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HIGHLIGHTS

- An artificial stock market with multi-agent model is developed.
- Information about fundamentals could be acquired from both market and social network.
- Switch behavior of agents are constrained by their information statuses.
- Fundamentalists and chartists play different roles in information diffusion.
- Different combinations of information efficiency play diverse roles in price dynamics.

Effects of fundamentals acquisition and strategy switch on stock price dynamics

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Abstract

An agent-based artificial stock market is developed to simulate trading behavior of investors. In the market, acquisition and employment of information about fundamentals and strategy switch are investigated to explain stock price dynamics. Investors could obtain the information from both market and neighbors resided on their social networks. Depending on information status and performances of different strategies, an informed investor may switch to the strategy of fundamentalist. This in turn affects the information acquisition process, since fundamentalists are more inclined to search and spread the information than chartists. Further investigation into price dynamics generated from three typical networks, i.e. regular lattice, small-world network and random graph, are conducted after general relation between network structures and price dynamics is revealed. In each network, integrated effects of different combinations of information efficiency and switch intensity are investigated. Results have shown that, along with increasing switch intensity, market and social information efficiency play different roles in the formation of price distortion, standard deviation and kurtosis of returns.

Keywords:
Stock price dynamics
Artificial stock market
Multi-agent based model
Social networks
Information efficiency
Strategy switch

1. Introduction

Different from representative agent models[1][2], heterogeneous agent-based models[3][4]have explained dynamics of the stock market from aspect of heterogeneous beliefs of investors. And equipped with multi-agent based models[5][6][7], artificial stock market (ASM), pioneered by SFI (Santa Fe Institute)[8][9], attempted to investigate traders psychology and behavior by assigning heterogeneities individually, or to study underlying market mechanisms by designing various structures of the ASM.

One mechanism that has long been investigated is acquisition and employment of information[10][11][12][13 The definition of information is ill-defined in existing agent-based models. However, it is reasonable to roughly divide it into two categories: non-fundamental information and fundamental one. Non-fundamental information normally refers to a specific trading strategy[10], a parameter specification in making trading decision[11], expected return[12], sentiment[13] and etc. Fundamental information,

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as a more essential element of the stock market, also attracts enormous attention of researchers and usually embodied as a constant intrinsic value[14], realizations of a dividend process[15] or a geometric Brownian motion[16].

Effects of fundamental information on price dynamics only emerge when such information is employed by informed investors. Thus, information acquisition is the first consideration before employing it. Hein et al.[17] and Zhang et al.[15] simply assume that agents can obtain the information at any time. And in Ref.[18], information is still not inaccessible, although with some cost. Another approach of being informed is social interaction such as random contact between agents proposed by Kirman[19]. After complex networks theory is introduced, it became a powerful tool to capture interaction in social activity. Hein et al.[17] found that fluctuation and distortion of prices to fundamentals are intensified when increasing reconnect probability in constructing a small-world network where information exchange happens. Other networks such as scale-free network[20], regular lattice[21] and random graph[22] are also studied. Results revealed that network structures have crucial effects on stock price formation[21][22] and behavior of investors[20][21][22][23]. However, information acquisition itself is not the study focus in any of above papers.

The purpose of being informed is utilizing the information to form more profitable strategies. And an obvious way to utilize information about fundamentals is applying the strategy of fundamentalist. A large number of literatures [24][25][26][27][28] have conducted studies containing the strategy of fundamentalist and switch behavior from one strategy to another. In these papers, agents could choose to be fundamentalists liberally, given that information about fundamentals is always available.

In real-world stock market, however, acquisition of information about fundamentals and strategy switch are much more complicated. First, information could be acquired from both the market and social connections. Second, new information is continuously poured into the market in an evolving economic environment. Thus, informed agents may not switch to the strategy of fundamentalist if the acquired information is outdated to the extent that it exceeds invest time horizons of traders. In addition, different types of investors play different roles in information acquisition process. It is fundamentalists, who already paid attention to fundamentals and factually employed them into strategy formation, rather than chartists are more likely to take effort to search latest fundamentals from the market and to spread it further to their neighbors. Therefore, analogous to Ref.[29], in which author assume that information cascade was shattered if experts just consider their private information and refuse to use information of others, chartists in the present paper may shattered the diffusion of fundamental information.

Motivated by above literatures and ideas, we constructed an ASM equipped with a multi-agent based model to study effects of information acquisition and strategy switch on stock price dynamics. The paper is organized as follows: section 2 describes our methodology; section 3 presents results of simulation; at last, conclusion is made in section 4.

2. The model

2.1. Heterogeneous agents and market mechanism

2.1.1. Utility maximization

It is assumed that a population of N agents of investment time horizon l exists in the ASM. They either participate into daily trading with probability $1/l$ or holding their positions, which makes average holding periods of portfolios agree with investment time horizons. Therefore, wealth of agents at trading day t is consisted of an amount of c_t cash and z_t shares of stock whose value is p_t, i.e. $W_t = c_t + z_t p_t$.

