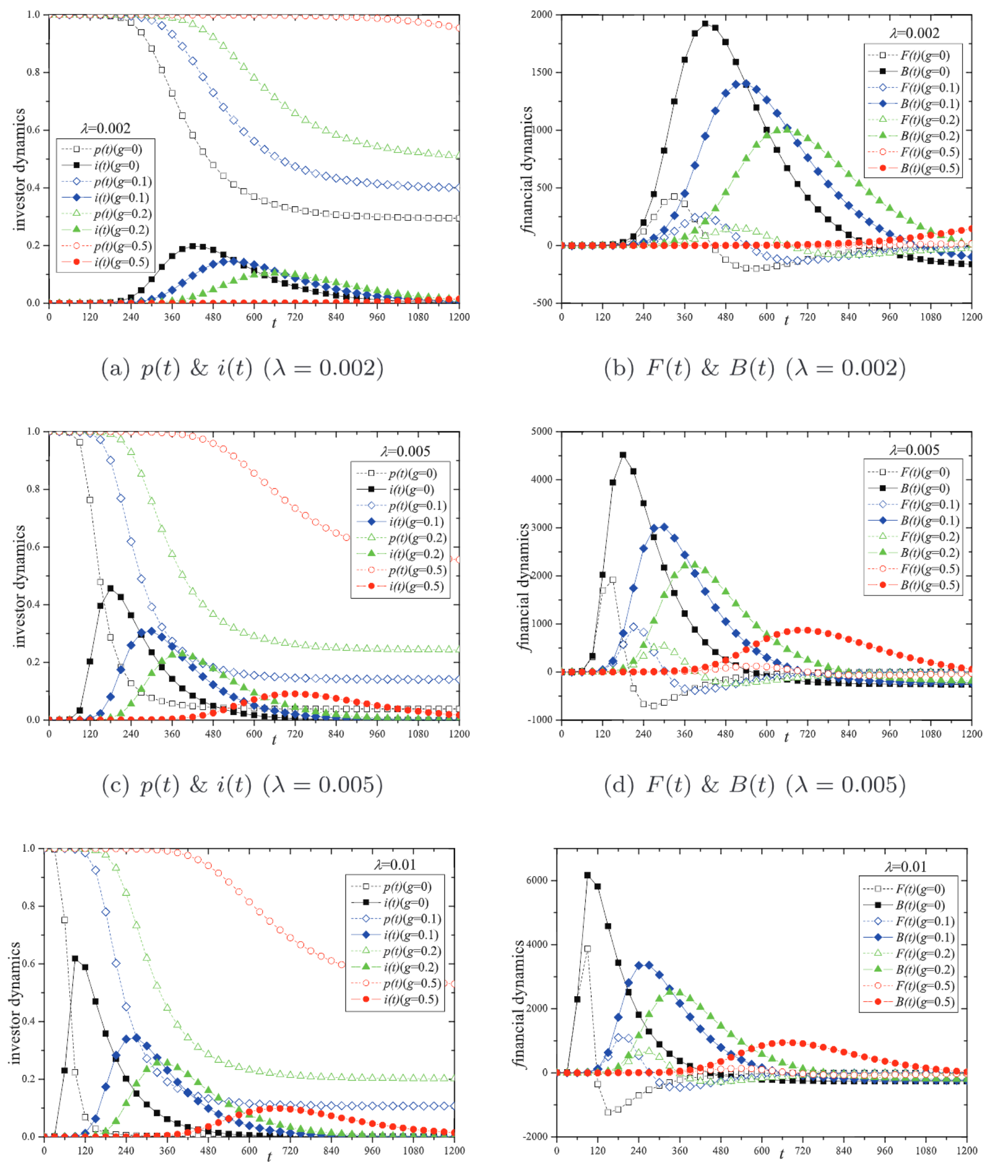


(a) $p(t)$ & $i(t)$ ($\lambda = 0.002$) (b) $F(t)$ & $B(t)$ ($\lambda = 0.002$)

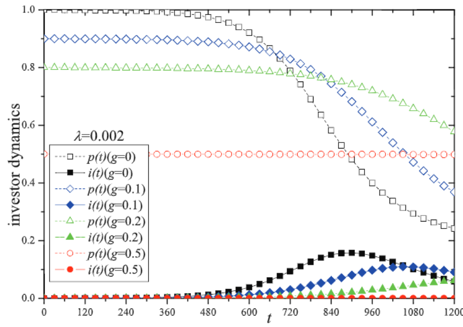
(c) $p(t)$ & $i(t)$ ($\lambda = 0.005$) (d) $F(t)$ & $B(t)$ ($\lambda = 0.005$)

(e) $p(t)$ & $i(t)$ ($\lambda = 0.01$) (f) $F(t)$ & $B(t)$ ($\lambda = 0.01$)

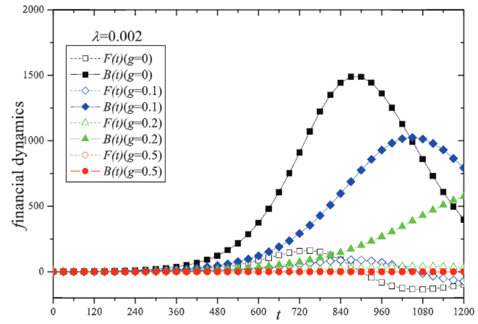
Fig. 2. (Color online) Uniform Protection Strategy: Comparison of investor and financial dynamics with different protection intensity gs of different spreading rate λs in BA networks with uniform immunization.

and 4(a), 4(c), 4(e)]. Additionally, the larger the spreading rate, the worse the financial outcome [referring to Figs. 3(b), 3(d), 3(f) and 4(b), 4(d), 4(f)].

