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Synergistic interactions promote behavior spreading and alter phase transition on multiplex networks

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Synergistic interactions are ubiquitous in the real world. Recent studies have revealed that, for a single-layer network, synergy can enhance spreading and even induce an explosive contagion. There is at the present a growing interest in behavior spreading dynamics on multiplex networks. What is the role of synergistic interactions in behavior spreading in such networked systems? To address this question, we articulate a synergistic behavior spreading model on a double layer network, where the key manifestation of the synergistic interactions is that the adoption of one behavior by a node in one layer enhances its probability of adopting the behavior in the other layer. A general result is that synergistic interactions can greatly enhance the spreading of the behaviors in both layers. A remarkable phenomenon is that the interactions can alter the nature of the phase transition associated with behavior adoption or spreading dynamics. In particular, depending on the transmission rate of one behavior in a network layer, synergistic interactions can lead to a discontinuous (first-order) or a continuous (second-order) transition in the adoption scope of the other behavior with respect to its transmission rate. A surprising two-stage spreading process can arise: due to synergy, nodes having adopted one behavior in one layer adopt the other behavior in the other layer and then prompt the remaining nodes in this layer to quickly adopt the behavior. Analytically, we develop an edge-based compartmental theory and perform a bifurcation analysis to fully understand, in the weak synergistic interaction regime where the dynamical correlation between the network layers is negligible, the role of the interactions in promoting the social behavioral spreading dynamics in the whole system.

I. INTRODUCTION

A central problem in network science and engineering is to understand, predict, and control the dynamics of virus or information spreading on complex networks [1–3]. Social contagion processes such as the propagation of an opinion, diffusion of a belief, and spread of a particular behavior, occur commonly in the real world [4–11]. With the modern technological advances, a variety of online social networking platforms (e.g., Facebook and Youtube) have become a routine necessity for a substantial fraction of individuals in the entire population. Spreading dynamics in modern online social networks have attracted a great deal of recent attention and a variety of mathematical models have been articulated to understand and predict the relevant phenomena [3, 12–14]. For example, the threshold model, a binary state spreading model, was introduced earlier to address the phenomenon of behavior adoption, where a node in a social network adopts a new behavior only when the number [15] or the fraction [16] of its nearest adopted neighbors exceeds a threshold value. A representative threshold model reveals the phenomenon that the final size of the nodes adopting the behavior first grows continuously and then decreases discontinuously as the mean degree of the network is increased [16]. Within the threshold model, the effects of parameters and network structure on the dynamics of social behavioral spreading have been studied, which include the initial seed size [17], the clustering coefficient [18–20], the community structure [21, 22] and multiplexity [23–25]. The dynamical process described by the threshold model, however, is Markovian because the state of a node depends only on the current state of its neighbors. The original model is thus not able to encompass an important aspect of real contagion dynamics: social reinforcement originated from the memory effect [26–29] - a feature that is characteristically non-Markovian. To overcome this deficiency of the classical threshold model, a non-Markovian behavior spreading model taking into account the received cumulative pieces of behavioral information for any node to adopt the behavior was introduced [30]. A prediction of the modified model is that the dependence of the final behavior adoption size on the information transmission rate can change from being discontinuous to being continuous through continuous changes in the dynamical or structural parameters. The non-Markovian behavior spreading model also allows additional issues such as the heterogeneity of adoption thresholds [31], the limited contact capacity [32], and the effect of temporal network structure [33] to be addressed.

Most previous works on network behavior spreading focused on a single social behavior contagion process through empirical methods [8, 9] and mathematical models [13–
In the real world, it is common for two or more distinct behaviors to spread simultaneously in a social system, where interactions between the corresponding spreading processes inevitably arise. For example, individuals who have adopted Windows services are more likely to use other services from the same company, e.g., Microsoft Office. In online networking systems, two different tweets on the same event or subject can diffuse on the twitter network at the same time. The user seeing one tweet will experience an increased exposure to the other tweet, and vice versa, since these two tweets are closely related. In this case, the two tweets spread synergistically as they mutually prompt each other in the process of retweeting [35]. The synergistic mechanism is also typical in the adoption of online services. A good example is the adoption of two online services, say Google and Youtube through two types of tweets: one containing the URLs with google and another with youtube. The numbers of the two types of tweets are synchronized most of the time, implying that they are synergistic to each other [36]. The synergistic effect also occurs in disease spreading, where the interaction between pathogens may mutually strengthen their spreading process, and such an effect may have played a role in the co-epidemic of the Spanish flu and pneumonia in 1918 [37–41]. In spite of its ubiquity, the synergistic mechanism among two or more simultaneously spreading behaviors was not investigated in previous studies [13–16, 30].

In this paper, we articulate a synergistic social behaviors spreading model to address and understand the impacts of synergistic interactions among multiple behaviors on their spreading. As the spreading of each behavior typically occurs on a different network layer, it is necessary to incorporate a multilayer network structure [42–44]. To be concrete, we consider the spreading dynamics of two distinct behaviors in two-layer coupled networks, where each layer supports the spreading of one behavior with its own transmission path, as described by a non-Markovian process. The synergistic mechanism between the two behavior adoption dynamics is that, once a node adopts a behavior in one layer, it becomes more susceptible to adopting the other behavior that spreads in the other network layer. We develop an edge-based compartmental theory to analyze and understand how the synergistic interactions impact the simultaneous spreading dynamics of the behaviors. We find, as suggested by intuition, that the synergistic interactions greatly facilitate the adoption of both behaviors. However, surprisingly, a phenomenon is that the adoption of one behavior can lead to a characteristic change in the adoption of the other behavior: its final adoption size versus its information rate can change from being discontinuous to continuous, where the former corresponds to a first-order phase transition while the latter to a second-order transition. Remarkably, the synergistic effect can induce a two-stage contagion process, in which nodes having adopted one behavior in one layer will adopt the other behavior in the other layer. When there is a sufficient number of seeds, i.e., when the number of nodes having adopted the other behavior in the other layer is sufficiently large, the remaining nodes will adopt the behavior quickly. While it is intuitively understandable that the synergistic interactions can promote the spreading dynamics of the distinct behaviors involved, our work lays a quantitative foundation for this phenomenon. Our model will not only serve as a useful framework to understand the interplay between synergy and simultaneous spreading of multiple behaviors or diseases, but will also provide insights into predicting or even controlling the underlying dynamics. Due to the ubiquity of synergy in different fields such as social science, computer science, biology and biomedicine, broad relevance of our model is warranted.