At the beginning of t, agents have to decide the proportion of W_t that they would like to invest into the stock by maximizing expected utility of wealth at the end of the trading day $t+l$. Since W_{t+l} is only determined by return of stock over the interval $[t, t+l]$ in the present paper, its evolution can be presented as

$$W_{t+l} = W_t + z_t p_\tau \rho_{t+l}, \tag{1}$$

where z_t denotes amount of shares that agents would like to hold at the end of the trading day $t+l$, represents quote of the order submitted at intraday time $\tau(\tau \in R^+)$, and ρ_{t+l} is expected return from t to $t+l$ computed according to Eq.(2)[30]

$$\rho_{t+l} = \hat{p}_{t+l}/p_\tau - 1 \simeq \ln \hat{p}_{t+l} - \ln p_\tau, \tag{2}$$

where ln denotes natural logarithm and $\hat{p}_{t+l} = E_{t-1}[p_{t+l}]$ means agents form their expected closing prices of the trading day $t+l$ based on the information gathered before trading day t. Based on extensively employed utility function of CARA (Constant Absolute Risk Aversion)[9][31][32][33][34], the objective of agents are maximizing expected $U(W_{t+l}, a) = -\exp(-aW_{t+l})$, where a is risk aversion coefficient. That is maximizing

$$\hat{U}_{t+l} = E_{t-1}[-\exp(-aW_{t+l})]. \tag{3}$$

With assumption of Gaussian distributed expected return of agents[30], the Eq.(3) can be written as Eq.(4), where $V_{t-1}[\bullet]$ denotes conditional variance.

$$\hat{U}_{t+l} = -\exp(-aE_{t-1}[W_{t+l}] + a^2 V_{t-1}[W_{t+l}]/2). \tag{4}$$

By differentiating Eq.(4) with respect to z_t, shares that agents would like to hold with price p_τ is

$$z_t(p_\tau) = \frac{\ln \hat{p}_{t+l} - \ln p_\tau}{aV_{t-1}p_\tau}, \tag{5}$$

where expected variance of returns V_{t-1} is substituted with actual variance of historical returns

$$V_{t-1} = \frac{1}{l}\sum_{j=0}^{l}(r_{t-1-j} - \bar{r})^2, \tag{6}$$

where $\bar{r} = \frac{1}{l}\sum_{j=0}^{l} r_{t-1-j}$ is the average return.

2.1.2. Heterogeneity

According to basic belief towards price evolution, agents could be divided into two categories: a population of N^f fundamentalists and a population of N^c chartists. Fundamentalists hold the idea that prices will converge to its fundamentals, while chartists believe that historical price trend will be continued (momentum traders) or reversed (contrarians).

The agent subscript i is added to variables to indicate a typical agent. We assume that the expected closing price $\hat{p}_{i,t+l_i}$ at trading day $t+l_i$ of agent i with time horizon l_i is determined by

$$\hat{p}_{i,t+l_i} = p_{t-1}e^{\hat{r}_{i,t+l_i}l_i}. \tag{7}$$

Where e is the Euler's constant and $\hat{r}_{i,t+l_i}$ denotes average expected return over the interval $[t, t+l_i]$. Expected return $\hat{r}_{i,t+l_i}$ is computed using Eq.(8) or (9), if agent i belongs to the group of chartists or fundamentalists. In equations, p_{t-1} denotes settled price of the former trading day, $p_{t-1-l_i^c}$ is the reference price when the chartist i looking back on historical prices based on its time horizon l_i^c, and $p_{i,t}^f$

is the fundamental value acquired by the fundamentalist i.

$$\hat{r}_{i,t+l_i} = \theta_1(\ln p_{t-1} - \ln p_{t-1-l_i^c})\Big/ l_i^c, \tag{8}$$

$$\hat{r}_{i,t+l_i} = \theta_2(\ln p_{i,t}^f - \ln p_{t-1})\Big/ l_i^f, \tag{9}$$

Since agents are not perfectly rational, reaction intensity to historical price trend θ_1 and to fundamentals θ_2 are independently drawn from uniform distributions $U[-0.5, 0.5]$ and $U[0, 0.5]$ separately. Similarly, time horizons of chartists and fundamentalists are $l_i^c \sim U[2, L_c]$ and $l_i^f \sim U[L_c + 1, L_f]$, in which L_c and L_f are reference levels. Chartists adopt the strategy of momentum or contrarian when $\theta_1 > 0$ or $\theta_1 < 0$, and are indifferent to historical price trend when $\theta_1 = 0$.

Fundamental value $p_{i,t}^f$ in Eq.(9) is exogenously given by $p_t^f = p_{t-1}^f e^{\varepsilon_t}(t = 1, 2, \ldots)$, where ε_t is drawn from the Gaussian distribution $N(0, \sigma_\varepsilon^2)$ independently at each time step. The specific value of $p_{i,t}^f$ acquired and employed by agent i, however, depend on the market information efficiency and diffusion efficiency on social networks. Thus, the information about fundamentals will be lagged and may be different for each agent due to an inefficient market and the process of diffusion which will be described in Fig.1 in section 2.1.1.

Initial values of risk aversion coefficient a for all agents are randomly drawn from the uniform distribution $U[0, 0.01]$, and evolve along with dynamics of the market. Following Ref.[30], we set risk aversion coefficient of fundamentalists $a_{i,t}^f$ as Eq.(10), if $p_{t-1} - p_{i,j}^f \neq 0$. And $\phi_1 > 0$ in the equation measures sensitivity to the misalignment between prices and fundamentals. An evolution process is also introduced for chartists as presented in Eq(11), where $Var_{t-1} \neq 0$ is variance of historical prices and $\phi_2 > 0$ represents reaction intensity of chartists to price fluctuation.

$$a_{i,t}^f = \frac{a_{i,t-1}^f}{\left|p_{t-1} - p_{i,t}^f\right|\Big/\phi_1}, \tag{10}$$

$$a_{i,t}^c = \frac{a_{i,t-1}^c}{Var_{i,t-1}/\phi_2}, \tag{11}$$

For agent i, expected transaction price (or quote of orders) $p_{i,\tau}$ is constrained by her endowments and dynamics of the order book she observed. Since no short selling and no short buying are allowed, an upper limit $p_{i,M1} = \hat{p}_{i,t+l_i} \geqslant p_{i,\tau}$ to ensure $z_{i,t}(p_{i,\tau}) > 0$ and a lower limit $0 < p_{i,m1} \leqslant p_{i,\tau}$ to fulfill budget constraint are obtained[31]. And assumed that 10 different quotes can be observed from the order book, therefore quote of agent i is also constrained by $p_{i,m2} = p_e - 10 \times \Delta$ and $p_{i,M2} = p_e + 10 \times \Delta$, where denotes the tick size and Δ is the former executed price. Therefore, in the present paper quote of an order is randomly drawn from the interval $[p_{i,m2}, p_{i,M2}]$ firstly, and constrained by the range$[p_{i,m1}, p_{i,M1}]$ as well.