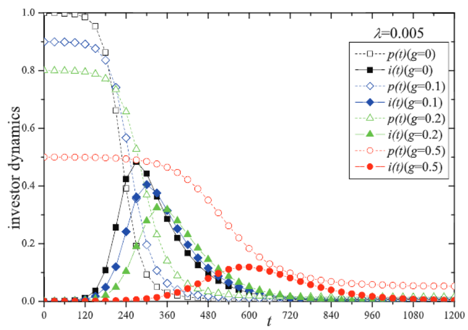
However, the performance of the random protection strategy is worse than that of the uniform protection strategy when we compare Fig. 1 with Fig. 3 and Fig. 2 with Fig. 4. With the same protection intensity (g), the peaks of $i(t)$ and $B(t)$ in the cases of the random protection strategy are larger than those of the uniform protection strategy. These phenomena are more significant for larger protection



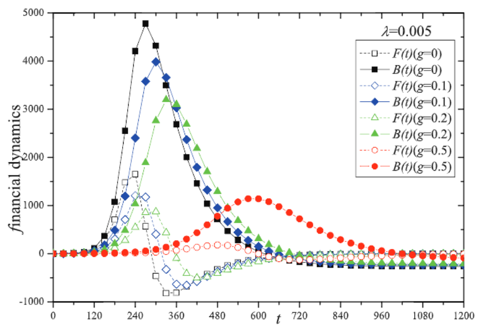
(a) $p(t)$ & $i(t)$ ($\lambda = 0.002$)



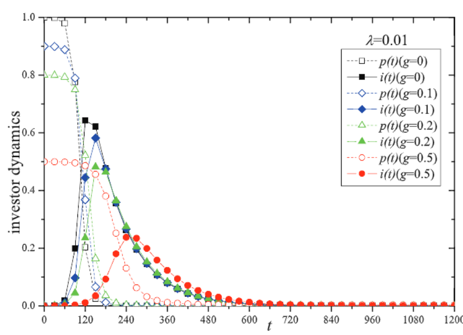
(b) $F(t)$ & $B(t)$ ($\lambda = 0.002$)



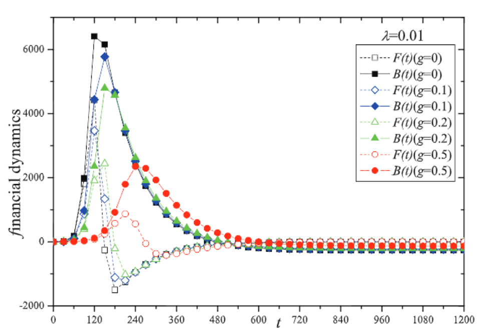
(c) $p(t)$ & $i(t)$ ($\lambda = 0.005$)



(d) $F(t)$ & $B(t)$ ($\lambda = 0.005$)



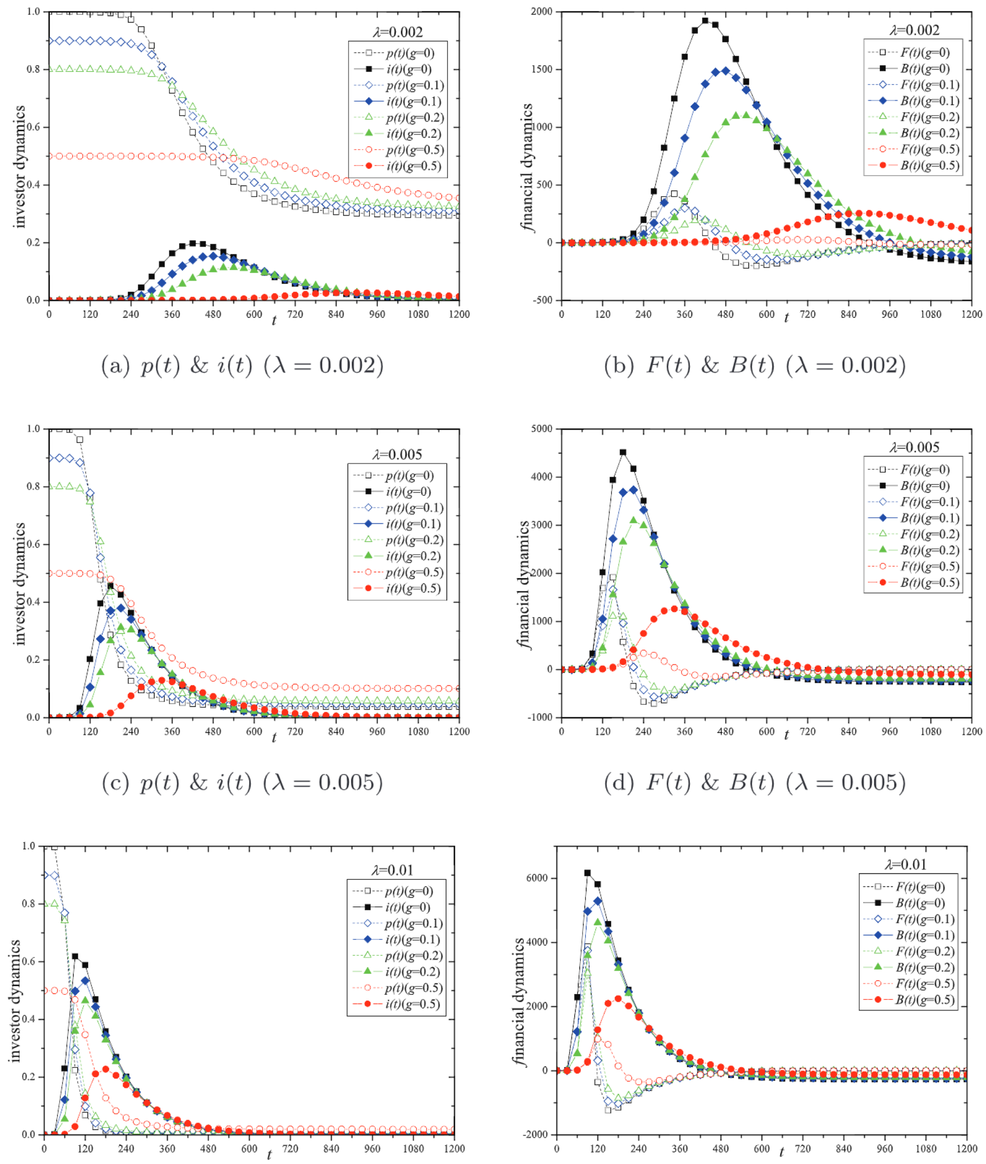
(e) $p(t)$ & $i(t)$ ($\lambda = 0.01$)



