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AN AGENT-BASED STUDY OF HERDING RELATIONSHIPS WITH FINANCIAL MARKETS PHENOMENA

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ABSTRACT

In this paper, an agent based model of stock market is developed. All agents fall under three general trading systems: fundamentalists, optimists and pessimists, while having different beliefs within each category. The model stresses interaction and learning among adaptive agents, which causes macroscopic properties to emerge in the market. The generated time series revealed that the model was able to reproduce some of the key stylized facts observed in actual financial time series and was consistent with empirical observations. Herding is one of the important emergent properties of financial markets, often leading to the creation of speculative bubbles that make markets unstable and prone to crashes. Using this validated framework, the necessary infrastructure is provided to explore the relationships of different market properties with this phenomenon. The study suggests that herding has significant causal relationship with volatility in the market, and vice versa.

1 INTRODUCTION

Financial markets are characterized by their complex and dynamic nature. They consist of large number of adaptive agents, interacting locally and giving rise to emergent phenomena and macroeconomic dynamics. Traditional and experimental economic models with their top-down approaches have lacked the means to properly explain and replicate financial markets in their full dynamic complexity (Tesfatsion 2002). Much of these approaches are based on the Efficient Markets Hypothesis (EMH), the notion that assumes all market participants are perfectly rational and homogeneous. EMH claims that market price movements incorporate all information rationally and instantaneously, and that past information has no impact on the future market (Lo 2005). Under this theory, markets should be efficient and stable because traders always act perfectly rational and correct the miss-pricing in the market almost immediately. Therefore, crashes and other market inefficiencies can only be triggered by exogenous shocks such as earthquakes or evolutions. However, careful investigation of some of the financial crises, such as the stock market crash of 1987 and the 2008 global financial crisis, have shown otherwise (Schwert 1990). The dramatic price volatility during these periods cannot be fully explained by the arrival of significant new information. This reveals that the price changes do not always reflect rational adjustments to the news in the market, and that other factors besides information-based trading can affect stock price volatility. In addition, these theoretical models fail to explain many of the statistical properties that are present in a wide range of markets and financial time series, otherwise known as ”stylized facts” (Hommes 2006).

The fact that EMH has a powerful theoretical and empirical basis cannot be ignored (Rubinstein 2001). However, as it was pointed out above, various empirical observations in financial markets such as volatility clustering, speculative bubbles and even financial crisis can not be explained in terms of this theory. The field of behavioral finance, which views finance from a broader social science perspective, is rapidly expanding. Previous works presented in this field have provided evidence that, in addition to information, emotions play a significant role in decision-making process (Nofsinger 2005). As Barberis and Thaler (2003) presented in their survey, behavioral finance argues that some financial phenomena can plausibly be understood using models in which agents are not fully rational. The goal of behavioral finance is to improve financial modeling by considering the psychology and sociology of agents. This field considers non-standard models, in which the price movements are influenced by the actions of heterogeneous boundedly rational traders, whose financial decisions are significantly driven by emotions. This type of models can explain the aforementioned stylized facts and market inefficiencies, which could not be explained by EMH. Agent-based modeling (ABM), which is the approach followed in this paper, is a flexible methodology for simulating such complex systems and their behaviors.

Herding is one of the emergent properties of financial markets. It happens when traders observe the choices of others and, regardless of their private information and consequences of their actions, start to imitate them (Schweitzer, Zimmermann, and Mühlenbein 2002). The existence of herding in financial markets has been fairly well documented by a number of studies (e.g. Devenow and Welch 1996). Herding in financial markets can often lead to the creation of speculative bubbles that inevitably make markets unstable and prone to major crashes (Sornette 2009), which makes it crucial to understand the origins and driving forces of such phenomenon.

The aim of this work is to propose a model of stock market that can improve the understanding of the origins and effects of herding in financial markets. An agent based model of financial market is developed that can reproduce and explain some of most important stylized facts observed in actual financial time series. Furthermore, the validate model is used as a platform to study herds and their relationships with other parameters of the market. The behavior of market and it's traders along herding phenomenon are also checked with respect to bullish and bearish markets. The major stylized facts that the model is able to reproduce are the existence of unit root in price time series, the occurrence of heavy tail in the distribution of returns and the presence of volatility clustering in the market.

The proposed model can confirm and replicate the empirical finding about the relationships between returns, volatility and herding. In addition, it sheds lights on the associations between bull/bear markets, the effects of different populations of various traders and other market phenomena such as volatility and herding. The remainder of the paper is as follows. Section 2 reviews the related works in this area. The proposed agent based stock market is illustrated in Sections 3. Finally, Section 4 presents the simulation results and Section 5 concludes the paper.