2.1.3. Orders submitting and clearing mechanism

By comparing amount of desired shares $z_{i,t}$ and holding shares $h_{i,t}$, order size $q_{i,t}$ and trading direction $d_{i,t}$ of agent i can be obtained. That is $q_{i,t} = z_{i,t} - h_{i,t}$, which is negative for sell orders ($d_{i,t} = -1$) and positive for buy orders ($d_{i,t} = 1$). Then agent i submits orders to buying or selling side of the order book, where the orders are stored, matched and cleared by the clearing mechanism of CDA (Continuous Double Auction).

Technical details of the CDA mechanism in the present paper are specified as follows. Orders are sequentially submitted by agents and stored in the order book by priority of price and priority of arrival

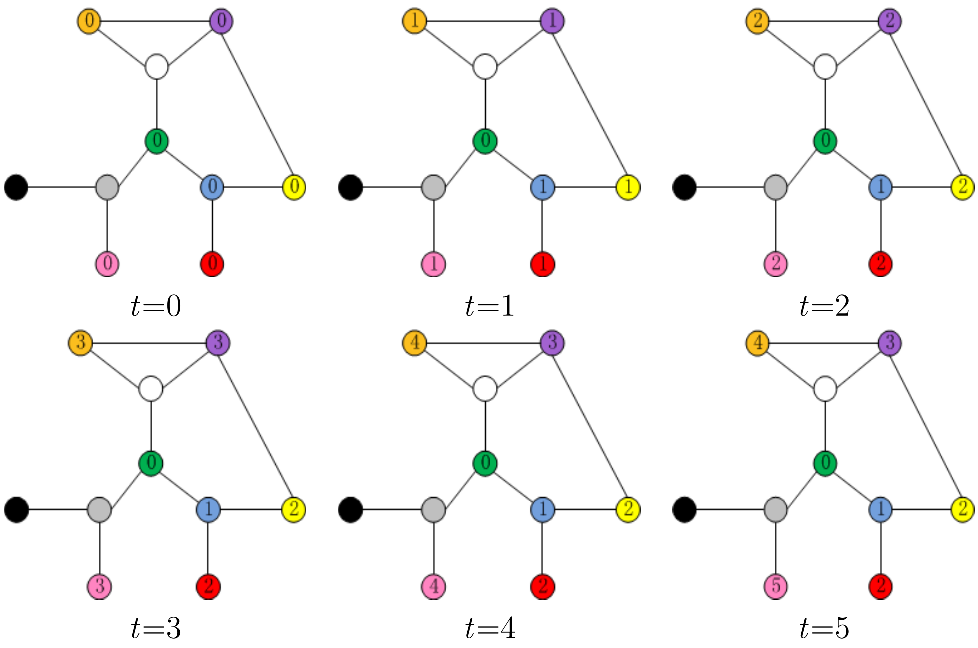

Figure 1: A typical process of information acquisition from t = 0 to t = 5. Colorized circles represent fundamentalists, white, gray and black circles represent chartists with different spatial positions and lines denote social connections between agents. Numbers in circles indicate lags of fundamentals.

time if prices are the same. The condition of transaction is fulfilled as long as the highest price on the buy side is greater than or equal to the lowest price on the sell side, and the transaction price p_e is the quote of earlier submitted one of matched orders. And the closing price p_t of trading day t is the last transaction price or equals to p_{t-1} if no transaction happens.

2.2. Information acquisition and strategy switch

2.2.1. Fundamentals acquisition from the market and social network

It is assumed that the information about fundamentals is not publicly known to all agents and could be acquired from the market and informed neighbors. And two assumptions about acquisition of information are made. First, only fundamentalists, who already paid attention to fundamentals and factually employed them into their strategy, take effort to search the information from the market. They acquire the latest information from the market with probability $\beta \sim U[0, \mathrm{B}]$ and spread it further on the social network with probability $\kappa \sim U[0, \mathrm{K}]$. This could be interpreted as individual information searching capacity β and spreading capacity κ are limited by information efficiency of market B and that of social network K. Second, agents are self-interested and only spread outdated information employed in last trading strategy to their neighbors. Based on assumptions above, we know that information may be lagged when agents acquired it and that both strategy switch and social network structure affect acquisition of fundamentals. To illustrate these, a typical information acquisition process is presented in Fig.1.

For simplicity, we assumed that agent green is the only fundamentalist who acquires the latest information from market and all agents will not change their strategy during this typical process. Before trading ($t = 0$), all fundamentalists are endowed with initial fundamental value of the stock, namely lag $j_i = 0$. At time $t = 1$, agent *green* updated her information and spread the outdated information to agent *blue* whose information was thus lagged for $j_i = 1$ day accordingly. When $t = 2$, agent *green* spread its information to agent *blue* who spread previous information further to agents *red* and *yellow*. This diffusion process continues as time goes by. At time $t = 5$, we can see obvious discrepancies between three branches stretched from agent *green*. Agents at lower right corner acquired information earlier than the upper corner where the direct information channel from agent *green* was shattered by agent *white*. And the agent *pink* at the lower left corner still hold the original information, i.e. her fundamental information is lagged for $j_i = 5$.