In Sec. II, we describe the network and the synergistic behavior spreading models. In Sec. III, we carry out a detailed theoretical analysis. In Sec. IV, we present extensive simulation results with respect to the theoretical predictions. In Sec. V, we summarize the main results and discuss a few pertinent issues.

II. MODEL

There are two components in our model: multiplex networks and spreading dynamics of synergistic behaviors. We first introduce the model of multiplex networks, and then present the synergistic behavior spreading model.

A. Model of multiplex networks

In general, network layers in an interdependent networked system have different internal structures and dynamical functions. To capture the essential dynamics of simultaneous spreading of distinct behaviors, we focus on multiplex networks [42–44]. Consider the simple setting of a duplex system consisting of two layers or subnetworks. Initially, we generate two independent layers, denoted as a and b, which have the same node set and support the spread of behaviors 1 and 2, respectively. We use the configuration model [45] to generate each subnetwork, where the degree distribution \( P_a(k_a) \) of layer a is completely independent of the distribution \( P_b(k_b) \) of layer b. For large and sparse subnetworks, the configuration model stipulates that both interlayer and intralayer degree-degree correlations are negligible.

B. Synergistic behavior spreading model

We use a representative non-Markovian spreading model, the susceptible-adopted-recovered (SAR) [30] model, to describe the dynamics of behavior spreading, and then introduce the synergistic mechanism between the spreading processes of the two behaviors.

For each behavior \( c \in \{1, 2\} \), at any time a node will be in one of the three states: susceptible \( (S_c) \), adopted \( (A_c) \) and recovered \( (R_c) \). A node in state \( S_c \) has not adopted behavior \( c \) but it has an interest in \( c \). A node in the \( A_c \) state has adopted the behavior and can transmit the information about the behavior (denoted as information \( c \)) to its neighbors. The node loses interest in transmitting the information when it is in the \( R_c \) state. The evolution process of behavior \( c \) can be
described, as follows. Initially, \( \rho_c(0) \) fraction of nodes are randomly chosen as the nodes that have adopted the behavior and the remaining nodes are set to be in the susceptible state. At each time step, each node in the \( A_c \) state transmits the information to each of its susceptible neighbors with the transmission rate \( \lambda_c \). Suppose a neighboring node \( v \) already has accumulated \( m - 1 \) pieces of information \( c \) from its distinct neighbors. One more successful transmission will make the number of information pieces to become \( m \). We assume non-redundant information transmission, i.e., once an adopted node has transmitted the information to node \( v \), the former will not transmit the same information to latter again. If the cumulative number \( m \) pieces of information \( c \) that the susceptible node \( v \) has is equal to or larger than a threshold, the node will adopt the behavior \( c \) and changes its state to \( A_c \). Simultaneously, each \( A_c \) node will turn to the \( R_c \) state at the recovery rate \( \gamma_c \). The behavior spreading process will terminate when all the adopted nodes have recovered. More specifically, \( \rho_1(0) \) and \( \rho_2(0) \) are the fractions of nodes randomly chosen as seeds (i.e., adopted nodes) for behavior 1 and 2 on each layer, respectively, where the remaining nodes are in the susceptible state. Information 1 (2) diffuses in layer \( a \) (\( b \)) with transmission rate \( \lambda_1 \) (\( \lambda_2 \)), and the recovery rates for behaviors 1 and 2 are \( \gamma_1 \) and \( \gamma_2 \), respectively.

In the general SAR model, each susceptible node has its own adoption threshold for a behavior. However, for simplicity in modeling the synergistic interaction between the spreading of the two behaviors, we assume that all nodes have the same adoption threshold for each behavior: we denote the adoption threshold for behavior 1 in layer \( a \) as \( T_1 \) and that for behavior 2 in layer \( b \) as \( T_2 \). As a manifestation of mutual synergy, a node having adopted one behavior will become more susceptible to adopting the other behavior. To quantify the synergistic effect, we assume that, once node \( i \) has adopted behavior 1 (2), it will generate an increase \( \Delta T_2 \) \( \Delta T_1 \) in the number of pieces of information about behavior 2 (1). The quantities \( \Delta T_1 \) and \( \Delta T_2 \) thus characterize the strength of the synergistic effect, and we have \( \Delta T_1 \in [0, T_1] \) and \( \Delta T_2 \in [0, T_2] \). For \( \Delta T_1 = 0 \), a node having adopted behavior 2 in layer \( b \) will not impact on its adoption of behavior 1 in layer \( a \). Similarly, the adoption of behavior 1 will have no effect on adopting behavior 2 if \( \Delta T_2 = 0 \). If a node has adopted behavior 2, it will adopt behavior 1 only if \( \Delta T_1 + m \geq T_1 \), where \( m \) represents the number of cumulative pieces of behavioral information 1 in layer \( a \) that this node has received from distinct neighbors.

### III. THEORY

We exploit the edge-based compartmental theory [30, 46–48] to analyze the dynamical process of behavior spreading subject to synergistic interactions, under the assumption that each subnetwork is large and sparse with no internal degree-degree correlations. We also assume that the degree distribution of network \( a \) is completely independent of that of network \( b \), so interlayer degree-degree correlation can be neglected too. The fraction of nodes in each state can be treated as a continuous variable. For each behavior \( c \in \{1, 2\} \), we denote \( S_c(t) \), \( A_c(t) \) and \( R_c(t) \) as the fractions of nodes being in the susceptible, adopted, and recovered state, respectively, for behavior \( c \) in the corresponding layer at time \( t \). During the spreading process, the susceptible nodes adopting behavior \( c \) decreases the value of \( S_c(t) \) but leads to an increase in \( A_c(t) \), and the recovery of the adopted nodes for behavior \( c \) decreases \( A_c(t) \) but increases \( R_c(t) \). Using these notations, the dynamical evolution equations for behavior \( c \) can be written as

\[
\frac{dA_c(t)}{dt} = -\frac{dS_c(t)}{dt} - \gamma_c A_c(t) \tag{1}
\]

and

\[
\frac{dR_c(t)}{dt} = \gamma_c A_c(t). \tag{2}
\]

For \( t \to \infty \), the states of all individuals remain unchanged and \( R_c(\infty) \) is the final adoption fraction of behavior \( c \).