(f) $F(t)$ & $B(t)$ ($\lambda = 0.01$)

Fig. 3. (Color online) Random Protection Strategy: Comparison of investor and financial dynamics with different protection intensity gs of different spreading rate λs in ER networks with random immunization.

intensities. For example, in the case of $g = 0.5$, the spreading is completely controlled in the ER network [referring to Figs. 1(a), 1(c), and 1(e)]. However, the peaks of $i(t)$ are not suppressed to 0 in the cases of $\lambda = 0.005$ (Fig. 3(c)) and $\lambda = 0.01$ (Fig. 3(e)). These results cause the financial outcomes to be worse for the random protection strategy. The peaks of $B(t)$ are not suppressed to 0 in the cases of $\lambda = 0.005$ [Fig. 3(d)] and $\lambda = 0.01$ [Fig. 3(f)]. The results are similar for the BA network. Moreover, the peaks of $i(t)$ [Figs. 4(c) and 4(e)] and $B(t)$ [Figs. 4(d) and



(a) $p(t)$ & $i(t)$ ($\lambda = 0.002$) (b) $F(t)$ & $B(t)$ ($\lambda = 0.002$)

(c) $p(t)$ & $i(t)$ ($\lambda = 0.005$) (d) $F(t)$ & $B(t)$ ($\lambda = 0.005$)

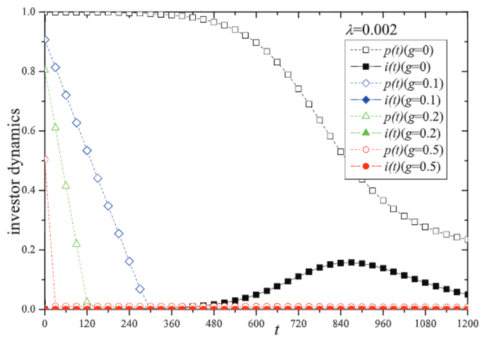
(e) $p(t)$ & $i(t)$ ($\lambda = 0.01$) (f) $F(t)$ & $B(t)$ ($\lambda = 0.01$)

Fig. 4. (Color online) Random Protection Strategy: Comparison of investor and financial dynamics with different protection intensity gs of different spreading rate λs in BA networks with random immunization.

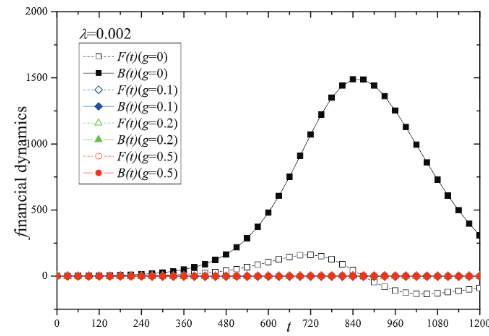
4(f)] for the random protection strategy occur earlier than those for the uniform protection strategy [Figs. 2(c), 2(e), 2(d) and 2(f)], in terms of the BA network. The earlier the peak comes, the larger the loss the investors face.