It is obvious that agents behavior of switching to or from the strategy of fundamentalist will accelerate or decelerate the process of information acquisition and diffusion over the network. Also, network structures such as average degree and path length have important impact on the process.

2.2.2. Strategy switch based on information acquisition

At trading day t, agent i computes her realized profit $v_{i,t}$ over interval $[t-l_i, t-1]$ according to Eq.(12), where buy ($d_{i,t-l_i} = 1$) or sell ($d_{i,t-l_i} = -1$) order of size $q_{i,t}$ is split into n small orders $\Delta q_{\tau,t-l_i}(\tau = 1,\dots n)$ and cleared at n executed prices $p_{e,\tau,t-l_i}(\tau = 1,\dots n)$.

$$v_{i,t} = d_{i,t-l_i} \times \sum_{\tau=1}^{n} \Delta q_{\tau,t-l_i}(p_{t-1} - p_{e,\tau,t-l_i}). \tag{12}$$

From the equation, we know that avoiding loss is equivalent to making profit in affecting switch behavior. The $v_{i,t}$ will be updated after agent i participates into daily trading and before the expectation is formed, and equals to 0 if a strategy is not employed before.

Then, performance of a strategy is calculated as $U_{i,t} = U_{i,t-l_i} + \eta \times v_{i,t}$, where η is the weight assigned to the latest profit. Based on performance of different strategies, agent i decides which strategy to employ at this trading day. We capture this switch behavior by modifying multinomial logit model in Ref.[19]. As showed in Eqs.(13), probabilities of agent i employing the strategy of fundamentalist ($\pi^{f}_{i,t}$), momentum trader ($\pi^{mo}_{i,t}$) and contrarian ($\pi^{co}_{i,t}$) are determined by according performances $U^{f}_{i,t}$, $U^{mo}_{i,t}$, $U^{co}_{i,t}$ and information status about fundamental information.

$$\begin{cases} \pi^{f}_{i,t} &= \delta e^{\phi U^{f}_{i,t}} \Big/ (\delta e^{\phi U^{f}_{i,t}} + e^{\phi U^{mo}_{i,t}} + e^{\phi U^{co}_{i,t}}) \\ \pi^{mo}_{i,t} &= e^{\phi U^{mo}_{i,t}} \Big/ (\delta e^{\phi U^{f}_{i,t}} + e^{\phi U^{mo}_{i,t}} + e^{\phi U^{co}_{i,t}}) \\ \pi^{co}_{i,t} &= e^{\phi U^{co}_{i,t}} \Big/ (\delta e^{\phi U^{f}_{i,t}} + e^{\phi U^{mo}_{i,t}} + e^{\phi U^{co}_{i,t}}) \end{cases} . \tag{13}$$

In equations, $\phi > 0$ denotes switch intensity of agent i, δ is an indicator function for information status. If the lags of acquired information exceeds investment time horizon of agent i or agent i is simply not informed, then $\delta = 0$. Otherwise $\delta = 1$. This ensures that agents will not switch to the strategy of fundamentalist if they do not possess corresponding information or questioned about the value of the information since it is rather outdated.

3. Simulations and results

3.1. Acquisition and employment of fundamentals under different network structures

Simulations in this subsection are performed with switch intensity ϕ =0.5, market information efficiency B=0.5 and social network efficiency K=0.5. Values and descriptions of other parameters are listed in Table 1.

To investigate acquisition and employment of information about fundamentals under various network structures, we constructed different small-world networks from regular lattice (RL) with eight neighbors to random graph (RG) by increasing reconnected probability from 0 to 1. Main characteristics of

Table 1: Parameter setting.

Parameters	Description	Values or ranges
N	Population of total investors	1000
N_0^f	Population of initial fundamentalists	100
N_0^c	Population of initial chartists	900
h_0	Initial holding shares	U[10,50]
c_0	Initial cash	300+100h_0
p_0^f	Initial fundamental value of stock	10
p_0	Initial settled price	10
σ_ε^2	Variance of fundamental returns	0.01
η	Weight of the latest profit when compute strategy performance	0.5
L_f	Reference level of time horizon for fundamentalists	100
L_c	Reference level of time horizon for chartists	50
Δ	Tick size	0.01
ϕ_1	Sensitivity to the misalignment between prices and fundamentals	2
ϕ_2	Reaction intensity to price fluctuation	0.2

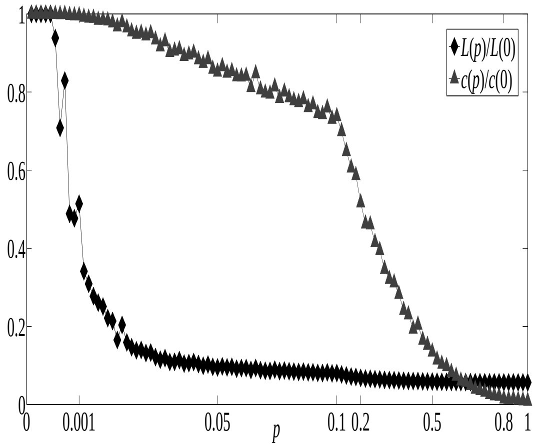

Figure 2: Ratios of average path length and cluster coefficient of studied small-world networks with respect to those of RL with, i.e. $L(p)/L(0)$ and $c(p)/c(0)$ are displayed. Denoted by these two indicators, networks global information efficiency and local information efficiency are respectively indicated.

