Examining the Effects of Traders' Overconfidence on Market Behavior

Chia-Hsuan Yeh and Chun-Yi Yang

Abstract Much attention has been paid in the past decade to how traders' psychological factors affect market properties. Overconfidence is one of most important characteristics of traders. Under an agent-based modeling framework, this paper examines how traders' overconfidence affects market properties. The preliminary results have shown that overconfidence increases market volatility, price distortion, and trading volume. Some stylized facts such as the fat-tail of the return distribution and volatility clustering would be more evident.

Keywords Rationality · Behavioral finance · Overconfidence · Artificial stock market · Agent-based modeling · Genetic programming

1 Introduction

It is well-known that modern financial economic theory relies heavily on the assumption that the representative agent in the market behaves rationally and has rational expectations. Under this assumption, it is shown that asset prices fully reflect all available information and always reflect their intrinsic value. In this situation, future price movements cannot be predicted on the basis of past information. Any financial regulation imposed on the market should generate no substantial effects but result in delayed revelation of the information. Milton Friedman is one of the strongest advocates for supporting the rational expectations approach.

Examining the efficiency of real financial markets has been an interesting topic in the past three decades. Many studies have questioned the validity of the efficient market hypothesis (EMH) in real financial markets and have provided the theoretical foundations or empirical evidence to show the existence of market inefficiency. De Long et al. [9] point out that noise traders may survive in the long run and exert an impact on price dynamics. Kogan et al. [13] further indicate that irrational traders can persistently maintain a large impact even though their relative wealth

C.-H. Yeh (✉) and C.-Y. Yang
Department of Information Management, Yuan Ze University, Chungli, Taoyuan 320, Taiwan
e-mail: imcyeh@saturn.yzu.edu.tw; ckhyde.yang@gmail.com

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becomes quite small. Lo and MacKinlay [14], Campbell and Shiller [4], Brock et al. [3], and Neely et al. [15] all find evidence of predictability and profitability in financial markets. In addition, the increasing empirical evidence has indicated that traditional asset pricing models such as the capital asset pricing model (CAPM), arbitrage pricing theory (APT), and intertemporal capital asset pricing model are unable to provide explanations regarding the stylized facts. Financial markets usually experience several anomalies, such as event-based return predictability, short-term momentum, long-term reversal, and high volatility of asset prices relative to fundamentals where bubbles and crashes never cease. These phenomena cannot be purely explained by the changes in fundamentals. Given these findings, it is reasonable to reexamine the theory of finance based on imperfect rationality.

Actually, studying economics and finance from the perspective of imperfective rationality has both theoretical and empirical foundations. The reason for economists holding the assumption of rational expectations is that economic systems without this restriction may produce numerous outcomes so that prediction is impossible. Simon [18] argues that agents possess imperfect information or knowledge regarding the environment and that they also have limited ability in processing information. Therefore, bounded rationality is a more reasonable and more appropriate description regarding agents' behavior than perfect rationality. The empirical evidence from cognitive psychology also supports the view that agents do not behave rationally. As mentioned in [12], traders in financial markets exhibit several phenomena that deviate from perfect rationality such as overreaction toward salient news, underreaction toward less salient news, anchoring, loss aversion, mental accounting, herding, and overconfidence.

In the past two decades, research studies devoted to financial economics have considered models that deviate from full rationality. One branch focuses on the effects of noise traders, e.g. [6–9, 17]. Their findings have demonstrated that the presence of noise traders can generate substantial effects which are quite different from those observed in the market populated by rational traders alone. The other branch focuses on the consequences resulting from traders' psychological biases. This line of research has been an important issue in the field of behavioral finance. Actually, the importance of this research trend that takes the behavioral characteristics into account has been noticed. As mentioned in [10]:

> Finally, given the demonstrated ingenuity of the theory branch of finance, and given the long litany of apparent judgment biases unearthed by cognitive psychologists ([5]), it is safe to predict that we will soon see a menu of behavioral models that can be mixed and matched to explain specific anomalies. (p. 291)