#### A. Edge-based compartmental theory

Despite that the spreading processes of behaviors 1 and 2 occur in different networks (\( a \) and \( b \), respectively) and the dynamical parameters such as the information transmission rates \( \rho_1 \) and \( \rho_2 \), the recovery rates \( \gamma_1 \) and \( \gamma_2 \), and the adoption thresholds \( T_1 \) and \( T_2 \), are different, the mathematical equations governing the underlying processes have identical forms. It thus suffices to derive the equations for behavior 1 spreading in layer \( a \).

To solve Eqs. (1) and (2), we need to calculate the fraction of susceptible nodes for behavior 1 at time step \( t \). First, for nodes of degree \( k_a \) in layer \( a \), two cases can arise where the nodes do not adopt behavior 1: (1) these nodes have not adopted behavior 2 on layer \( b \) and the cumulative number of received pieces of information 1 in layer \( a \) is less than \( T_1 \), and (2) these nodes have already adopted behavior 2 in layer \( b \), but the cumulative number of received pieces of information 1 in layer \( a \) is less than \( T_1 - \Delta T_1 \). Under the assumption that there is no dynamical correlation between the layers, we have that the fraction of susceptible nodes of degree \( k_a \) for behavior 1 at time \( t \) is given by

\[
S_1(k_a, t) = S_2(t) \sum_{m=0}^{T_1-1} \phi_1(k_a, m, t) + [1 - S_2(t)] \sum_{m=0}^{T_1-1-\Delta T_1} \phi_1(k_a, m, t). \tag{3}
\]

In Eq. (3), the first term on the right side is the probability that a node of degree \( k_a \) in layer \( a \) at time \( t \) does not adopt behavior 1. This term contains two parts that describe the following two situations, respectively: (1) the received cumulative number of pieces of information 1 is less than \( T_1 \) with probability \( \sum_{m=0}^{T_1-1} \phi_1(k_a, m, t) \), and (2) with probability \( S_2(t) \), a random node in layer \( b \) does not adopt behavior 2 at time \( t \) (i.e., a node in layer \( b \) does not adopt behavior 2 and is still in the susceptible state), where the quantity \( \phi_1(k_a, m, t) \) is the probability
for a node of degree $k_a$ to have received $m$ pieces of information 1 by time $t$ in layer $a$. Combining the two parts, we find that the first term is identical to the second term in Eq. (3). Using the degree distribution of network $a$, we can express the fraction of susceptible nodes for behavior 1 as

$$S_1(t) = \sum_{k_a} P_a(k_a) S_1(k_a, t). \tag{4}$$

In Eq. (3), the quantity $\phi_1(k_a, m, t)$ can be expressed as

$$\phi_1(k_a, m, t) = [1 - \rho_1(0)] B_{k_a, m} [\theta_1(t)], \tag{5}$$

where $B_{k_a, m}(w)$ denotes the binomial distribution $B_{k_a, m}(1 - w)^m w^{k_a - m}$ and $\theta_1(t)$ is the probability that a random neighbor $v$ of node $u$ in layer $a$ has not transmitted the behavioral information 1 to node $u$ by time $t$. To take into account the dynamical correlations among the states of the adjacent nodes, we make use of the cavity theory [30, 46–48] to analyze the quantity $\theta_1(t)$, where node $u$ is in the cavity state so that it cannot transmit the behavioral information to its neighbors but it can receive the information from its neighbors.

To solve Eqs. (3) and (4), we need the value of $\theta_1(t)$ [the computation of $S_2(t)$ is the same as that of $S_1(t)$]. Noting that a random neighbor $v$ of node $u$ in layer $a$ can be in one of the following three states: $S_1$, $A_1$ and $R_1$, we have that $\theta_1(t)$ is the sum of the probabilities that the neighbor $v$ does not transmit information 1 to $u$ when $v$ is in the $S_1$, $A_1$ or $R_1$ state. We have

$$\theta_1(t) = \xi^S_1(t) + \xi^A_1(t) + \xi^R_1(t), \tag{6}$$

where $\xi^S_1(t)$, $\xi^A_1(t)$ or $\xi^R_1(t)$ denotes the susceptible (adopted or recovered) neighbor $v$ of $u$ which has not transmitted information 1 to node $u$ up to time $t$ in layer $a$.

Suppose a random neighbor $v$ of degree $k'_u$ of node $u$ is susceptible initially, node $u$ cannot transmit information 1 to $v$ since $u$ is in the cavity state. Node $v$ can only receive the information from its other $k'_u - 1$ neighbors. The probability that node $v$ has received $m$ pieces of information 1 in layer $a$ by time $t$ is then

$$\tau_1(k'_u, m, t) = B_{k'_u - 1, m} [\theta_1(t)]. \tag{7}$$

Similar to Eq. (3), we have that the probability that the neighboring node $v$ is still in the susceptible state for behavior 1 at time $t$ is given by

$$\Phi_1[k'_u, \theta_1(t), \theta_2(t)] = S_2(t) \sum_{m=0}^{T_1-1} \tau_1(k'_u, m, t) \tag{8}$$

$$+ \frac{T_1 - 1 - \Delta T_1}{T_1 - 1} \sum_{m=0}^{T_1 - 1 - \Delta T_1} \tau_1(k'_u, m, t).$$

For uncorrelated networks, the probability for a random edge to connect a node of degree $k'_u$ is $k'_u P(k'_u)/\langle k'_u \rangle$, where $\langle k'_u \rangle$ is the average degree of network layer $a$. A neighboring node in the susceptible state cannot transmit the behavioral information. Thus, $\xi^S_1(t)$ is equal to the probability that the neighboring node is in the susceptible state, which is

$$\xi^S_1(t) = [1 - \rho_1(0)] \sum\limits_{k'_u} k'_u P(k'_u) \Phi_1[k'_u, \theta_1(t), \theta_2(t)] \tag{9}$$

$$\langle k'_u \rangle.$$
where the form of \( \Phi_2[k'_b, \theta_1(t), \theta_2(t)] \) in Eq. (15) is similar to \( \Phi_1[k'_b, \theta_1(t), \theta_2(t)] \), and \( \phi_2(k_b, t) \) in Eq. (16) is similar to \( \phi_1(k_b, t) \). It is thus not necessary to write down the expressions again. Using the degree distribution of network \( b \), we have the fraction of susceptible nodes at time \( t \) in layer \( b \) as

\[
S_2(t) = \sum_{k_b} P_b(k_b) S_2(k_b, t). \tag{17}
\]