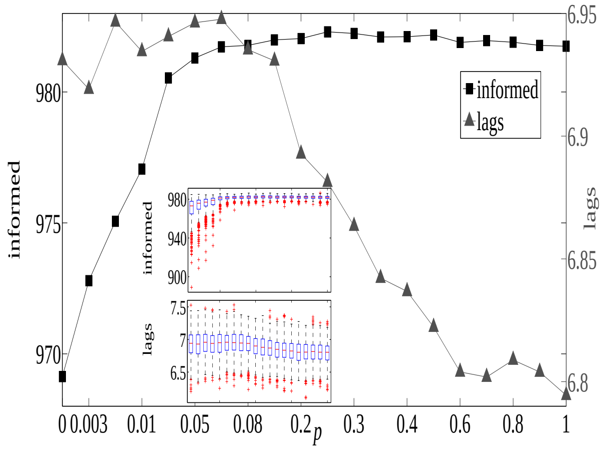

Figure 3: Information statuses of agents organized on different social networks. Left and right y-axes indicate the number of agents who have acquired fundamental information (the informed) and according lags of the information (lags).

generated networks, which are essentially confirmed by theoretical results in Ref.[35], are illustrated in Fig.2.

Taking continuity and distinctiveness of those characteristics into account, aside from RL and RG, networks generated with 18 different reconnected probabilities are chosen to perform simulations on. On each network, we conduct 500 times simulations, each of which contains 3000 simulation time steps (interpreted as trading days). Presented results are calculated by averaging results of 500 times simulation, based on which according box plots are also drew and embed in figures. And results of the first 500 time steps, as run-in period, of each simulation are discarded.

According to analysis in subsection 2.2.1, information statuses of agents vary with different social network structures. As illustrated in Fig.3, number of the informed peaks at reconnected probability p=0.25 with rapidly increase before and slowly decrease after. The result imply that when p <0.25 the sharply decreased average path length (see Fig.2), i.e. increased global efficiency, has more impact on accelerating information diffusion than that of slowly decreased cluster coefficient, i.e. decreased local efficiency, have on decelerating the diffusion.

However, the information diffusion process will be slow down when local interaction on the network is extremely rare, i.e. a very small value of cluster coefficient, even with a short average path length at the same time. These are consistent with findings of Panchenoko et al.[36] who put forward that the speed of information diffusion was affected by characteristic path length, cluster coefficient and the number of neighbors of each agent. Average lags showed in Fig.3 experienced an increase first then dropped rapidly. This is because higher global efficiency only prompts diffusion of outdated information rather than facilitate acquisition of the latest information. And, only the existence of large population of the informed, i.e. potential fundamentalists may acquire new information from the market, thus reduce lags of information.

Given an information status, whether an agent switches to the strategy of fundamentalist is essentially determined by its performance. As depicted in Fig. 4, the population of fundamentalists increases along with that of agents whose strategy of fundamentalist outperformed other strategies. Rather than decreasing with the declining number of the informed after p=0.25 (see Fig.3), the population of fundamentalists maintain its climbing trend in a mild manner.

To reveal general relation between information acquisition and employment on different social networks and price dynamics, simulations are performed on 20 chosen networks. Results of price dynamics are reported in terms of kurtosis and standard deviation of returns and distortion of price to funda-

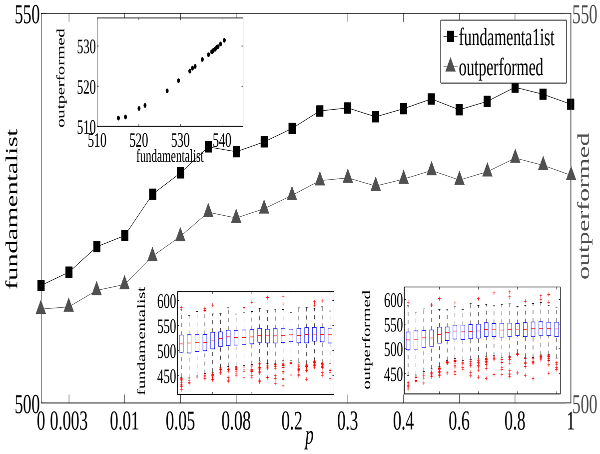

Figure 4: The population of fundamentalists and the quantity of agents, whose strategy of fundamentalist outperformed other strategies, on different networks. Embedded scatter plot indicates a linear relation between them.

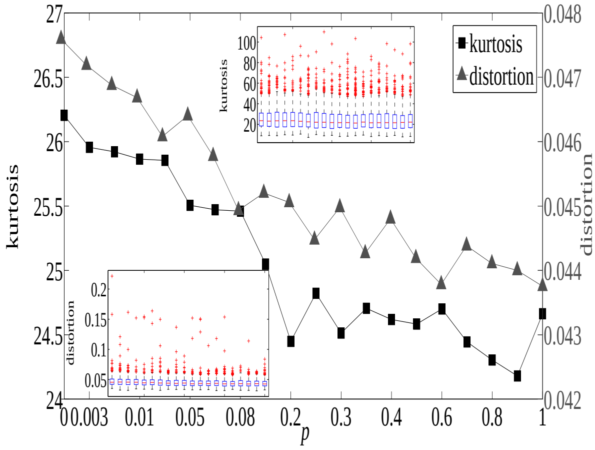

Figure 5: Kurtosis and distortion of prices to fundamentals v.s reconnected probability in constructing small-world networks.

mentals $p_d = \frac{1}{2500}\sum_{t=501}^{3000} \left| p_t - p_t^f \right| \Big/ p_t^f$ derived from Ref.[10]. Overall declining trend of kurtosis and distortion are displayed in Fig. 5, and no obvious tendency is found for standard deviation. The ubiquitous phenomenon of fat-tailed distribution is revealed by excessive kurtosis. The results imply that the market is more stabilized with increasing population of fundamentalists.

