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Ponzi scheme diffusion in complex networks

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HIGHLIGHTS

- High and unbalanced connectivity help Ponzi scheme diffusion in social networks.
- High speed diffusion alleviates interest burdens and improves financial outcomes.
- The peak of diffusion implies the start of financial worsening.
- The zero-crossing of fund flux is an index for predicting the forthcoming collapse.
- Ponzi scheme is more harmful when diffusing through modern social networks.

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ABSTRACT

Ponzi schemes taking the form of Internet-based financial schemes have been negatively affecting China's economy for the last two years. Because there is currently a lack of modeling research on Ponzi scheme diffusion within social networks yet, we develop a potential-investor–divestor (PID) model to investigate the diffusion dynamics of Ponzi scheme in both homogeneous and inhomogeneous networks. Our simulation study of artificial and real Facebook social networks shows that the structure of investor networks does indeed affect the characteristics of dynamics. Both the average degree of distribution and the power-law degree of distribution will reduce the spreading critical threshold and will speed up the rate of diffusion. A high speed of diffusion is the key to alleviating the interest burden and improving the financial outcomes for the Ponzi scheme operator. The zero-crossing point of fund flux function we introduce proves to be a feasible index for reflecting the fast-worsening situation of fiscal instability and predicting the forthcoming collapse. The faster the scheme diffuses, the higher a peak it will reach and the sooner it will collapse. We should keep a vigilant eye on the harm of Ponzi scheme diffusion through modern social networks.

1. Introduction

The Ponzi scheme is a fraudulent investment operation named after Charles Ponzi. The Ponzi operator lures and recruits new investors by promising high-yield and low-risk returns and uses their money to pay interest to earlier investors [1]. Because an abnormally high interest rate is always viewed as risk rather than as a temptation by investors, the operator must strive to fabricate plausible investment projects and then convincingly promote and hard-sell them to the prospective investors. Victims will not swallow the bait in the early stage until they witness previous investors in safe possession both of their principal investment and of the promised interest. On the other hand, victims prefer to believe in an operator because

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of the operator's personal prestige and position. Madoff, the former chairman of the NASDAQ Stock Exchange, established his reputation on Wall Street. Few investors perceived the hazards of his fund until he publicly admitted to having run a massive Ponzi scheme of US$65 billion [2]. Having been a successful businessman, Madoff might not have initially intended to operate a Ponzi scheme until his legitimate businesses failed to bear the promised high returns. Whatever the initial situation, any financial scheme requiring an ever-increasing inflow of money from new investors to sustain high returns would probably ultimately become a Ponzi scheme (e.g. the China's shadow banking market [3] and banks' hiding of loan losses [4]).

Microeconomic models of the dynamics of Ponzi schemes are not difficult to create. Artzrouni [5] developed a first-order linear differential equation based on an exponential capital inflow function and a fixed withdrawal rate. His model intuitively interpreted the relationship between investment rate and withdrawal rate in the fund's mid-term and long-term tendencies. However, his model was not concerned with social networking. Baker et al. [6,7] investigated the case of the *Fountain Oil and Gas Company* investment fraud and found that contagion within the group of victim investors rarely occurred because the majority of victims were afraid that telling others about the scarce investment opportunity might cause incremental demand and price rise; subsequently resulting in potential loss of reinvestment opportunities. However, Nash et al. [8] drew a nearly contradictory conclusion after she carefully sketched out the nomination network of the *Eron mortgage fraud*, another case of pre-planned mortgage fraud spanning the period 1992–1997. They found that opinion leaders and investors themselves unknowingly spread the fraud through their social networks by recruiting their friends and family to invest in the Eron scheme.

As Ponzi schemes are usually linked to pyramid schemes, intermediaries are thought of the active spreaders. But, with the rapid growth of Internet-based financing, investors themselves will be the spreaders, too. Positive word-of-mouth (WOM) endorsements by earlier beneficiaries are easier to disseminate in online social communities. In addition, the formalized e-print contracts cause investors to make quick decision and the wide usage of mobile payment with smartphone apps makes ordinary investors conveniently transfer their spare money into the scheme. All these changes help Ponzi schemes diffuse automatically and spontaneously in social networks. Shiller [9] proposed that the positive or negative information and ideas of the stock market would be epidemically spreading among the investors, leading to the over-fluctuation of the asset price. Chan et al. [10] found that users in online social communities perceive their social circles as a "cushion" to mitigate financial losses and increase their financial risk-taking. Baucus et al. [11] warned that crowdfunding might give illegal entrepreneurs new opportunities to launch Ponzi ventures. In fact, as many as one thousand Peer-to-Peer (P2P) lending companies have collapsed in China during 2014–2015 because of suspected Ponzi fraud through Internet-based financing [12].

The small-world phenomenon [13] and scale-free degree distribution [14] result in the complex characteristics of social network dynamics. A rich body of literature has evolved over the past few years to address the quasi-biological epidemic model of complex networks (e.g. rumor spreading [15–18] and information dissemination [19–22]). The latest comprehensive reviews can be found in Refs. [23,24]. However, interpersonal fraud diffusion in different types of social network structures has rarely been formulated and studied. To fill this research gap, we investigate the dynamics of Ponzi scheme operation and diffusion within homo- and inhomogeneous complex networks. The rest of this paper is organized as follows. In Section 2, we use an example to illustrate the diffusion process of a Ponzi scheme in a social network and we set up the assumptions and definitions of our diffusion model. Next, in Sections 3 and 4, we establish the mean-field diffusion equations both in homo- and inhomogeneous networks. We also investigate the zero-crossing point of each fund flux function. In Section 5, numerical analysis is conducted to visualize the different effects of specific parameters and structures on diffusion dynamics. Finally, Section 6 will summarize the data and draw main conclusions from the findings of this study.

2. The model and definitions

We use a diffusion example, illustrated in Fig. 1, to make our Ponzi scheme model clear. Circles a_2, a_8, a_{10}, and a_{11} are potential investors who have the possibility of putting their money into the fund in the future. Circles a_1, a_4–a_7, and a_9 are investors who have put their money into the fund. Circle a_3 is the divestor who have become an investor during the first and second interest-calculating period (1τ to 2τ), then withdraws his/her principal and interest after the third interest-calculating period 3τ and never comes back. Investors will influence the investment decision-making of their connected neighbors, and investment adoption will spread throughout each investor's social network. We merge the information spreading and adoption diffusion into one process. That is, from 1τ to 2τ, a_3 and a_4 are informed by a_1 and make the investment decision; from 2τ to 3τ, a_5 and a_7 are influenced by a_4 to join in; from 3τ to 4τ, a_5 and a_7 persuade a_6 and a_9 to invest, respectively.

Therefore, we assume that the investors' social network is a connected, undirected, and finite network with N nodes, consisting of three types of actors: potential investors, investors, and divestors. We name our model the potential-investor–divestor (PID) investment diffusion model. To simplify our model, we first set up a series of assumptions as follows:

1. The amount of principal that each investor puts into the fund is equal to W.
2. The interest-calculating period is divided into equal interval τ, and the system will consider all the financial operations, including investment counting, principal withdrawal, and interest distribution at the beginning of each period.
3. Divestors will withdraw their entire principal and interest when they exit the fund, and they will never come back.