Iterating Eqs. (1)-(4) and (14)-(17), we can obtain the fractions of susceptible nodes at time \( t \) in both layers: \( S_1(t) \) and \( S_2(t) \). In addition, we can substitute \( S_1(t) \) [\( S_2(t) \)] into Eqs. (1) and (2) and calculate the fractions of the adopted nodes and of the recovered nodes in layer \( a(b) \) at time \( t \). Taking the limit \( t \rightarrow \infty \), we can obtain the final fractions of adoption of the two behaviors. Results on the final adoption fractions from direct numerical simulations together with the corresponding theoretical predictions for different parameter values are shown in Fig. 1. We obtain a good agreement between theory and numerics. For example, for \( T_1 = 2 \) and \( T_2 = 4 \), Fig. 1(b) shows that, without the synergistic effect of behavior 1, i.e., \( \Delta T_2 = 0 \), behavior 2 will not exhibit any outbreak. For \( \Delta T_2 = 2 \), behavior 2 is adopted globally. When there are mutual synergistic effects, e.g., \( \Delta T_1 = 1 \) and \( \Delta T_2 = 3 \) or \( T_1 = 3 \) and \( T_2 = 4 \), the adoption of both behaviors is enhanced, as shown in Figs. 1(c) and 1(d), respectively. Note that there are some outliers (e.g., there are one black square in Fig. 1(a) and two black squares in Fig. 1(d)) around the critical transmission rate where the SAR model is not a deterministic threshold model, which is in contrast to the Watts threshold model. The randomness exists in the process of simulations when the behavior information transmission rate is smaller than 1. Supposing a susceptible node with adoption threshold equal to 3, when it has three adopted neighbors it will not adopt the behavior if one of its adopted neighbor does not succeed in transmitting the behavior information. As shown in the inset of Fig. 1(d), there are some stochastic simulations that \( R_2(\infty) \) does not increase from a very smaller value to a value close 1 directly.

A fundamental issue in spreading dynamics in complex networks is phase transitions [3]. As a system parameter (e.g., the infection rate) changes through a critical point, the final size of the infected nodes starts to increase from zero. An abrupt and discontinuous increase in the final size signifies a first-order phase transition, while a gradual and continuous change is indicative of a second-order phase transition. An objective of our study is then to uncover and understand the effect of synergistic interactions on the phase transitions associated with the social behavior spreading dynamics. To analyze the phase transition, we focus on the fixed point (root) of Eqs. (14) and (15) associated with the final state (i.e., \( t \rightarrow \infty \)). Simplifying notation as \( \theta_1 = \theta_1(\infty) \) and \( \theta_2 = \theta_2(\infty) \), we write Eqs. (14) and (15) as

\[
\theta_1 = f_1(\theta_1, \theta_2), \tag{18}
\]

and

\[
\theta_2 = f_2(\theta_1, \theta_2), \tag{19}
\]

respectively, where

\[
f_1(\theta_1, \theta_2) = \frac{[1 - \rho_1(0)] \sum_{k'_a} k'_a P_a(k'_a) \Phi_1(k'_a, \theta_1, \theta_2)}{\langle k_a \rangle} + \frac{\gamma_1}{\lambda_1} [1 - \theta_1(1 - \lambda_1)], \tag{20}
\]

and

\[
f_2(\theta_1, \theta_2) = \frac{[1 - \rho_2(0)] \sum_{k'_b} k'_b P_b(k'_b) \Phi_2(k'_b, \theta_1, \theta_2)}{\langle k_b \rangle} + \frac{\gamma_2}{\lambda_2} [1 - \theta_2](1 - \lambda_2). \tag{21}
\]

Because of the nonlinear functions \( \Phi_1(k'_b, \theta_1, \theta_2) \) in Eq. (20) and \( \Phi_2(k'_a, \theta_1, \theta_2) \) in Eq. (21), to analyze the whole parameter space is infeasible. We thus focus on some representative or benchmark cases to gain certain analytic understanding of the numerical results. Specifically, we consider two cases in terms of the adoption thresholds of the two behaviors: (1) the adoption threshold of one behavior is less than that of the other behavior \( T_1 < T_2 \) or \( T_1 > T_2 \), and (2) \( T_1 = T_2 \).

### B. Solutions for \( T_1 < T_2 \)

For \( T_1 < T_2 \), \( \Delta T_1 = 0 \) and \( \Delta T_2 > 0 \), indicating that the adoption of behavior 2 has no effect on the spread of behavior 1 but the adoption of the latter will enhance the spread of former, as shown in Fig. 1. Because Eqs. (18) and (19) are nonlinear functions of \( \theta_1 \) and \( \theta_2 \), typically there are multiple roots. In addition, there is persistent transmission of behavioral information from individuals in an adopted state (i.e., \( A_1 \) or \( A_2 \)) to their neighbors, so \( \theta_1(t) \) and \( \theta_2(t) \) decrease with time. Thus, if Eqs. (18) and (19) possess more than one stable fixed point, only the one with the maximum value is physically meaningful [30]. Since Eq. (18) contains the parameters \( \lambda_1 \) and \( \theta_1 \) only, for a given value of \( \lambda_1 \), we can obtain the value of \( \theta_1 \). For given values of the parameters \( \lambda_2 \) and \( \Delta T_2 \), with \( \theta_1 \) we can solve Eq. (19) numerically. As shown in top panel of Fig. 2, we see that Eq. (19) typically has a non-zero trivial solution even for small values of \( \lambda_2 \), indicating that, even when the initial adopted fraction of behavior 2 is small (e.g., \( \rho_2(0) = 0.05 \)), it will always be adopted by a certain fraction of the nodes. However, the initial fraction of seeds will have an effect on the final adoption size [17, 30]. To better focus on the effect of synergistic interactions on simultaneous spreading of the two behaviors, we set \( \rho_1(0) = \rho_2(0) = 0.05 \) and calculate the final adoption size versus the behavioral information transmission rate with a particular eye on the possible type of phase transitions.