3.2. Features of typical time series

In this section, we investigate detailed price dynamics generated from three typical networks, that is regular lattice, random graph and small-world network that give rise to the largest amount of informed investors, i.e. constructed on $p = 0.25$. On the one hand, we validate the present multi-agent based model by reporting several stylized facts which are ubiquitously found in real-world stock market. On the other hand, some contrasts and comparisons between dynamics produced from different networks are made.

Fig.6 shows overall fluctuations of prices around fundamentals and occasional over- and under-reactions. These indicate the dominance of fundamentalists and the effect of chartist respectively. Similar with Ref.[37], prices tracking changing fundamentals imply outcomes of sluggish information acquisition process. Results also demonstrated influences of chartists in the market that basically domi-

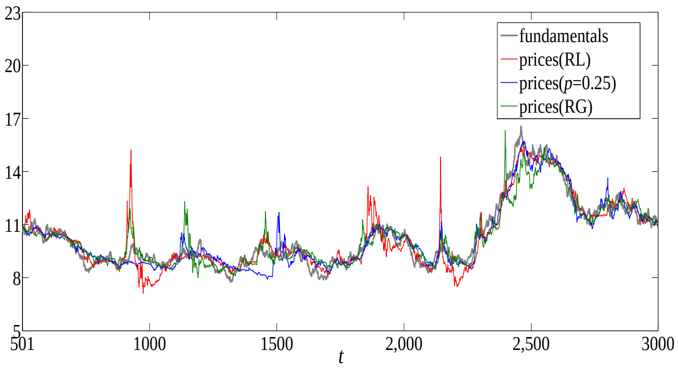

Figure 6: Fundamentals and price dynamics generated from three typical networks, that is regular lattice (RL), random graph (RG) and small-world network with reconnected probability $p = 0.25$.

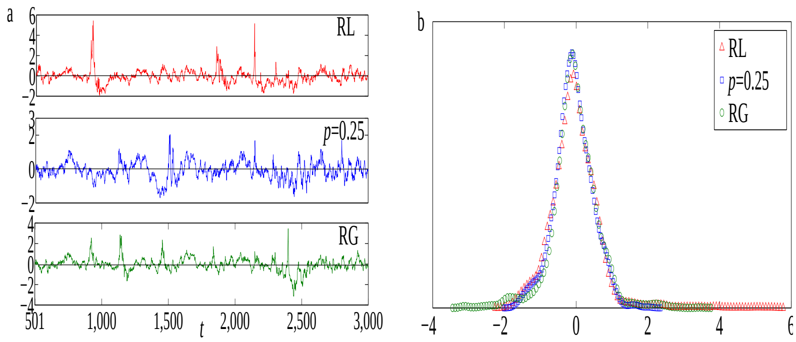

Figure 7: Differences between prices and fundamentals $p_t - p_t^f$ $(t = 501, \ldots, 3000)$ (a) and corresponding empirical density functions (b).

nated by fundamentalists. This may be attributed to the shorter time windows and higher participation frequency of chartists.

To get deeper insights into price dynamics, differences between prices and fundamentals are displayed in Fig.7(a) and studied. The graph shows that the differences are insignificant for most time steps of simulations and large deviations are shortly corrected by the convergence of prices to fundamentals. These features are demonstrated by the unimodal and fat-tailed distribution of differences showed in Fig.7(b). A particularly interesting thing is that the largest deviation is not occurred around the vicinity of the global maximum of fundamentals. However, it is not that inconceivable if we take the relative short investment time horizon and limited endowments of chartists into account. By studying Fig.6 more closely, we find that before the time step of 2,500 there are two local maximums during the long climbing trend which have weakened the demand of chartists at the end of the trend. Furthermore, distortions of prices to fundamentals at each time step whose values and dynamics features agreed with that of differences are depicted in Fig.8.

So far dynamics of prices and its relation to fundamentals are revealed. And based on the former results, we further study characteristics of returns. Time series and empirical density distributions of simulated returns are respectively displayed in Fig.9(a) and (b), where visual effects of volatility clustering, peakedness, and fat-tails are observed. By comparing Fig.6 and Fig.9(a), we find that volatility clustering occurs at the moment of over-reaction of prices to fundamentals and following undue correction. Moreover, Fig.10 displays autocorrelations of raw, absolute and squared returns of each price series. In Fig.10 (b), (c) and (d), except for raw returns, long-memory is found in both absolute and squared returns, which is consistent with real-life stock market. And, long-memory is not

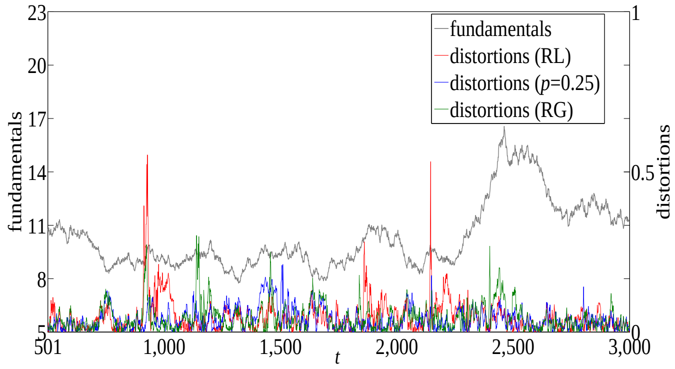

Figure 8: Time series of fundamentals and distortions of prices to fundamentals from time step 501 to 3000.