4.3. *The performance of the targeted protection strategy*

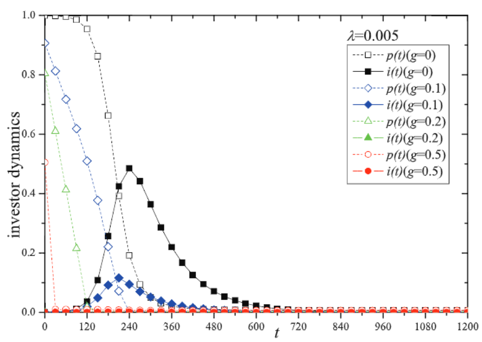
The performance of targeted protection strategies on the ER network and BA networks are demonstrated in Figs. 5 and 6, respectively. Similar to the uniform and



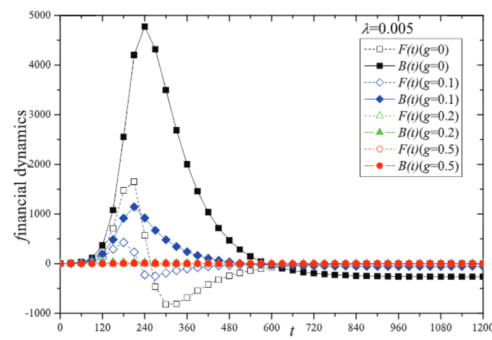
(a) $p(t)$ & $i(t)$ ($\lambda = 0.002$)



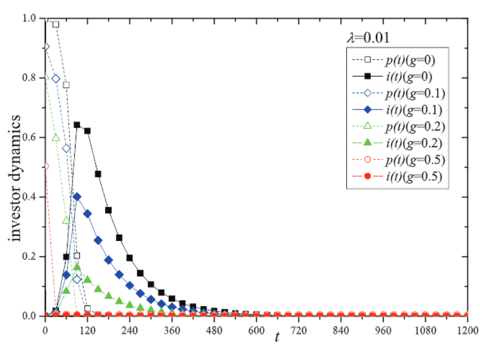
(b) $F(t)$ & $B(t)$ ($\lambda = 0.002$)



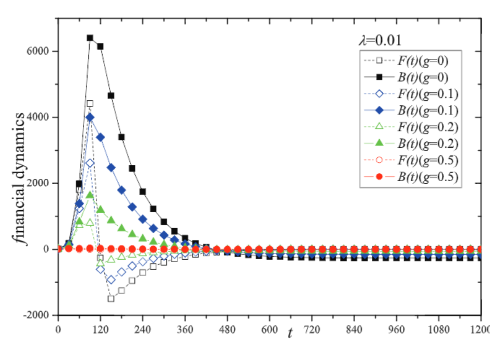
(c) $p(t)$ & $i(t)$ ($\lambda = 0.005$)



(d) $F(t)$ & $B(t)$ ($\lambda = 0.005$)



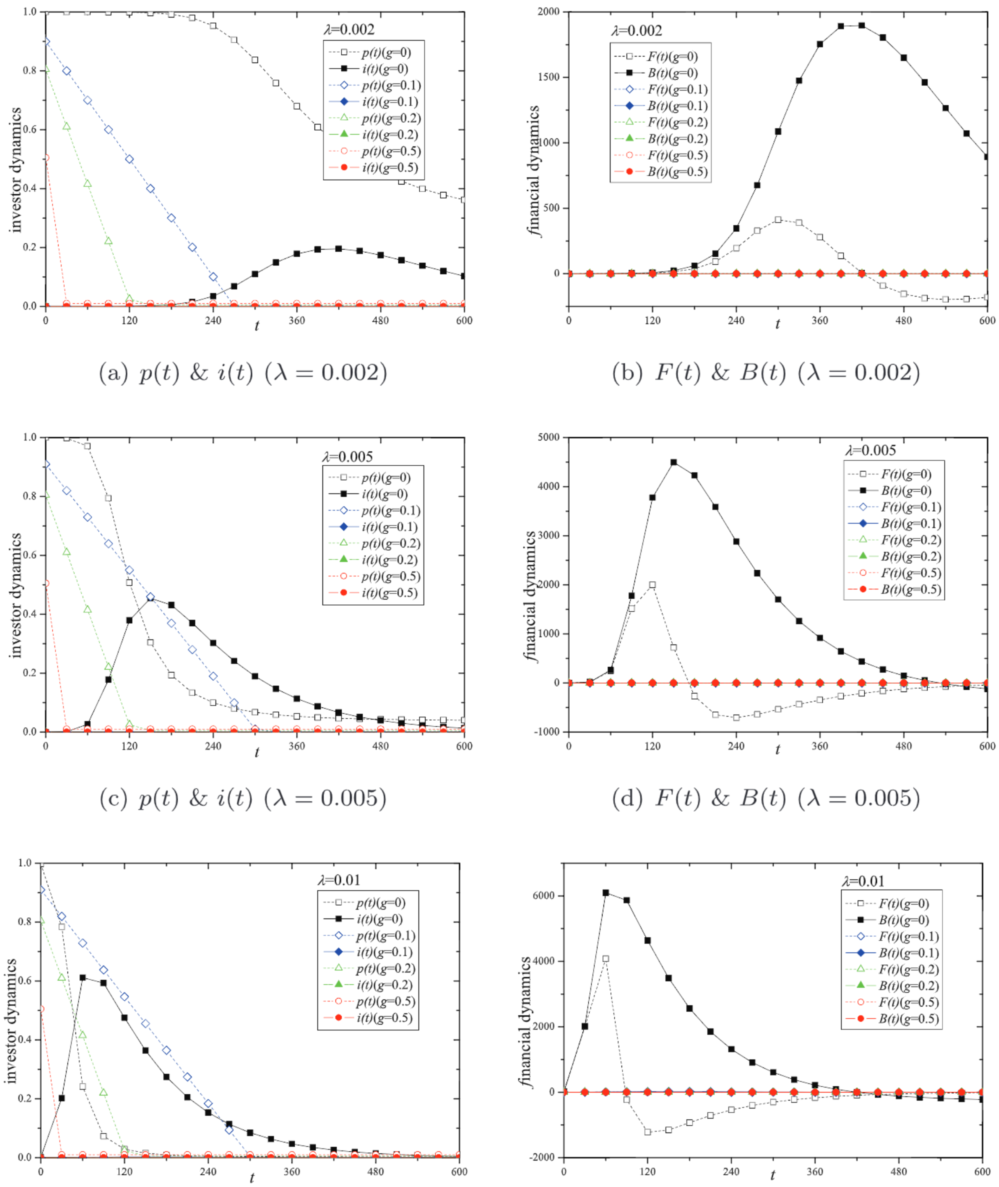
(e) $p(t)$ & $i(t)$ ($\lambda = 0.01$)