DeBondt and Thaler [5] state that perhaps the most robust finding in the psychology of judgment is that people are overconfident. In [19], it is pointed out that traders' overconfidence may be due to an "anchoring and adjustment" process. The anchor has a major influence so that the adjustment is usually insufficient. Therefore, traders have tight subjective probability distributions. This phenomenon is also evidenced in the empirical literature on judgment under uncertainty. Benos [2] then believes that selection and survivorship biases may also be sources of overconfidence and successful traders usually overestimate their own contribution to their success. Such a reasoning is supported by the attribution theory, e.g. [1], which describes that individuals usually attribute outcomes that support the validity of their decisions to high ability, and outcomes that are inconsistent with the decisions to external noise.

However, theoretical results rely heavily on specific assumptions regarding the characteristics of traders as well as the market environments, and the information structures. Since many factors are involved, and traders' behavior may generate externalities on others, there would be a clearer and more concrete picture regarding the effects of traders' psychological biases if a heterogeneous-agent framework were to be employed. In fact, Hirshleifer [12] mentions that:

> The great missing chapter in asset-pricing theory, I believe, is a model of the social process by which people form and transmit ideas about markets and securities. (p. 1577)

Under a well-controlled heterogeneous-agent environment where traders' psychological factors are considered, we are able to examine the market phenomena from the perspective of a micro-foundation. However, such a framework would be too complicated so that analytical results would be difficult to derive. Therefore, a simulated framework composed of many heterogeneous and bounded-rational traders whose learning behavior is appropriately represented would be a better architecture. In this paper, we provide an agent-based artificial financial market to examine the effects of traders' overconfidence on several stylized facts such as volatility clustering and fat tails for the return series.

The remainder of this paper is organized as follows. The basic framework of the model which includes the market environment, the traders' learning behavior, and the mechanism of price determination are described in Sect. 2. Section 3 presents the simulation design and the results. Section 4 concludes.

2 The Model

2.1 Market Structure

The basic framework of the artificial stock market considered in this paper is the standard asset pricing model with many heterogeneous traders. All traders are characterized by bounded rationality in which they are equipped with adaptive learning behavior represented by the genetic programming (GP) algorithm. In the framework of GP, traders are freely allowed to form various types of forecasting functions which may be fundamental-like or technical-like rules in different time periods.

Our framework is very similar to that used in [21]. However, to calibrate the model so that it is able to fit different time horizons of real financial markets, we follow the design proposed in [11].

Consider an economy with two assets. One is the risk free asset called money which is perfectly elastically supplied. Its gross return is $R = 1 + r/K$, where r is a constant interest rate per annum and K represents the trading frequency measured over 1 year. For example, $K = 1$, 12, 52, and 250 stand for the trading periods of a year, month, week, and day, respectively. The other asset is a stock with a stochastic dividend process (D_t) not known to traders. The trader i's wealth at $t+1$, $W_{i,t+1}$, is given by

$$W_{i,t+1} = RW_{i,t} + (P_{t+1} + D_{t+1} - RP_t)h_{i,t}, \tag{1}$$

where P_t is the price (ex dividend) per share of the stock and $h_{i,t}$ denotes the shares of the stock held by trader i at time t. Let R_{t+1} be the excess return at $t+1$, i.e. $P_{t+1} + D_{t+1} - RP_t$, and $E_{i,t}(\cdot)$ and $V_{i,t}(\cdot)$ are the forecasts of trader i regarding the conditional expectation and variance at $t+1$ given his information up to t (the information set $I_{i,t}$), respectively. Then we have

$$E_{i,t}(W_{t+1}) = RW_{i,t} + E_{i,t}(P_{t+1} + D_{t+1} - RP_t)h_{i,t} = RW_{i,t} + E_{i,t}(R_{t+1})h_{i,t}, \tag{2}$$

$$V_{i,t}(W_{t+1}) = h_{i,t}^2 V_{i,t}(P_{t+1} + D_{t+1} - RP_t) = h_{i,t}^2 V_{i,t}(R_{t+1}), \tag{3}$$