For \( \Delta T_2 = 0 \), the number of roots (fixed points) of the function \( g_2(\theta_1, \theta_2) = f_2(\theta_1, \theta_2) - \theta_2 \) is 1 or 3, as shown in Fig. 2(a). Because the physically meaningful solution is the maximum value of the stable fixed point of Eq. (19), there is no global outbreak in behavior 2 [verified numerically, see Fig. 4(a)]. For \( \Delta T_2 = 2 \), the function \( g_2(\theta_1, \theta_2) \) is tangent to the horizontal axis at \( \theta_2^* \) for the critical value of \( \lambda_2^* \approx 0.74 \). Further increasing \( \lambda_2 \) above \( \lambda_2^* \) removes the tangent point and
leaves \( g_2(\theta_1, \theta_2) \) with only one intersection point with the horizontal axis. Importantly, from the standpoint of bifurcation analysis, we see that, at this point, the physically meaningful fixed point \( \theta_2 \) decreases abruptly to a small value, signifying a first-order phase transition. The critical value \( \lambda^c_2 \) for a given \( \lambda_1 \) can be obtained by using the criterion that a nontrivial solution of Eq. (19) emerges, which corresponds to the point at which the function \( g_2(\theta_1, \theta_2) \) is tangent to horizontal axis at the critical value of \( \theta_2^c \). That is, the critical condition for this case can be obtained by combining Eqs. (18) and (19) and the following equation

\[
\frac{dg_2(\theta_1, \theta_2)}{d\theta_2} |_{\theta_2^c} = 0. \tag{22}
\]

For \( \Delta T_2 = 3 \) and \( \lambda_1 = 0.12 \), Eq. (19) has a single root whose value decreases with \( \lambda_2 \), as shown in Fig. 2(c). This means that \( R_2(\infty) \) increases with \( \lambda_2 \) continuously.

For a given value of the transmission rate \( \lambda_1 \) of behavior 1, the critical condition is then that behavior 2 will be adopted if its transmission rate \( \lambda_2 \) is larger than \( \lambda^c_2 \). Similarly, we can compute the minimal information transmission rate of behavior 1 required for a global outbreak of behavior 2. In particular, setting \( \lambda_2 \) to be the maximum value (i.e., \( \lambda_2 = 1.0 \)) and substituting it into Eqs. (19) and (22), we get the critical values of \( \theta_1 \) and \( \theta_2 \). Substitute these values into Eq. (18), we obtain \( \lambda_2^{\infty} \), the minimal information transmission rate of behavior 1.

Numerical solutions of Eq. (19) also show that, for large values of \( \lambda_1 \) and \( \Delta T_2 > 0 \), it has one fixed point only when varying \( \lambda_2 \), so \( R_2(\infty) \) increases with \( \lambda_2 \) continuously. As a result, there exists the critical parameter value \( \theta_1^c \) (i.e., \( \lambda_1^{\infty} \)), across which the dependence of \( R_2(\infty) \) on \( \lambda_2 \) changes from being discontinuous to continuous. For the special case of \( T_1 < T_2 \) (e.g., \( T_1 = 1, T_2 = 4, \Delta T_1 = 0 \) and \( \Delta T_2 > 0 \)), we can numerically solve Eqs. (19) and (22), together with the condition [49]

\[
\frac{d^2g_2(\theta_1, \theta_2)}{d\theta_2^2} |_{\theta_2^c} = 0. \tag{23}
\]

Once \( \theta_1^c \) is determined, we can substitute the value of \( \theta_1^c \) into Eq. (18) to get \( \lambda_1^{\infty} \). In particular, \( R_2(\infty) \) increases with \( \lambda_2 \) discontinuously for \( \lambda_1 < \lambda_1^{\infty} \) and the increasing pattern becomes continuous for \( \lambda_1 \geq \lambda_1^{\infty} \). Using the same approach, we can de-
where $f_\theta$ is plotted as a function of $t$ for $\Delta T_2 = 0$ (a), $\Delta T_2 = 2$ (b) and $\Delta T_2 = 3$ (c). The fixed points of Eqs. (17) and (18) are the intersections between the respective curves and the horizontal axis. Other parameters are $\Delta T_1 = 0$, $\lambda_1 = 0.12$, and $\rho_1(t) = \rho_2(t) = 0.05$. The lower panels show the cases of $T_1 = T_2$ for $T_1 = T_2 = 3$, $\Delta T_1 = \Delta T_2 = \Delta T$, and $\lambda_1 = \lambda_2 = \lambda$, where the values of $g(\theta)$ are plotted as a function of $\theta$ for $\Delta T = 0$ (d), $\Delta T = 1$ (e) and $\Delta T = 2$ (f). The fixed points of Eq. (24) are the intersections between the respective curves and the horizontal axis. The initial adoption fraction is $\rho(0) = 0.05$. The blue dots in (b), (e) and (f) denote the points of tangency. Other parameters are $\gamma_1 = \gamma_2 = 1$.

For simplicity, we denote $\theta_2$ for $\Delta T_2 = 0$ (a), $\Delta T_2 = 2$ (b) and $\Delta T_2 = 3$ (c). The fixed points of Eqs. (17) and (18) are the intersections between the respective curves and the horizontal axis. Other parameters are $\Delta T_1 = 0$, $\lambda_1 = 0.12$, and $\rho_1(t) = \rho_2(t) = 0.05$. The lower panels show the cases of $T_1 = T_2$ for $T_1 = T_2 = 3$, $\Delta T_1 = \Delta T_2 = \Delta T$, and $\lambda_1 = \lambda_2 = \lambda$, where the values of $g(\theta)$ are plotted as a function of $\theta$ for $\Delta T = 0$ (d), $\Delta T = 1$ (e) and $\Delta T = 2$ (f). The fixed points of Eq. (24) are the intersections between the respective curves and the horizontal axis. The initial adoption fraction is $\rho(0) = 0.05$. The blue dots in (b), (e) and (f) denote the points of tangency. Other parameters are $\gamma_1 = \gamma_2 = 1$.