(f) $F(t)$ & $B(t)$ ($\lambda = 0.01$)

Fig. 5. (Color online) Targeted Protection Strategy: Comparison of investor and financial dynamics with different protection intensity gs of different spreading rate λs in ER networks with targeted immunization.

random protection strategies, we compare three groups of spreading rates, i.e., $\lambda = 0.002$, $\lambda = 0.005$, and $\lambda = 0.01$. The targeted protection strategy demonstrates strong efficiency. For both the ER and BA networks, $i(t)$s are reduced very close to 0 when the protection intensity $g = 0.5$ [referring to Figs. 5(a), 5(c), 5(e) and 6(a), 6(c), 6(e)]. This implies that the fraud has almost no chance to spread under the intensively targeted protection. The financial outcomes ($B(t)$) are also close to 0 when $g = 0.5$, implying that the fraud will not suffer losses after it ends



(a) $p(t)$ & $i(t)$ ($\lambda = 0.002$)

(b) $F(t)$ & $B(t)$ ($\lambda = 0.002$)

(c) $p(t)$ & $i(t)$ ($\lambda = 0.005$)

(d) $F(t)$ & $B(t)$ ($\lambda = 0.005$)

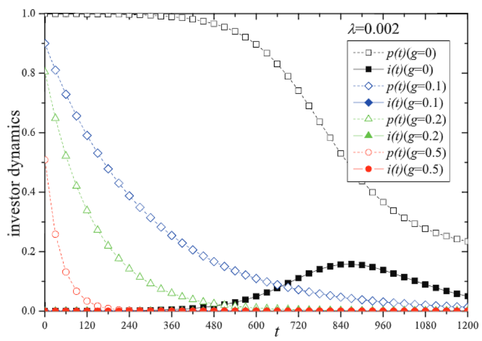
(e) $p(t)$ & $i(t)$ ($\lambda = 0.01$)

(f) $F(t)$ & $B(t)$ ($\lambda = 0.01$)

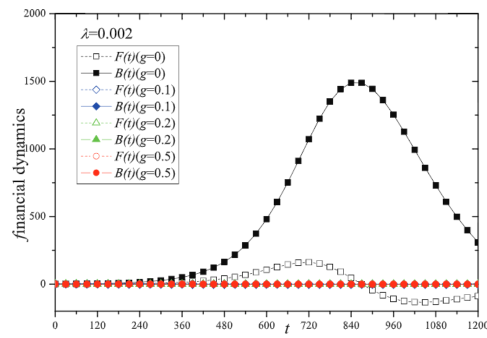
Fig. 6. (Color online) Targeted Protection Strategy: Comparison of investor and financial dynamics with different protection intensity gs of different spreading rate λs in BA networks with targeted immunization.

[referring to Figs. 5(b), 5(d), 5(f) and 6(b), 6(d), 6(f)]. In addition, for the other two protection intensities (i.e., $g = 0.1$ and $g = 0.2$), the targeted protection strategy also presents excellent performance. The peaks of $i(t)$ and $B(t)$ are extremely suppressed. For example, the peak of $i(t)$ is suppressed from 0.7 (no protection) to 0.2 ($g = 0.2$) in the case of $\lambda = 0.01$ [referring to Fig. 5(e)]. Correspondingly, the financial risk and losses are also reduced. The peak of $B(t)$ is suppressed from more than 6000 (no protection) to near 2000 ($g = 0.2$) in the case of $\lambda = 0.01$ [referring to

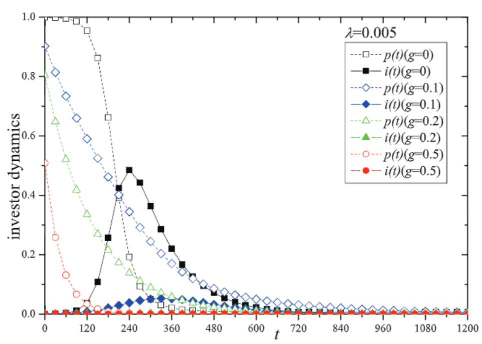
Fig. 5(f)]. The performances are great, especially for the BA network. For $g = 0.1$, $g = 0.2$, and $g = 0.5$, the fraud almost cannot start, and the peaks of $i(t)$ and $B(t)$ are all close to 0 (referring to Fig. 6). Therefore, these results imply that if the most influential agents are regulated such that they do not participate and spread the fraud, the fraud will not spread and will instead become strongly threatened.