Assume that all traders follow the same constant absolute risk aversion (CARA) utility function, i.e. $U(W_{i,t}) = -exp(-\lambda W_{i,t})$, where λ is the degree of absolute risk aversion. At the beginning of each period, each trader myopically maximizes the one-period expected utility function subject to (1). Therefore, trader i's optimal share of stock holding, $h_{i,t}^*$, solves

$$\max_h \{E_{i,t}(W_{t+1}) - \frac{\lambda}{2} V_{i,t}(W_{t+1})\}, \tag{4}$$

that is,

$$h_{i,t}^* = \frac{E_{i,t}(R_{t+1})}{\lambda V_{i,t}(R_{t+1})}. \tag{5}$$

If it is supposed that the current stock holding for trader i is at the optimal level, i.e. $h_{i,t}^* = h_{i,t}$, then the trader's reservation price, $P_i^{\mathfrak{R}}$, can be derived.

$$P_i^{\mathfrak{R}} = \frac{E_{i,t}(P_{t+1} + D_{t+1}) - \lambda h_{i,t} V_{i,t}(R_{t+1})}{R}. \tag{6}$$

2.2 Learning of Traders

According to (6), it is shown that traders' reservation prices rely on their conditional expectations and variances. We adopt the functional form for $E_{i,t}(\cdot)$:

$$E_{i,t}(P_{t+1} + D_{t+1}) = \begin{cases} (P_t + D_t)\left[1 + \theta_0 \tanh\left(\frac{\ln(1+f_{i,t})}{\omega}\right)\right] & \text{if } f_{i,t} \geq 0.0, \\ (P_t + D_t)\left[1 - \theta_0 \tanh\left(\frac{\ln(|-1+f_{i,t}|)}{\omega}\right)\right] & \text{if } f_{i,t} < 0.0, \end{cases} \tag{7}$$

where $f_{i,t}$ is evolved using GP based on $I_{i,t}$.[1]

[1] Regarding the formation of a function by means of GP as well as the implementation of GP, the reader should refer to [20].

The modeling of traders' conditional variances also plays an important role. Let $\sigma^2_{i,t}$ denote $V_{i,t}(R_{t+1})$. Here we consider the following form of the conditional variance:

$$\sigma^2_{i,t} = (1-\theta_1-\theta_2)\sigma^2_{i,t-1} + \theta_1(P_t+D_t-u_{t-1})^2 + \theta_2[(P_t+D_t) - E_{i,t-1}(P_t+D_t)]^2, \tag{8}$$

where

$$u_t = (1-\theta_1)u_{t-1} + \theta_1(P_t+D_t). \tag{9}$$

Traders update their own estimated conditional variance of the active rule at the end of each period.

Each trader's overconfidence level is modeled as the degree of underestimation about the conditional variance. Therefore, the conditional variance shown in (8), $\sigma^2_{i,t}$, is replaced by $\Omega^2_{i,t}$:

$$\Omega^2_{i,t} = \gamma(t)\sigma^2_{i,t}, \tag{10}$$

where

$$\gamma(t) = \begin{cases} \gamma_1, & \text{if profit} > 0, \\ \gamma_2, & \text{if profit} < 0, \\ 1, & \text{if profit} = 0, \end{cases} \tag{11}$$

and profit is defined by $W_{i,t} - W_{i,t-1}$ which measures the performance of the trader i's investment profile, the allocation of both the risky and the risk-free assets. The values of γ_1 (γ_2) should be smaller (greater) than 1, and $|1-\gamma_1| > |\gamma_2 - 1|$. The last condition is used to model the behavior of biased self-attribution.

Each trader possesses several models, say N_I, which are represented by GP. The performance of each forecasting model is indicated by the value of strength which is defined by

$$s_{i,j,t} = -\Omega^2_{i,j,t}, \tag{12}$$

where $s_{i,j,t}$ is the strength of the jth model for trader i in period t. Traders learn to make better forecasts through an adaptation process that abandons the model with the poorest performance and generates a new one by means of an evolutionary process devised in GP. The evolutionary process takes place every N_{EC} period (evolutionary cycle) for each trader asynchronously. Traders' learning works as follows. At the beginning of each evolutionary cycle, each trader randomly chooses N_T out of N_I models. The one with the highest strength value is selected as the model he uses in these periods of this evolutionary cycle. At the end of each evolutionary cycle, the model with the lowest strength is replaced by the model which is created by means of crossover, mutation, or immigration.