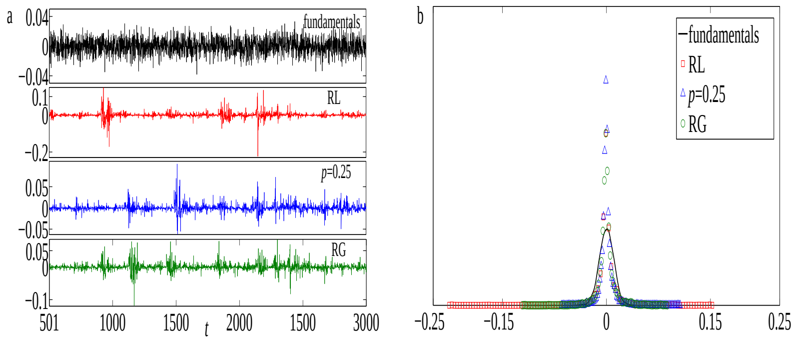

Figure 9: Time series (a) and empirical density functions (b) of returns generated from three typical networks. Time series and empirical density function of fundamental returns are also displayed as the benchmark for contrast.

observed for all fundamental returns as presented in Fig.10(a).

3.3. Integrated effects of switch intensity and information efficiency

Simulations are conducted on three typical networks to investigate integrated effects of switch intensity and different combinations of information efficiencies on stock price dynamics. It has been found that former mentioned price dynamics and stylized facts of returns are retained when reference levels of information efficiencies K and B are set within the interval of [0.3,0.7]. Therefore, to introduce conspicuous discrepancy, following simulations are respectively performed with B=0.3, K=0.7 and B=0.7, K=0.3 along with switch intensity ϕ changing from 0.1 to 1. For robustness, all simulations in this section are also conducted for 500 times. And results, in terms of standard deviation and kurtosis of returns and distortion of prices to fundamentals, are obtained by averaging outcomes of 500 times simulations and displayed in Fig.11.

In the graph, global climbing trends for all indicators are observed regardless of different networks and different combinations of information efficiency. Thus the impact of strategy switch and its intensity have on stock price dynamics is demonstrated. It is worth to note that standard deviation of returns grow persistently over the changes of ϕ, but is quite stable with respect to changing information statuses of investors as reported in section 3.1. Thus we may conclude that standard deviation is sensitive to switch behavior rather than information statuses of investors. Aside from standard deviation, overall values of distortion and kurtosis derived from RL are greater than those obtained from RG and small-world network. These results consist with findings in section 3.1.

In order to analyze integrated effects of different information efficiency combinations and switch intensity under different networks, we examine each column in Fig.11 from top to bottom. Increasing

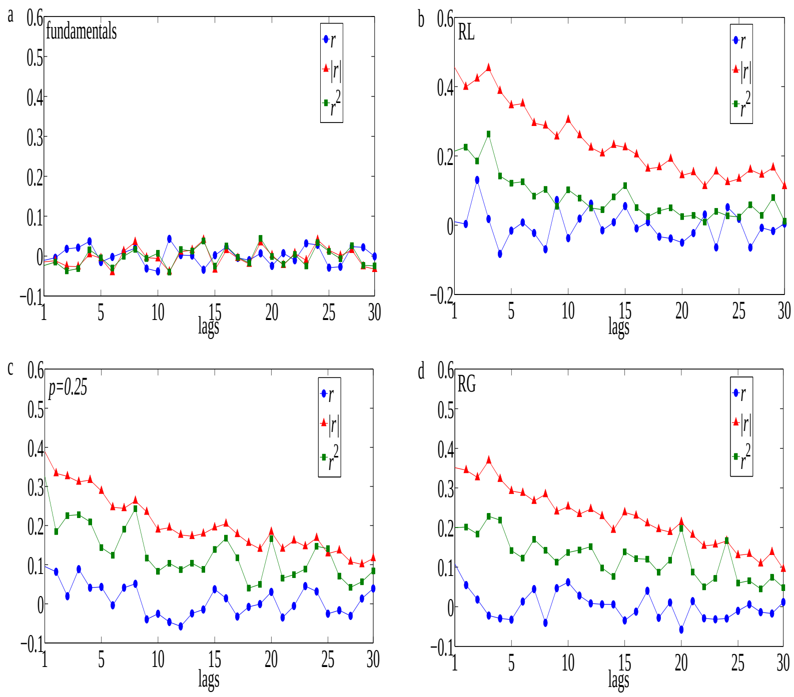

Figure 10: Autocorrelation of raw return r, absolute return $|r|$ and squared returns r^2 of fundamentals (a) and prices generated from RL (b), small-world network (c) and RG (d).

trends of standard deviation with B=0.3 , K=0.7 and B=0.7 and K=0.3 on each network show no visible discrepancy. Because different information statuses caused by those combinations will not affect formation of standard deviation as reported in section 3.1.

As for kurtosis and distortion of prices to fundamentals, combinations of B=0.3 , K=0.7 and B=0.7 , K=0.3 also make no difference on RL, given that low global efficiency of RL decelerates diffusion process of either new and outdated information. But on RG and small-world network, the combination of higher market efficiency and lower social efficiency, i.e. B=0.7 and K=0.3 incur significantly larger value of distortion and kurtosis than those caused by B=0.3 and K=0.7 when switch intensity is relatively small. Combined with a high efficiency of social network, i.e. K=0.7, high global efficiency of RG and small-world network will promptly propagate new information throughout the social network even the odds of searching the latest information from the market is low. This brings stable price dynamics, i.e. low value of distortion and kurtosis. But the discrepancy diminished when price dynamics is dominated by intensive switch behavior rather than information statuses of investors.