2 RELATED WORK

In this section, some of the previous agent based financial market models along with literature on herding are reviewed. In general, there are two types of traders that are commonly used in the literature: fundamentalist and chartist (trend follower, technical trader). The proof of existence of these two types of traders in real markets can be traced back to the fifties (Baumol 1957). Later on, a number of literature including (Friedman 1953) argued that chartists, due to their irrational beliefs, would eventually lose all their money and vanish from the market. Despite the popularity of this idea, some authors like Kemp (1963) nearly immediately presented counterexamples to it. It is safe to say that the dollar bubble from the eighties and technology bubble which burst in 2000 have proved that not all financial agents are fully rational in real markets (Samanidou et al. 2007). Fundamentalists make the market stable by forcing the price towards the fundamental value while chartists are the destabilizing force in the market by causing positive feedback by extrapolating (Hommes 2006).

There are various approaches towards modeling herd behavior in the literature. Some models like (Banerjee 1992) attempt to model herding with a sequential characteristic, in which traders make decisions one at a time and consider the actions of the traders before them in their decision making process. On the other hand, Orléan (1995) introduced a non-sequential model of herding, where agents interact simultaneously while modifying their decisions at each time step. He studied the Bayesian equilibria resulting from identical agents with the same imitation tendency who make binary decisions. By setting the imitation rate low, the model leads to a Gaussian distribution, whereas strong imitation setting leads to a bimodal distribution with nonzero modes interpreted as equivalent to crashes in market. Another example is the Kirman's 2-type model (Kirman 1993), where at each time step, two agents might meet at random, and with a fixed probability convince the other agent to follow their opinion. there is also a small probability that agent changes his opinion independently.

The decision structure of non-sequential models seems to be more realistic since traders participate in the market simultaneously, and cumulative market variables like asset prices is determined by the aggregation of different orders. Although non-sequential setting is better suited for financial markets, neither of these two approaches can reproduce heavy tail of returns as such observed in empirical properties of stock returns. Cont and Bouchaud (2000) have proposed a different approach that is non-sequential but avoids Orlean's impractical results by revising his assumption of all agents having the same imitation rate. In this methodology agents interact on a basis of random communication network, which leads to formation of groups of agent such that each group makes independent decisions while agents within each group mimic the behavior of each other.

The proposed model uses a non-sequential approach and differs from the aforementioned works in the modeling of social interactions and imitation among agents. A local interaction method is proposed where, at each time step, agents meet and exchange information with their surrounding neighbors. They either compare strategy profits and change their tactic accordingly, or blindly choose to imitate the most popular trading decision in their neighborhood. This method contributes to a deeper understanding of decision making and evolution of the agents. In addition, the investigation of causal and linear relationships between different market characteristics sheds light on causes and effects of bull/bear markets, volatility and herding.

3 AGENT BASED STOCK MARKET MODEL

In this section, an econometric model of stock market is proposed. For the purpose of traceability, the two-typed design model of Westerhoff (2008) is adapted. However, through the course of simulations, the model is transformed to an N-type design by the means of introducing two types of chartist: optimist and pessimist, and increasing heterogeneity in the following forms:

- Agents are endowed with different initial wealth drawn from a power law distribution.
- Agents are assigned different reaction intensities to price (in case of optimists and pessimists) and fundamentals (in case of fundamentalists) changes.
- Agents are assigned different trading horizons and use different time windows to analyze the price trends (in case of optimist and pessimists) and past profits.

Following consideration of the aforementioned enhancements, the aggregate dynamics of the market along with the micro behavior of agents can be improved by means of increasing the degree of autonomy. The model represents an stock market in which N traders can place market orders for a single risky asset, which are immediately executed at the current market price. In this model, one trading decision is made daily by each agent, since the empirical investigations on trading data report the lack of intraday trading persistence (Eisler and Kertész 2007). The listed price of the asset at time t is denoted by p_t, which is set by the market maker, and since there is no bid-ask spread in the model, there is only one current price at each time step in the market. At the beginning of the simulation, the agents are spread randomly across a

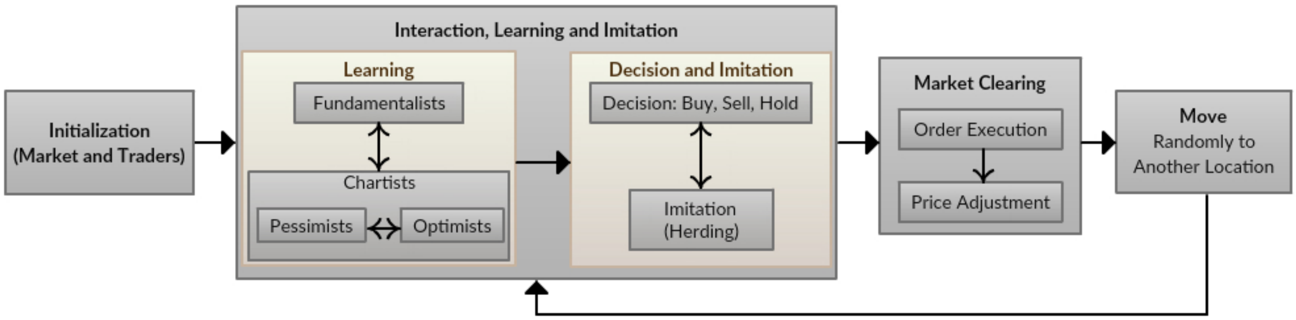


Figure 1: Model evolution flowchart.

pseudo-landscape grid of square cells and are assigned to one of three general trading strategies. As the simulation runs, each trader can interact with the traders on its eight neighboring patches and change his strategy to maximize his profit or follow the crowd. The agent's action space is:

$$Action = \begin{cases} 1 & \text{Buy one unit of stock.} \\ -1 & \text{Sell one unit of stock.} \\ 0 & \text{No trade.} \end{cases}$$

The overall flowchart of the model is presented in Figure 1, which will be discussed in this section.