A simplified double auction (DA) is employed as the trading mechanism. Each period is decomposed into N_R rounds. At the beginning of each round, a new random permutation of all traders is performed to determine the order of their bid and ask.

Each trader, based on his own reservation price and current best bid or ask, makes a decision regarding his offer. If a bid (ask) exists, any subsequent bid (ask) must be higher (lower) than the current one. For the sake of simplicity, only a fixed amount of stock (Δh) is traded in each transaction. The last transaction price (closing price) in each period is recorded as the market price for this period.[2]

3 Simulations

One of the reasons why the results obtained in an agent-based financial market model may be convincing has to do with whether or not the model can replicate the stylized facts. The basic statistical properties of the Dow Jones Industrial Average Index (DJIA), Nasdaq Composite Index, and the S&P 500 are summarized in Table 1. The third and fourth columns show the minimum and maximum returns in percentage terms, respectively. The market volatility in terms of the average of absolute returns is described in the fifth column. The sixth column is the kurtosis K. It is evident that the kurtosis of all markets is greater than 3, which is an indication of fat tails. The tail index α which is a more reliable estimator of a fat tail is presented in the seventh column. The α value is obtained based on 5% of the largest observations. The smaller that the α value is, the fatter the tail is. The Hurst exponent is employed to examine whether a time series follows a random walk or whether it possesses underlying trends. The value of the Hurst exponent (H) lies between 0 and 1. A random series has the value of 0.5, while $0.5 < H < 1$ ($0 < H < 0.5$) implies a time series with persistence (anti-persistence). The Hurst exponents of the raw returns and absolute returns are shown in the last two columns, respectively. In Table 1, the raw return series of all markets are close to the random series. By contrast, the absolute return series exhibit strong signs of volatility clustering. These phenomena can be also observed in Fig. 1 which displays the basic properties of the Nasdaq. Figure 1 is the time series plot during 1972–2007. The distribution of the returns is presented in the third panel of Fig. 1 in which the black curve is the normal distribution with the same variance. It is clear that the return distribution of the Nasdaq possesses higher probabilities around the mean and the tails than those of the normal distribution. In addition, at the 5% significance level,

Table 1 Stylized facts of financial markets

Series	Period	$r_{\min}$	$r_{\max}$	$\lvert r\rvert$	K	α	H_r	$H_{\lvert r\rvert}$
DJIA	1972–2007	−29.22	9.21	0.72	77.03	4.25	0.53	0.96
Nasdaq	1972–2007	−12.80	12.41	0.79	13.53	3.39	0.57	0.97
S&P 500	1972–2007	−25.73	8.34	0.70	53.96	4.69	0.53	0.97

[2] For a more detailed implementation, please refer to [21].