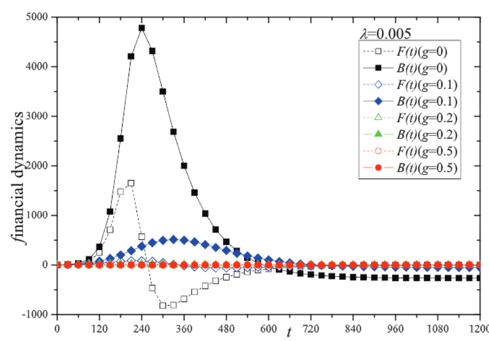
(a) $p(t)$ & $i(t)$ ($\lambda = 0.002$)



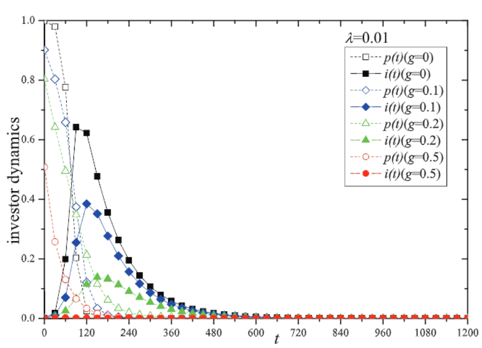
(b) $F(t)$ & $B(t)$ ($\lambda = 0.002$)



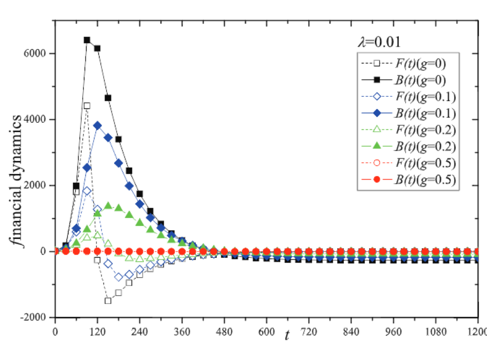
(c) $p(t)$ & $i(t)$ ($\lambda = 0.005$)



(d) $F(t)$ & $B(t)$ ($\lambda = 0.005$)