4. Conclusion

We developed an artificial stock market equipped with multi-agent model to investigate effects of fundamental information acquisition and strategy switch on stock price dynamics. Through the strategy of fundamentalist employed by investors, fundamentals are absorbed into prices which synchronously evolve along with adaptation of investors based on their information statuses and strategy switch behavior.

Simulations performed on different network structures show that average path length and cluster coefficient collectively determine information statuses of investors. Based on the statuses, the quantity of fundamentalists essentially relies on performances of different strategies. General results revel that distortion of prices to fundamentals and kurtosis of returns are decreasing with increment of reconnected

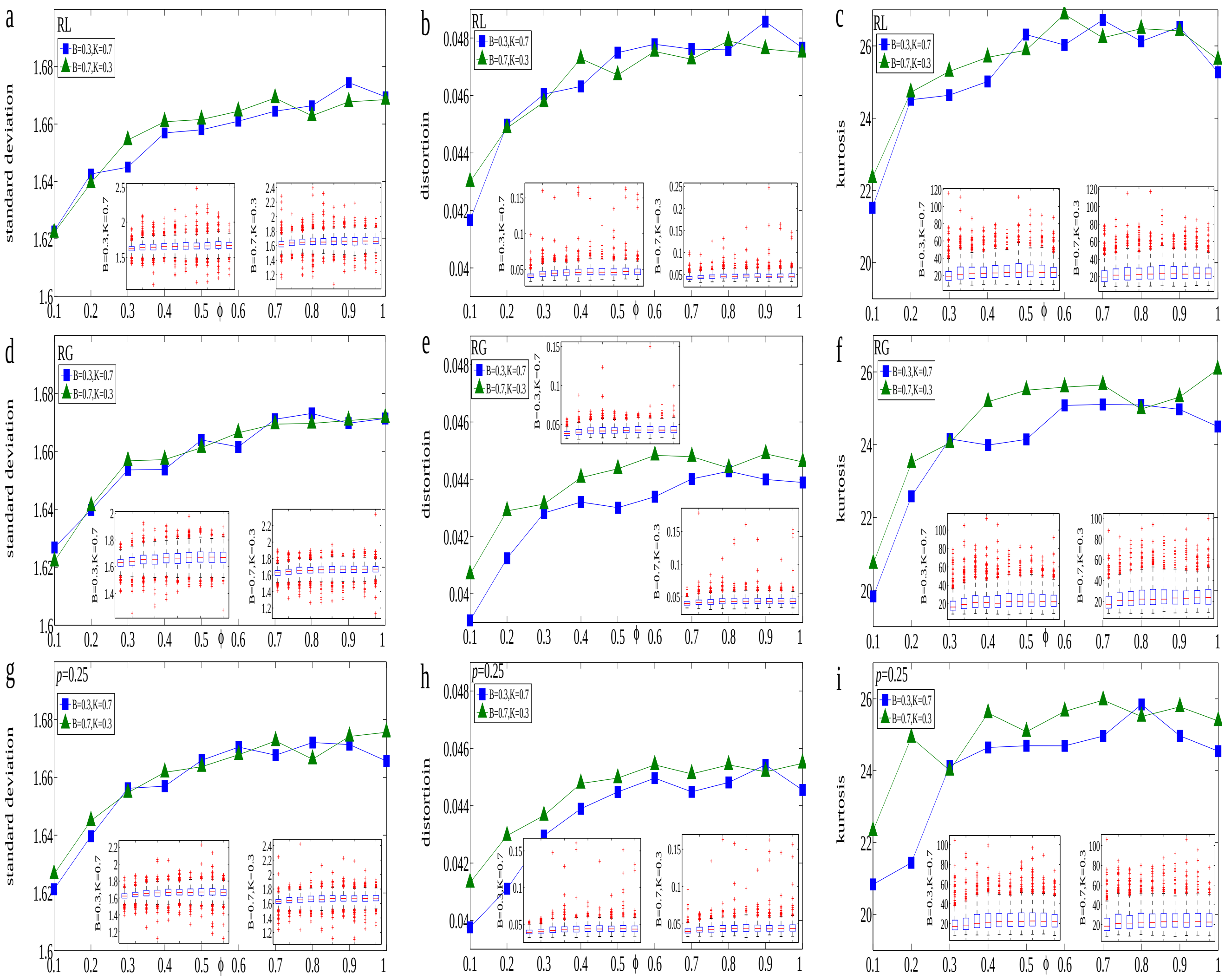

Figure 11: Integrated effects of different combinations of information efficiency and increasing switch intensity have on price dynamics. Mean values of kurtosis, standard deviation and distortion of prices to fundamentals are displayed. And box plots based on 500 times simulation results are also embed.

probability in constructing small-world networks, while standard deviation of returns is not affected by changing network structures.

Under the framework of asymmetric information about fundamentals, market fraction and adaptive behavior of strategy switch, multi-agent model in the present paper transfer fundamentals following geometric Brownian motion into time series with stylized facts of real-life stock market. Based on three typical networks, integrated effects of different combinations of information efficiency and switch intensity have on price dynamics are further studied. It is found that increasing switch intensity is a persistent driven force of stock market instability.

Along with the increment of switch intensity, different combinations of information efficiency have diverse impacts on stock price dynamics in terms of standard deviation, distortion and kurtosis under various network structures. And discrepancies between impacts caused by different information efficiency combinations are diminished by intensive switch behavior of investors.

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