### C. Solutions for $T_1 = T_2$

This is the symmetric case where $\Delta T_1 = \Delta T_2 = \Delta T$, $\lambda_1 = \lambda_2 = \lambda$, $(k_a) = (k_b)$, and $P_a(k) = P_b(k) = P(k)$. The symmetry implies $\theta_1(t) = \theta_2(t)$ and $f_1(\theta_1, \theta_2) = f_2(\theta_1, \theta_2)$. For simplicity, we denote $\theta(t) \equiv \theta_1(t)$ and $f[\theta(t)] \equiv f_1[\theta(t), \theta_2(t)]$. Equations (18)-(21) can be written as

$$\theta = f(\theta),$$  \hspace{1cm} (24)

where

$$f(\theta) = \frac{[1 - \rho(0)]}{\lambda} \sum_k kP(k)\Phi(k, \theta) + \frac{\gamma}{\lambda}(1 - \theta)(1 - \lambda).$$

Similar to treating Eq. (8), we have

$$\Phi(k, \theta) = S(\infty) \sum_{m=0}^{T-1} B_{k-1,m}(\theta)$$

$$+ [1 - S(\infty)] \sum_{m=0}^{T-1-\Delta T} B_{k-1,m}(\theta).$$

The final fraction of the susceptible nodes of behavior 1 (2) in layer $a$ ($b$) is given by

$$S(\infty) = [1 - \rho(0)] \sum_k P(k)\{S(\infty) \sum_{m=0}^{T-1} B_{k,m}(\theta)$$

$$+ [1 - S(\infty)] \sum_{m=0}^{T-1-\Delta T} B_{k,m}(\theta)\}. \hspace{1cm} (26)$$

Using the same analysis method as for the case $T_1 < T_2$, we find that the number of fixed points of Eq. (24) is 1 or 3, as shown in the lower panel of Fig. 2. Whether there is a tangent point between the function $g(\theta) = f(\theta) - \theta$ and the horizon axis depends on the strength $\Delta T$ of synergistic interactions. For $\Delta T = 0$, there is no tangent point and only the maximum value of the fixed point of Eq. (24) is physically meaningful, indicating that behavior 2 is adopted by a small fraction of nodes only. For $\Delta T = 1$ and $\Delta T = 2$, the function $g(\theta)$ can be tangent to the horizon axis, as shown in Figs. 2(e) and 2(f). When $\lambda_2$ is increased passing through $\lambda_2^*$, the tangent point disappears and the function $g(\theta)$ has only one intersecting point with the horizontal axis. In this case, the fixed point $\theta$ changes discontinuously to a small value, signifying a first-order phase transition.
In this section, we perform extensive simulations of behavior spreading on different multiplex networks. We use the notation “RR-RR” to denote the case where both layer a and layer b host the random regular networks. The notation “ER-SF” represents the setting where layer a is an Erdös-Rényi (ER) random network [50] and layer b hosts a scale-free (SF) network [51]. Other possible combinations are “ER-ER”, “SF-SF” and “SF-ER”. The size of each network is $N_a = N_b = 5 \times 10^4$ and the average degree is $\langle k \rangle = 10$ for both networks. The initial adoption fractions of behavior 1 in layer a and behavior 2 in layer b are set to be $\rho_1(0) = \rho_2(0) = 0.05$. To calculate the pertinent statistical averages, we use 20 multiplex network realizations and at least $10^5$ independent dynamical realizations for each parameter setting. Unless otherwise specified, the above parameters are adopted in the simulations. Let $X_t$ denote the situation where a node is in the A or R state in layer a so, for example, the notation $X_1 S_2$ means that, in layer a, a node is in the adopted state or recovered state but it is in the susceptible state in layer b. Similarly, $A_1 S_2$ indicates that a node is in the adopted state in layer a and is in the susceptible state in layer b, which means that the node adopts behavior 1 but not behavior 2.

IV. NUMERICAL VALIDATION

We first perform direct numerical simulations of behavioral spreading dynamics on double layer networked systems consisting of two random regular networks to provide support for our theoretical predictions.

Our theoretical analysis in Sec. III B gives that, for $T_1 < T_2$, synergistic interactions can promote behavior adoption and spreading. To be concrete, we set $T_1 = 1$ and $T_2 = 4$. Figure 3(a) shows the time evolution of the fraction $R_2(t)$ of the recovered nodes in layer b for different values of the synergistic interaction strength $\Delta T_2$. We see that behavior 2 will not outbreak if $\Delta T_2 = 0$. For $\Delta T_2 = 2$ and $\Delta T_2 = 3$, $R_2(t)$ exhibits a two-stage contagion process, where nodes having adopted behavior 1 in layer a will first adopt behavior 2, until then when there is a sufficient number of seeds (i.e., nodes having adopted behavior 2) in layer b to stimulate the remaining nodes. When this happens, behavior 2 will be adopted quickly in layer b. This phenomenon can be explained by noting that, for a small fraction of the initial seeds for behavior 2 [i.e., $\rho_2(0) = 0.05$], if the synergistic effect of adoption of behavior 1 is absent [i.e., $\Delta T_2 = 0$], behavior 2 will not be adopted globally and only the recovery of the seeds can lead to an increase in the value of $R_2(t)$. Note that the number of $X_1 S_2(t)$ nodes increases with the adoption of behavior 1 in layer a [Fig. 3(b)] since the $S_1$ nodes will change to $X_1$.

FIG. 3. Time evolution of behavior spreading subject to synergistic interactions. For random regular double-layer networks, (a, d) the fraction of recovered nodes $R_2(t)$ versus time t, (b, e) the fraction of nodes in state $X$ in layer a and in state $S$ in layer b versus time, (c, f) the fraction of nodes in the $S$ state in both layers a and b versus time. (d)-(f) are the simulation results when $\Delta T_2 = 2$ for different network sizes $N$. The parameters are $\lambda_1 = 0.06$, $\lambda_2 = 0.8$, $T_1 = 1$, $T_2 = 4$, and $\Delta T_1 = 0$. The symbols are simulation results and the lines are theoretical prediction in (a)-(c). In the theoretical analysis of the state $X_1 S_2(t)$, dynamical correlations between the layers are ignored. Other parameters are $\gamma_1 = \gamma_2 = 0.5$. 

A. RR-RR multiplex networks
nodes and there is no decrease in the number of $S_2$ nodes in the network. For $\Delta T_2 = 2$, nodes that have adopted behavior 1 are more likely to adopt behavior 2 compared to those that have not adopted behavior 1. Nodes having adopted behavior 1 in layer $a$ will first adopt behavior 2 in layer $b$, as indicated by the decrease in the number of the $X_1 S_1(t)$ nodes in Fig. 3(c). Before most of the $X_1 S_2$ nodes have adopted behavior 2, the seeds (i.e., adopted nodes for behavior 2) in layer $b$ are sufficient to stimulate the remaining nodes to adopt behavior 2, inducing a two-stage contagion process. A similar phenomenon occurs for $\Delta T_2 = 3$. When the simulation results are compared with the theoretical predictions, we find the former matches well with the latter for $\Delta T_2 = 0$. While the deviation emerges when $\Delta T_2 = 2$, which are derived from the finite-size effects of the networks and the dynamical correlation between layers. From the bottom panels of Fig. 3, we will find the deviation is decreased when increasing the network size, but the deviation will still exist since the interlayer dynamical correlations are ignored in the method.