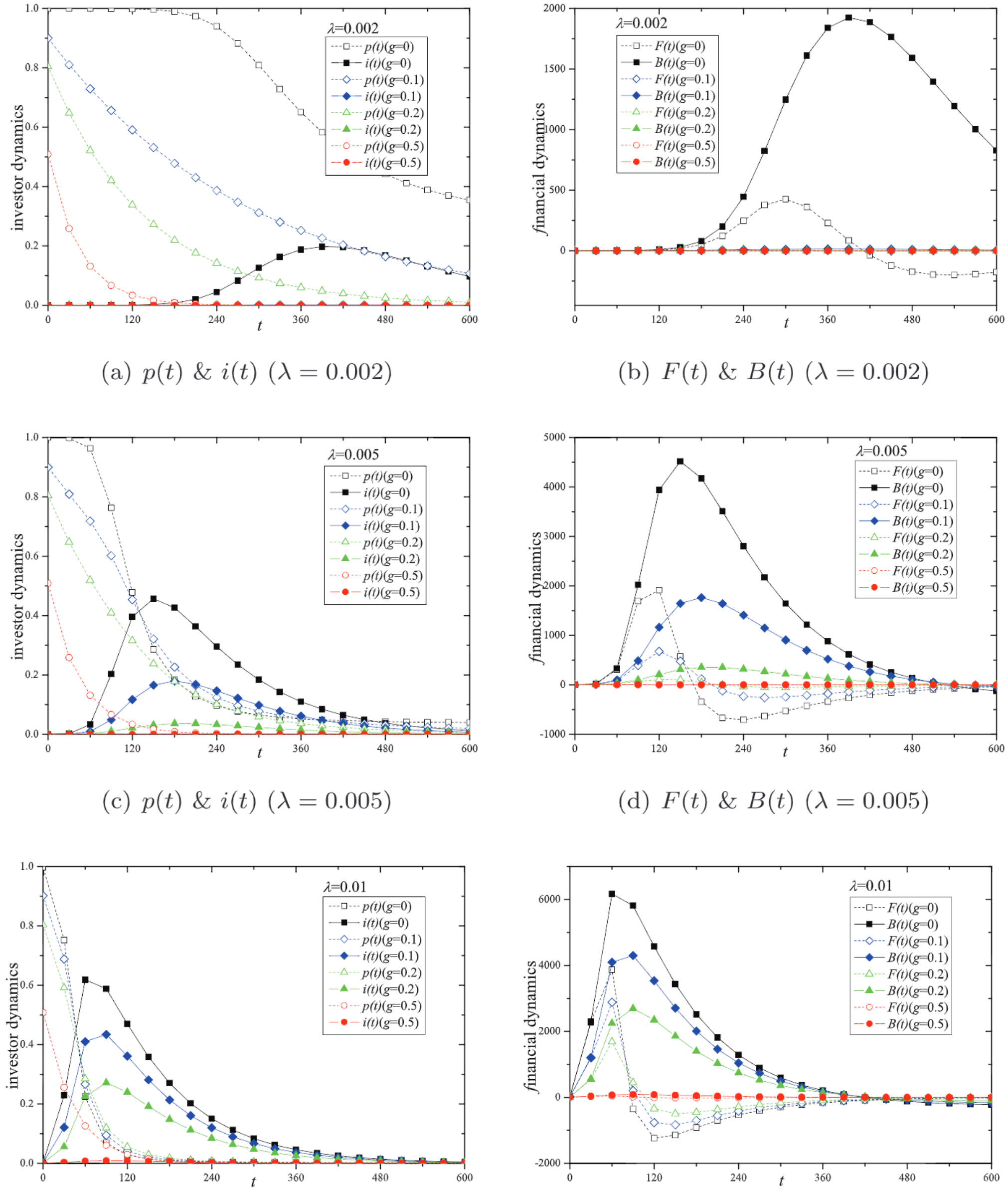


(e) $p(t)$ & $i(t)$ ($\lambda = 0.01$)



(f) $F(t)$ & $B(t)$ ($\lambda = 0.01$)

Fig. 7. (Color online) Acquaintance Protection Strategy: Comparison of investor and financial dynamics with different protection intensity gs of different spreading rate λs in ER networks with acquaintance immunization.



(a) $p(t)$ & $i(t)$ ($\lambda = 0.002$)

(b) $F(t)$ & $B(t)$ ($\lambda = 0.002$)

(c) $p(t)$ & $i(t)$ ($\lambda = 0.005$)

(d) $F(t)$ & $B(t)$ ($\lambda = 0.005$)

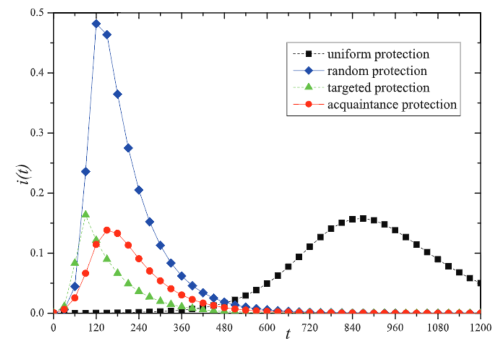
(e) $p(t)$ & $i(t)$ ($\lambda = 0.01$)

(f) $F(t)$ & $B(t)$ ($\lambda = 0.01$)

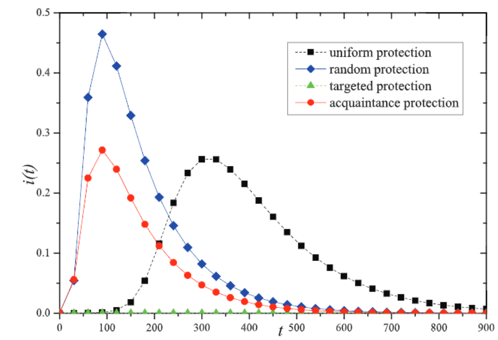
Fig. 8. (Color online) Acquaintance Protection Strategy: Comparison of investor and financial dynamics with different protection intensity gs of different spreading rate λs in BA networks with acquaintance immunization.

4.4. *The performance of the acquaintance protection strategy*

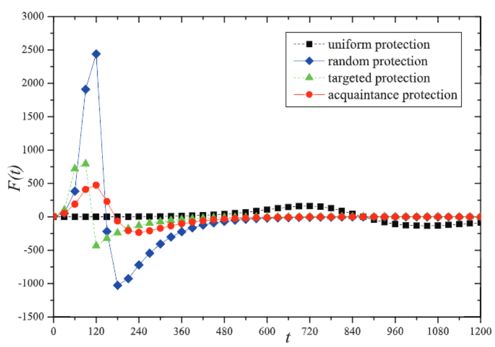
The performance of acquaintance protection strategies on the ER network and BA networks are demonstrated in Figs. 7 and 8, respectively. Similar to the former three protection strategies, we compare three groups of spreading rates, i.e., $\lambda = 0.002$, $\lambda = 0.005$, and $\lambda = 0.01$. The acquaintance protection strategy is expected to achieve as good a performance as the targeted protection strategy without requiring the investor network information. Similar to the targeted protection strategy, for deep immunization cases ($g = 0.5$), $i(t)$s are also reduced closely to 0 in both ER and BA networks [referring to Figs. 7(a), 7(c), 7(e) and 8(a), 8(c), 8(e)]. The financial outcomes ($B(t)$) are also close to 0 when $g = 0.5$, implying that the fraud will not suffer losses after it ends [referring to Figs. 7(b), 7(d), 7(f) and 8(b), 8(d), 8(f)]. In addition, the peaks of $B(t) \approx 4000$ (for $g = 0.1$) and $B(t) \approx 1800$