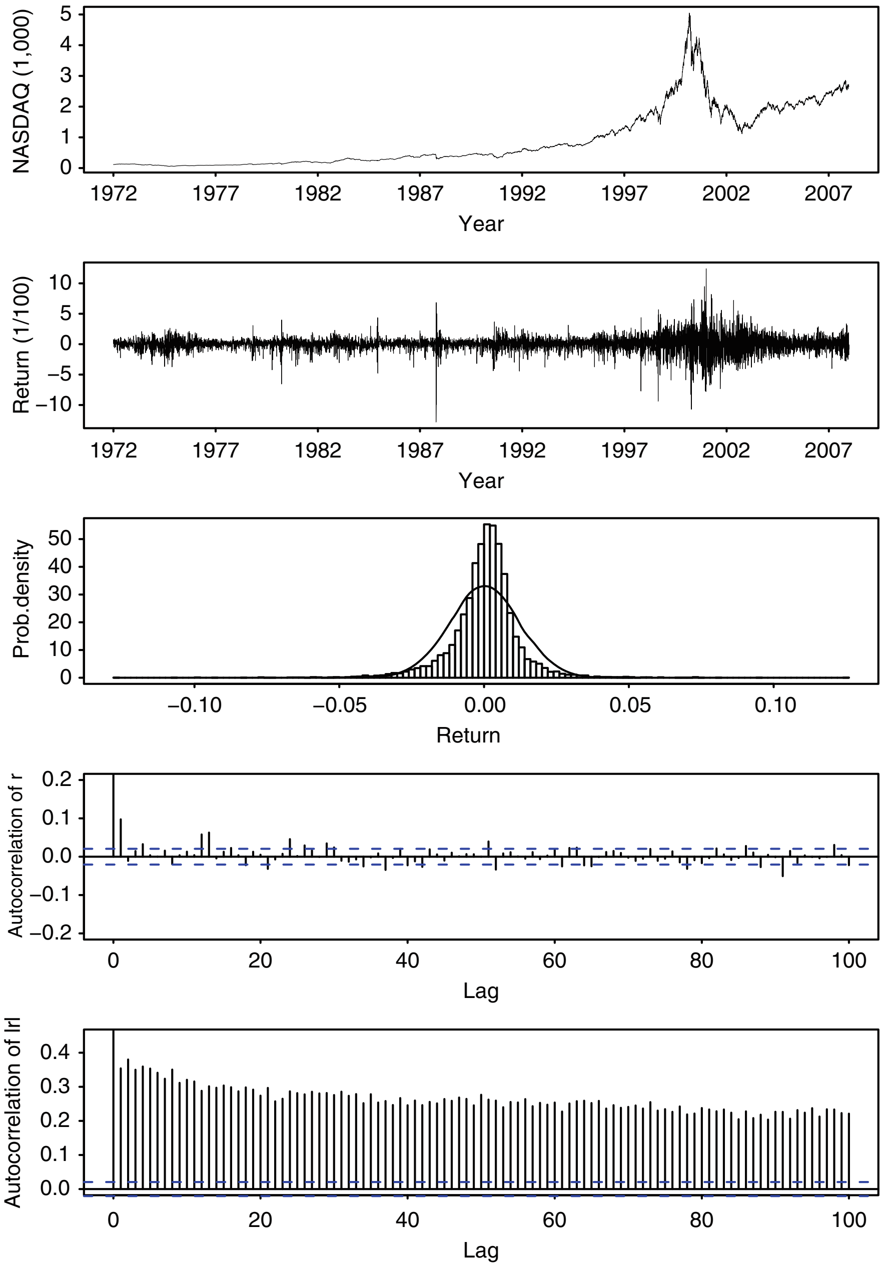

Fig. 1 Time series properties of Nasdaq

the insignificant autocorrelation features of the raw returns for most lag periods and the significant autocorrelation features of the absolute returns are exhibited in the last two panels.

To calibrate the model for mimicking the stylized facts of the daily data in the financial markets observed in Table 1 and Fig. 1, we adopt the same setup as [11]. The annual interest rate r is set as 5%, i.e. the daily interest rate $r_d = 0.05/250 = 0.02\,\%$. The daily dividend process is assumed to follow a normal distribution with mean $\overline{D} = 0.02$ and variance $\sigma_D^2 = 0.004$. The other parameters used in this model are shown in Table 2. Under full information and homogeneous expectations, the homogeneous REE price is given below

$$P_f = \frac{1}{R-1}(\overline{D} - \lambda\sigma_D^2 h) \tag{13}$$

where h is the average of the shares of the stock for each trader. Therefore, the fundamental price is 90.0. Short selling and buying on margin are prohibited.

