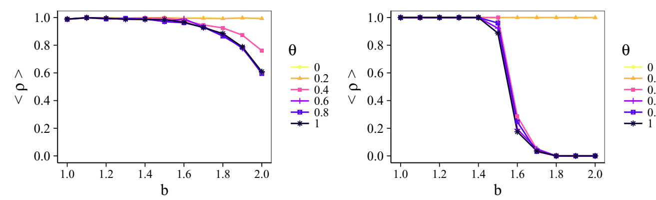
D. Vigilance dynamics with giving-up option

So far the dynamics for the vigilance layer accounted that once an agent has become vigilant, she cannot scape this situation. In real situations, people can stop feeling social pressure or just decide to change their opinion or action. In this subsection, we take into account the possibility of giving up being vigilant. We approach this by two means: (1) using the threshold of vigilance in a reverse way and (2) with a probability of giving up vigilant. We analyze this situation for a duplex of Barabási-Albert networks.

First, let us consider the vigilance dynamics as composed by two processes: becoming vigilant and becoming nonvigilant. The process of becoming vigilant is the same as in Eq. (2).



(a)Inverse threshold model.



(b)Probability of giving up vigilance.

FIG. 6. Average fraction of cooperators $\langle\rho\rangle$ for a duplex structure of Barabási-Albert networks when actors can give up being vigilant: (a) There is not enough social pressure in the neighborhood or (b) with a probability $p = 0.05$. The average degree of both layers of the duplex is the same and takes the values $z = 4$ (left) and $z = 16$ (right). The maximum SE of all $\langle\rho\rangle$ values in the figure is 0.03.

The process of giving up vigilance $V_i^{1\to 0}$ follows an inverse threshold model, where an agent become nonvigilant because there are not enough vigilant actors in her neighborhood:

$$V_i^{1\to 0}(m_i,k_i) = \begin{cases} 1 & \text{if } m_i/k_i \leqslant \theta_i, \\ 0 & \text{if } m_i/k_i > \theta_i, \end{cases} \tag{5}$$

As Fig. 6(a) shows, the average fraction of cooperation $\langle\rho\rangle$ is still influenced by the threshold of vigilance θ. Cooperation is most costly now and is only promoted when actors do not need much social pressure to become vigilant [$\theta < 0.4$, which is inferior to the threshold needed to promote cooperation in the case in Fig. 3(b) (bottom panels)].

If actors become vigilant again following a threshold model [Eq. (2)] but can give up vigilance with a probability $p = 0.05$, then we find comparable results [Fig. 6(b)]. Slightly higher cooperation levels can be found for the case with $z = 4$ and $\theta = 0.4$ [Fig. 6(b), left panel] related to the scenario in Fig. 6(a). Broadly, we can conclude that giving the option of stopping the vigilance action does not hinders cooperation, but there are few θ values for which cooperation is enhanced.

IV. CONCLUSIONS

Summarizing, we have presented a computational analysis of the interplay between vigilance network dynamics and game dynamics, showing that the pressure of being watched plays a significant role in the outcome of cooperation, having both the effect of a booster and dismantler. When agents are easily affected by social pressure (low θs in our model), cooperation can be promoted. But if the vigilance action is costly for the agents, it can also happen than defection is promoted, so it might be a double-edged sword. When these dynamics occur over a duplex structure of networks, the vigilance dynamics studied in this work became dominant over the game dynamics, so one could focus on studying the characteristics of the vigilance network and pay less attention to the structure of the game interactions. Moreover, the existence of layer degree correlations between the duplex layers can affect cooperation, mainly when these correlations are maximally negative, in which case it is more difficult to promote cooperation based on vigilance. Hence, we show that the conditions for the observability effect to emerge are not trivial, and subsequent experimentation with real humans would be of much interest to fully understand the impact of being watched on cooperation.

These results clear the ground for a framework to quantify the promotion of cooperation in structured populations that use vigilance to enhance prosocial behavior.

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