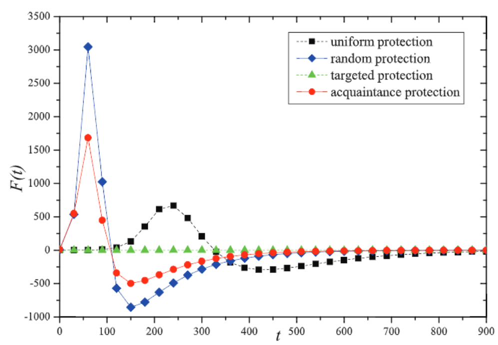
(a) $i(t)$ of ER networks



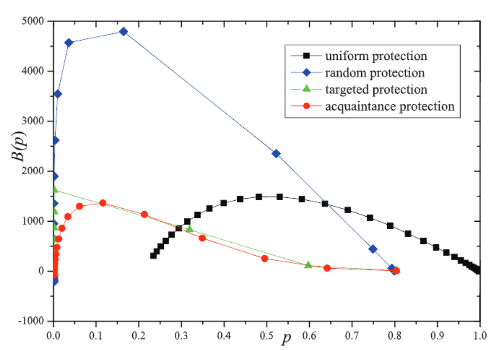
(b) $i(t)$ of BA networks



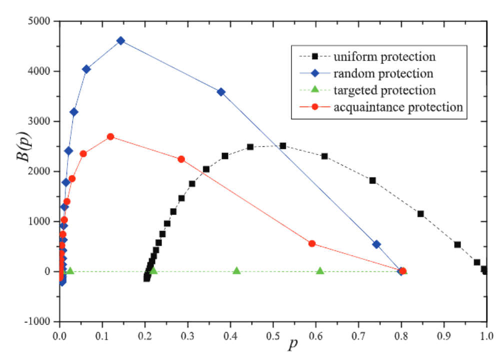
(c) $F(t)$ of ER networks



(d) $F(t)$ of BA networks



(e) $B(p(t))$ of ER networks



(f) $B(p(t))$ of BA networks

Fig. 9. (Color online) Comparison of investor, financial dynamics, and collapse point with different immunization strategies in both ER and BA networks. In all cases, we set $\lambda = 0.01$ and $g = 0.2$.

(for $g = 0.2$) perform worse than those of the targeted protection strategies for ER networks [compared with Figs. 5(f) and 7(f)]. The peaks of $B(t) \approx 4200$ (for $g = 0.1$) and $B(t) \approx 3000$ (for $g = 0.2$) also perform worse than those of the targeted protection strategies for BA networks [compared with Figs. 6(f) and 8(f)]. However, the acquaintance protection strategy presents an easier way to achieve better financial outcomes for the BA networks than the targeted protection strategy.

4.5. *Comparison of the four protection strategies*

Figure 9 demonstrates comparisons of the four protection strategies together. We choose $\lambda = 0.01$ and $g = 0.2$ for better presentation. The four protection strategies can prevent investors from becoming involved in financial fraud collapses [referring to Figs. 9(a) and 9(b)]. In comparison, the targeted protection strategy achieves the best performance, while the random protection strategy performs the worst in both the ER and BA networks. Additionally, the uniform and acquaintance protection strategies perform closely in terms of the peak of involved investors. However, the uniform protection strategy delays the arrival of the peak more than the acquaintance protection strategy. This feature will directly influence the financial output. According to the fund flux function shown in Figs. 9(c) and 9(d), the fund flux peaks of the uniform protection strategy are more suppressed than those of the acquaintance protection strategy in both the ER and BA networks, indicating that the uniform protection strategy will reduce the negatively financial risk more than the acquaintance protection strategy. It is likely that the targeted protection strategy is the best solution, while the random protection strategy is the worst solution in terms of the fund flux function. Finally, according to Figs. 9(e) and 9(f), the balance functions present the similar results. The uniform protection strategy is better than the acquaintance protection strategy because it involves a small population, although the balance peak is similar. The acquaintance protection strategy performs closely to the targeted protection strategy for the ER network because it is difficult to select the nodes with a larger degree. However, for the BA network, the targeted protection strategy presents an absolute advantage.

5. Conclusions and Discussion

Financial fraud collapses can ruin many participants and their families, and disrupt the economic health of the society. However, most of the time, financial fraud cannot be initially identified, and thus potential investors remain unaware of the scheme. In fact, there are few victims at the beginning of a scheme, and regulators may ignore their warnings or reports. After a fraud has grown too large to be controlled, it may take action to camouflage itself. It may pretend to be a very successful and promising project, with more victims becoming involved in the fraud. Any fraud will eventually collapse, and the regulator always tries to minimize losses. By referring to the four immunization strategies, this study identifies four protection strategies from the perspective of social dynamics (i.e., the uniform protection strategy, the random protection strategy, the targeted protection strategy, and the acquaintance protection strategy). The PID model is adapted to investigate the performances of the four protection strategies from the perspective of both epidemic dynamics and financial dynamics. The simulation results show that the targeted protection strategy is the best solution for both ER and BA networks. It is difficult to identify the *a priori* knowledge of the network structure. However, the regulator can prevent the most influential agents from participating in fraud. They have the advantages of professional knowledge and social connections. Among the remaining three strategies, the random protection strategy is the least efficient solution. A random protection strategy requires spreading a large number of anti-fraud messages to achieve relatively good performance. The acquaintance protection strategy performs closely to the targeted protection strategy in terms of social dynamics. However, the uniform protection strategy is better than the acquaintance protection strategy because it involves fewer victims when it collapses. This implies that financial literacy education will increase the vigilance of agents, consequently slowing down fraud's spread and reducing the number of victims involved. In conclusion, in the era of digital finance, financial fraud is more likely to produce serious and adverse results through social networks. Regulators should protect investors from financial fraud collapses by promoting financial literacy education and regulating the behaviors of influential people.

Acknowledgment

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