Table 2 Parameters for simulations

The stock market	
Shares of the stock (h) for each trader	1
Initial money supply for each trader	\$100
Interest rate (r, r_d)	(0.05, 0.0002)
Stochastic process (D_t)	$N(\overline{D}, \sigma_D^2) = N(0.02, 0.004)$
Amount for each trade (Δh)	1
Maximum shares of stock holding	10
Number of rounds for each period (N_R)	50
Number of periods (N_P)	20,000
Traders	
Number of traders (N)	100
Number of strategies for each trader (N_I)	20
Tournament size (N_T)	5
Evolutionary cycle (N_{EC})	5
λ	0.5
θ_0	0.5
ω	15
θ_1	0.01
θ_2	0.001
γ_1	0.99
γ_2	1.005
Parameters of genetic programming	
Function set	$\{$`if-then-else;and,or,not;`$\geq,\leq,=$ `+,-,`$\times$`,%,sin,cos,abs,sqrt`$\}$
Terminal set	$\{P_{t-1},\ldots,P_{t-5},D_{t-1},\ldots,D_{t-5}\}$
Selection scheme	Tournament selection
Tournament size	2
Probability of creating a tree by immigration	0.1
Probability of creating a tree by crossover	0.7
Probability of creating a tree by mutation	0.2

Table 3 Statistical properties of the calibrated model

	$r_{\min}$	$r_{\max}$	$\|r\|$	P_D	K	V	σ_V	α	H_r	$H_{\|r\|}$
Minimum	−13.85	11.80	0.31	21.16	18.57	157.18	18.50	1.91	0.47	0.90
Median	−20.11	17.32	0.49	39.11	49.23	168.26	21.15	3.41	0.52	0.91
Average	−23.38	20.76	0.50	40.56	45.33	167.81	21.56	3.38	0.52	0.92
Maximum	−45.11	32.10	0.78	63.12	81.11	173.70	26.13	4.96	0.57	0.94

The information set that each trader uses to form his expectations consists of the stock price and dividend history up to the last five periods.

Table 3 summarizes the basic statistical properties for 20 simulations and Fig. 2 displays the time series properties of a typical run. In comparison with the results obtained in real financial markets, our model fits these stylized facts very well. The fifth, seventh, and eighth columns of Table 3 are the price distortion (P_D), the trading volume and its standard deviation, respectively. Price distortion which measures the degree of price deviation from the fundamental price is defined as

$$P_D = \frac{100}{N_P} \sum_{t=1}^{N_P} \left| \frac{P_t - P_f}{P_f} \right| \tag{14}$$

Based on the parameters shown in Table 2, we examine the consequences of overconfident traders. Traders' overconfidence is represented by the way in which they underestimate their conditional variances. Each trader's overconfidence level is determined by two parameters, γ_1 and γ_2. In this paper, we choose $\gamma_1 = 0.99$ and $\gamma_2 = 1.005$. The results of 20 simulation runs are presented in Table 4, and the time series properties of a typical run are plotted in Fig. 3.

For most of the runs, our simulated market with overconfident traders still provides a good fit of the stylized facts. For example, the return distribution displays the property of a fat-tail. The autocorrelation of the raw return series is insignificant and that for the absolute returns is quite significant. Overconfidence makes markets exhibit richer dynamics and stronger characteristics. First, the price dynamics is more volatile and the scale of the bubble and crash is larger. There is no doubt that price distortion would be more serious. In the market without overconfident traders, the median of market volatility is 0.49%. By contrast, it is 1.90% in the market composed of overconfident traders. Second, from comparing the second panels of Figs. 2 and 3, it is clear that overconfidence results in larger return variation. In Table 3, the median of the minimum (maximum) of returns is −20.11% (17.32%) among 20 runs, while it is −47.30% (47.24%) when traders are overconfident. Overconfidence also causes more significant volatility clustering. This can be evidenced from the higher autocorrelation of absolute returns. Third, from Tables 3 and 4, we observe that trading volume as well as its volatility increase when traders are overconfident. Basically, our findings confirm the analytical results derived in [2] and [16] where they conclude that overconfidence results in increased price volatility and trading volume. However, our results are obtained based on an environment with many heterogeneous traders. Such an outcome has important implications. First, the