Figure 4(a) shows, for $T_1 = 1$, $T_2 = 4$ and $\lambda_1 = 0.12$, $R_2(\infty)$ versus $\lambda_2$ for different values of $\Delta T_2$, where the fraction of the $X_1 S_2$ nodes in the system is about 0.393. As the synergistic interaction strength $\Delta T_2$ is increased, behavior 2 is adopted more readily since the number of information pieces about it is decreased. A remarkable phenomenon is the characteristic change in the dependence of $R_2(\infty)$ on $\lambda_2$. In particular, for $\Delta T_2 = 2$, $R_2(\infty)$ increases with $\lambda_2$ discontinuously but the increasing pattern becomes continuous for $\Delta T_2 = 3$. The reason for the characteristic change is that, for $\Delta T_2 = 2$, the nodes having adopted behavior 1 still need to receive additional new (i.e., $T_2 - \Delta T_2$) pieces of information to adopt behavior 2. The system will accumulate a relatively large number of nodes in the subcritical state when the behavioral information transmission rate approaches the critical point, as shown in the inset of Fig. 4(a). Therein, the subcritical state is defined as the node in such state will adopt the behavior if it receives one additional piece of behavior information [30]. A slight increase in $\lambda_2$ will cause a node in this state to receive an additional piece of information and thus adopts behavior 2. The node can then transmit the information to its neighbors, which will cause its subcritical neighbors to adopt behavior 2 accordingly, and so on, leading to an avalanche of behavior adoption for the $X_1 S_2$ nodes. When most of the $X_1 S_2$ nodes have adopted behavior 2 in an abrupt fashion, there is a sufficient number of $A_2$ nodes in layer $b$ to stimulate the remaining $S_1 S_2$ nodes to adopt behavior 2. As a result, increasing $\lambda_2$ slightly can lead to a discontinuous change in the value of $R_2(\infty)$. However, for $\Delta T_2 = 3$, only one additional piece of information about behavior 2 is needed for the $X_1 S_2$ nodes to adopt this behavior. As the value of $\lambda_2$ is increased from zero, some $X_1 S_2$ nodes may receive one piece of information about behavior 2 and adopt it, leading to a continuous decrease in the number of nodes in the subcritical state, as shown in the inset of Fig. 4(b). This is equivalent to the dynamical process in the susceptible-infected-recovered (SIR) model, in contrast to the cascading process in, for example, the Watts threshold model. As a result, the value of $R_2(\infty)$ first increases with $\lambda_2$ continuously. When most of $X_1 S_2$ nodes have adopted behavior 2, the fraction of adopted nodes in layer $b$ is sufficient to stimulate the remaining $S_1 S_2$ nodes to adopt behavior 2. Since the fraction of adopted nodes is relatively large [e.g., $X_1(\infty) \approx 0.393$], the value of $R_2(\infty)$ increases with $\lambda_2$ continuously [30] at a faster rate, as shown in Fig. 4(a). The same process occurs for $\Delta T_2 = 4$. These numerical results agree well with our bifurcation analysis based theoretical prediction.

Figure 4(b) shows the dependence of $R_2(\infty)$ on $\lambda_1$ for different values of $\lambda_2$. For a relatively small value of $\lambda_2$ (e.g., $\lambda_2 = 0.5$), $R_2(\infty)$ increases with $\lambda_1$ continuously, which can be understood by noting that, in this case, a global adoption of behavior 2 requires more seeds in layer $b$, and the spread of this behavior depends strongly on the spread of behavior.
FIG. 5. Dependence of final adoption size of behavior 2 on the transmission rates. For random regular networks, color coded values of $R_2(\infty)$ in the parameter plane $(\lambda_1, \lambda_2)$ of the two information transmission rates: (a) numerical results and (b) theoretical prediction based on solutions of Eqs. (1)-(4) and (16)-(19). The plane is divided into three regions by the two vertical lines, where the dotted vertical line ($\lambda_1 = \lambda_2^m$) is from Eqs. (18), (19) and (22) for $\lambda_2 = 1$, and the dashed vertical line ($\lambda_1 = \lambda_1^c$) is determined by Eqs. (18), (19), (22) and (23). In region I, only a small fraction of the nodes is exposed to adopting behavior 2. In regions II and III, there are a discontinuous (first-order) and a continuous (second-order) phase transition, respectively. The green circles and the red line in region II, respectively, indicate the numerically obtained critical information transmission rate of behavior 2 and the theoretical prediction from Eqs. (17), (19) and (22) for a given value of $\lambda_1$. The inset in (b) shows the final adoption fraction of behavior 1 versus the information transmission rate of this behavior. Other parameters are $T_1 = 1$, $\Delta T_1 = 0$, $T_2 = 4$, $\Delta T_2 = 3$, and $\gamma_1 = \gamma_2 = 1$.

1. However, for relatively large values of $\lambda_2$ (e.g., $\lambda_2 = 0.7$ and $\lambda_2 = 0.8$), $R_2(\infty)$ versus $\lambda_1$ can exhibit an abrupt or discontinuous increase. In this case, a slight increase in the fraction of seeds for behavior 2 is sufficient for it to spread globally by its own dynamics. Both the continuous growth for small values of $\lambda_2$ and the discontinuous increase for larger values of $\lambda_2$ are predicted by our bifurcation analysis based on Eqs. (18), (19), (22) and (23) by replacing $\theta_2$ with $\theta_1$ in Eqs. (22) and (23). There is a good agreement between numerics and theory.

Our analysis and numerical computations indicate that, with synergistic interactions between the spreading dynamics of two behaviors, both $\lambda_1$ and $\lambda_2$ can affect $R_2(\infty)$ and the associated phase transition characteristically. To further demonstrate the role of the synergistic interactions, we show in Fig. 5 color coded values of $R_2(\infty)$ in the parameter plane $(\lambda_1, \lambda_2)$ for $T_1 = 1$, $T_2 = 4$, $\Delta T_1 = 0$, and $\Delta T_2 = 3$. There are three regions in the parameter plane, determined by the two vertical lines at $\lambda_1^m$ and $\lambda_1^c$, respectively, which are associated with characteristically distinct behavioral adoption dynamics. In region I ($\lambda_1 < \lambda_1^m$), only a small fraction of the nodes in layer $b$ adopt behavior 2. In region II ($\lambda_1^m < \lambda_1 \leq \lambda_1^c$), there is a discontinuous phase transition, where a larger fraction of nodes adopt behavior 2 for $\lambda_2 > \lambda_2^c$ (white solid line). In region III ($\lambda_1 > \lambda_1^c$), there is a continuous phase transition. The distinct types of phase transition are predicted through our bifurcation analysis in Sec. III.

To gain further insights into the effects of synergistic interactions in behavioral adoption dynamics, we study the special case where the two types of behaviors are completely symmetric to each other. Fig. 6 (a) shows, for $T_1 = T_2 = T$, $\Delta T_1 = \Delta T_2 = \Delta T$, and $\lambda_1 = \lambda_2 = \lambda$, the dependence of $R(\infty)$ on $\lambda$ for different values of $\Delta T$. In the absence of
synergistic interactions, i.e., when the adoptions of behaviors 1 and 2 have no effect on each other, neither behavior can spread globally and either behavior can only be adopted by a small fraction of the nodes in the network. For $\Delta T > 0$ (i.e., $\Delta T = 1, 2$), the nodes that have adopted behavior 1 (2) only need additional $T - \Delta T$ pieces of information to adopt behavior 2 (1). As a result, the mutually cooperative spreading of behaviors 1 and 2 leads to a wide adoption of both behaviors. Increasing the synergistic interaction strength makes the dynamical correlation between the two layers stronger. The discontinuous phase is more clear when the network size is enlarged. However, the improvement in decreasing the deviation of the critical threshold is less, as shown in Fig. 6 (b). In this regime, the deviation is mainly because the theoretical method can not capture the strong dynamical correlation between layers.

B. General multiplex networks

We consider more general network topology for the network layers in the multiplex system, such as ER-ER, SF-SF, ER-SF and SF-ER. We use the standard configuration model [45] to construct SF networks with the degree distribution $P(k) = \Gamma k^{-\gamma}$, where $\gamma = 3$ is the degree exponent and the coefficient is $\Gamma = 1/\sum_{k_{\min}}^{k_{\max}} k^{-\gamma}$ with the minimum degree $k_{\min} = 3$ and maximum degree $k_{\max} \sim N^{1/(\gamma - 1)}$. The average degrees of SF and ER networks are set as $\langle k \rangle = 10$, and the network size is $N = 5 \times 10^4$. For $T_1 < T_2$, e.g., $T_1 = 1$ and $T_2 = 4$, we fix the final adoption size of behavior 1 and vary the type of network in layer $a$.

To facilitate comparison, we set $\lambda_1 = 0.12$ when layer $a$ is an ER network and $\lambda_1 = 0.113$ if network $a$ is SF, so that the final adoption sizes of behavior 1 for both cases are approximately 0.44. As shown in Fig. 7(a), the network type in layer $a$ over which behavior 1 spreads has little effect on the spread of behavior 2. For the symmetric case $T_1 = T_2$, the dependence of $R(\infty)$ on $\lambda$ changes from being discontinuous to continuous as the network becomes more heterogeneous (i.e., SF) [30], as a strong heterogeneity makes it harder for nodes in the subcritical state to adopt a behavior simultaneously. Regardless of the network type, in general synergistic interactions can facilitate adoption of both behaviors and alter the nature of the associated phase transition.

V. DISCUSSION

To understand social contagions in the human society at a quantitative level is of great importance in the modern time. While the spread of a single contagion can be analyzed through the traditional models of network spreading dynamics, the simultaneous presence and spreading of two or more contagions poses a challenge due to the mutual interplay between the underlying dynamical processes. As an initial effort to address this problem, we articulate a spreading model of multiple social behaviors on multiplex networks subject to synergistic interactions. For simplicity, we consider two-layer coupled networks and limit the number of distinct behaviors to two: one on each layer. The manifestation of the synergistic mechanism is that the adoption of the behavior by a node in one layer will increase the chance for the node that is simultaneously present in the other layer to adopt the behavior that spreads in that layer. The concrete setting enables us to develop an edge-based compartmental theory and a bifurcation analysis to uncover and explain how the synergistic interactions affects the spreading dynamics in terms of the final adoption size and the distinct phase transitions.

There are two types of synergistic interactions: asymmetric and symmetric. In the asymmetric case, the adoption threshold of one behavior in one network layer is less than that of the other behavior in the other layer. In this case, the adoption of the behavior with the higher threshold has no effect on the adoption of the other behavior. However, synergistic interactions can promote the adoption of both behaviors. In fact, the
interaction strength and the information transmission rate of
the behavior with the smaller threshold value can affect the
nature of the phase transition of the behavior with the larger
threshold: a small (large) value of the transmission rate of
the former can lead to a discontinuous (continuous), first- (sec-
dond-) order phase transition in the latter. In addition, a two stage
spreading process arises: nodes adopting the small threshold
behavior in one layer are more likely to adopt the large thresh-
old behavior in the other layer, which stimulates the remaining
nodes in this layer to quickly adopt the behavior. In the case of
symmetric synergistic interactions, the adoption processes in
both layers can affect each other on an equal footing. In this
case, the interactions will greatly enhance the spreading of
both behaviors in their respective layers through a first-order
phase transition.

Many issues remain, such as the effect of heterogeneity in
the synergistic strengths of the individual nodes on behavioral
spreading and the impacts of degree correlation between the
network layers. In general, there are two kinds of dynamical
correlation: intralayer and interlayer. In each layer, the cor-
relation can be described by the edge-based compartmental
theory. To make a theoretical analysis feasible, we have ne-
glected interlayer correlation, i.e., the dynamical correlation
among nodes in distinct layers. However, in real situations,
dynamical correlation may exist between the same node in
different layers, depending on the strength of the synergis-
tic interaction. If the interaction strength is not too large, in-
terlayer dynamical correlation is weak. In this case, there is
a good agreement between the theoretical prediction and the
simulation results (e.g., Figs. 1 and 4). For relatively strong
synergistic interaction (e.g., Fig. 6 for $\Delta T = 2$), the simul-
ation results deviate from the theoretical prediction. Increasing
the size of network will not help reduce the deviation, as in-
terlayer correlation can no longer be regarded as insignificant.
A more accurate theory incorporating interlayer correlation is
thus needed for synergistic affected information spreading in
the strong interaction regime [52].

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