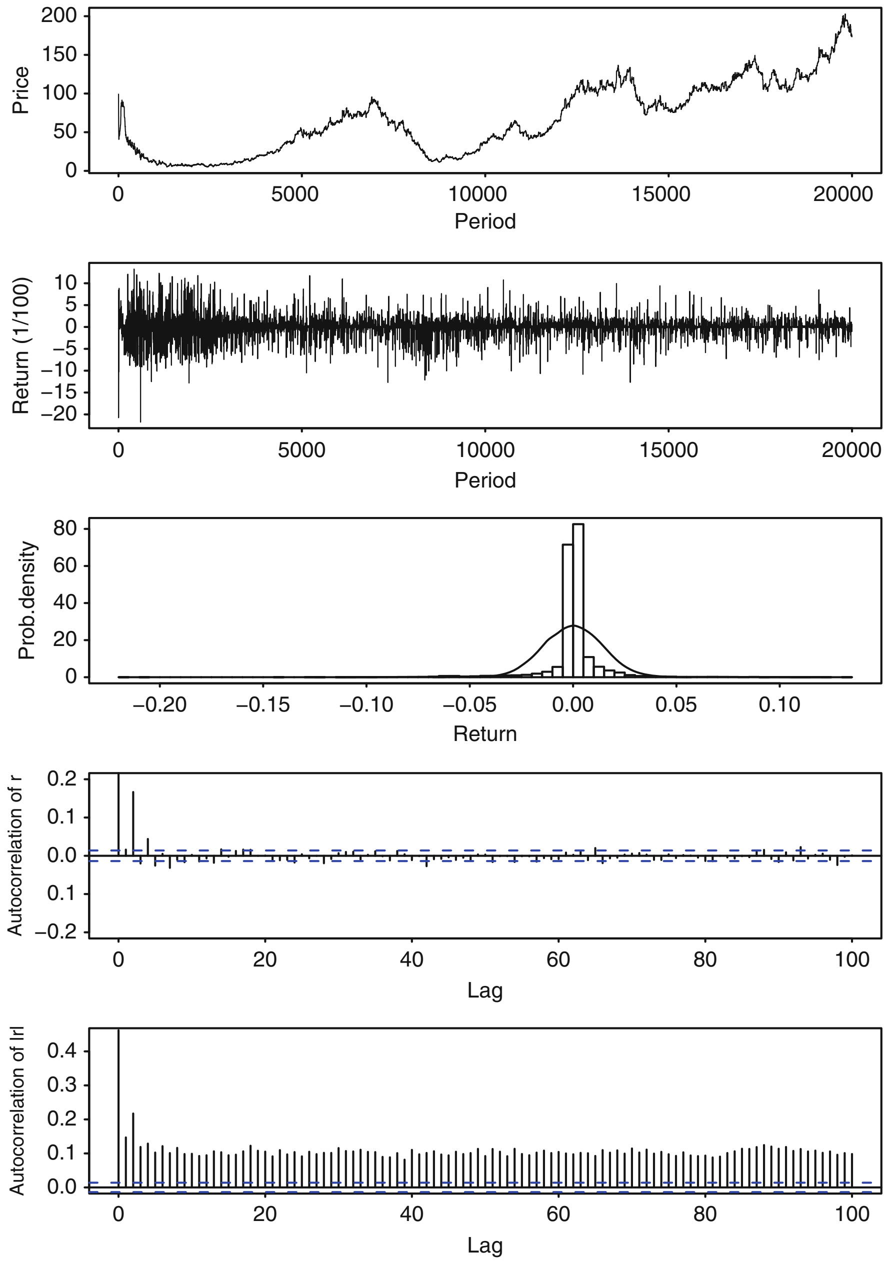

Fig. 2 Time series properties of the calibrated model

usefulness of the agent-based approach is validated. Second, we are able to examine the consequence of overconfident traders under a more realistic framework in which traders are heterogeneous in many respects.

Table 4 Statistical properties of the model with overconfident traders

	$r_{\min}$	$r_{\max}$	$\lvert r \rvert$	P_D	K	V	σ_V	α	H_r	$H_{\lvert r \rvert}$
Minimum	−16.08	19.23	0.73	45.19	9.47	161.15	30.36	1.32	0.50	0.82
Median	−47.30	47.24	1.90	98.26	23.54	177.11	49.73	3.68	0.56	0.95
Average	−57.95	963.36	5.97	96.28	209.09	179.81	47.52	3.60	0.59	0.93
Maximum	−99.81	5400.00	32.97	127.56	1128.09	222.91	55.00	7.10	0.77	0.97

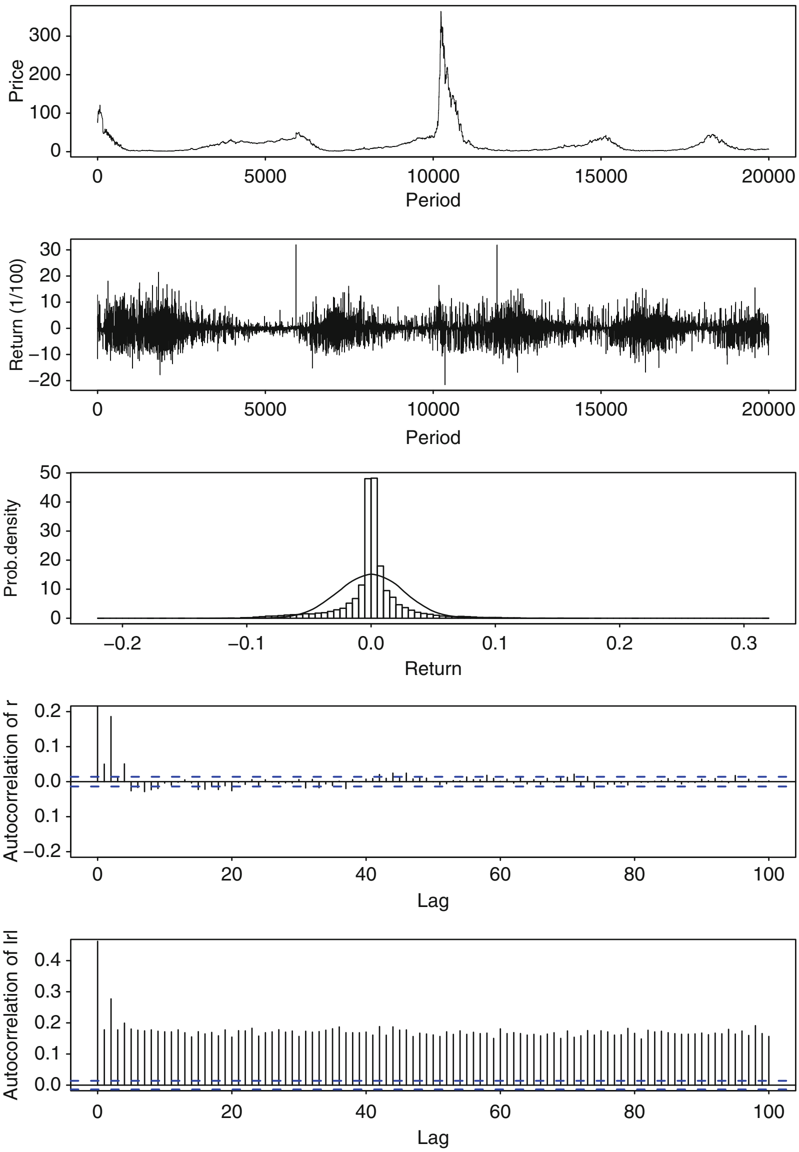

Fig. 3 Time series properties of the model with overconfident traders

4 Conclusion

Examining the effects of traders' overconfidence has been an important issue in behavioral finance and cognitive psychology. This paper develops an agent-based artificial financial market which consists of many heterogeneous and bounded-rational traders to examine the impacts of traders' overconfidence on market properties. Traders' learning behavior is modeled by a genetic programming algorithm. In such a framework, we show that the existence of overconfidence results in higher market volatility, price distortion, and trading volume. These results are consistent with those obtained in the theoretical framework. In addition, overconfidence also induces more significant stylized facts. Of course, our results crucially rely on the design of traders' overconfident behavior. Further investigation regarding this issue would be necessary in future studies.

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