3.1 Expectations and Trading Strategies

There are three general types of traders in this market model, fundamentalists, optimists and pessimists. However, since each of the traders within these groups has unique characteristics, its is considered as a N-type model. Fundamental traders make trading decisions based on the difference they observe between market price and the assumed fundamental value of stock. This intrinsic value is made available to all the traders and is considered public information. Still, each fundamentalist has different conception of the speed with which the price will return to its fundamental value. In this model, we use the following equation to formulate the fundamentalist expected price for the next period, taking into consideration the fundamental value of the stock:

$$E_t^f[p_{t+1}] = p_t + f*(F_t - p_t) + \tau, \tag{1}$$

where, $0 < f < 1$ accounts for fundamentalists mean-reverting belief and specifies the speed with which fundamentalists expect the price to return to fundamental value. At the beginning of each simulation, a unique f is drawn from a Gaussian distribution and assigned to each agent. F_t is the fundamental value, derived as an first order auto-regressive (AR(1)) process $F_t = F_{t-1} + \eta$. The τ is a normal, IID noise process with zero mean and constant standard deviation σ_τ, added to the equation to account for diversity and uncontrollable elements. Fundamentalists make decision based on the difference between the current price in the market and their expectation of the future price as in (1). They will buy or sell one share of the risky asset if that difference is higher than a certain threshold, which is defined as k and is determined in the calibration phase of the simulation in Section 4.

Chartists, on the other hand, base their expectations on the past price changes, patterns and trends. An empirical study done by Menkhoff (2010) suggests that chartist traders have varying investment horizons and thus use different time windows to analyze the trend and patterns in the price time series. Here, each agent is assigned a different memory length T, drawn randomly from a uniform distribution. The estimated maximum investment horizon used here is 50 days. By having different investment horizons in the market, the model not only conforms to real-world market traders, but also has an increased autonomy degree which will improve the macro dynamics of the artificial market.

In this model, following the methodology used by Lux and Marchesi (2000), two types of chartist are introduced; optimists and pessimists. Optimists extrapolate and predict the price change rate to be proportional to the latest observed pattern in the price history. Whereas pessimists, while still looking at the past movements of the price, act against the trend, anticipating that the trend will soon be finished and reversed. The formulation of their expectation of next periods price is as follow:

$$E_t^{co}[p_{t+1}] = p_t + c_o * (p_t - MA_t) + \beta_1, \tag{2}$$
$$E_t^{cp}[p_{t+1}] = p_t + c_p * (p_t - MA_t) + \beta_2, \tag{3}$$

where, $0 < c_o < 1$ and $c_p \leq 0$ are the reaction coefficients of optimists and pessimists respectively, conveying the sensitivity of chartists to price changes and trends. These two parameters are different for each chartist and are drawn from a Gaussian distribution at the beginning of simulation. β_1 and β_2 are random normal IID noise processes (with zero means and constant standard deviations σ_{β_1} and σ_{β_2}), added to capture the diversity and uncontrollable elements in chartist analysis. $p_t - MA_t$ indicates the trend, where MA_t is the moving average of the past prices, based on an exponential weighting process:

$$MA_t = \phi \sum_{i=1}^{T} (1-\phi)^{i-1} p_{t-i}, \tag{4}$$

where, ϕ is the weighting factor, which is estimated to be between 0.3 and 0.99 for memory length of 50 and 1, respectively, and interpolated for values between.

3.2 Wealth and Portfolio

It was first observed by Pareto (1964) that the income distribution across several countries follows a power law. Later, it was discovered that wealth is also distributed according to a power law (Drăgulescu and Yakovenko 2001), which implies rather extreme wealth inequality. The probability density function that describes the Pareto distribution is of the form:

$$W(x) = x^{-(1+w)}, \tag{5}$$

where, w is the Pareto exponent, which measures the level of wealth inequality and was estimated by him as $w = 1.5$. The same power law distribution is used to initially endow each agent with a different amount of money, in agreement with human population. At the beginning of each simulation, all traders are endowed with different amount of cash drawn from the distribution stated at (5). All of the agents are also assigned a same number of shares of stock, G. Anytime during the course of simulation, the portfolio worth of each agent and therefor their wealth can be calculated as:

$$Portfolio_t = G_t * p_t + W_t, \tag{6}$$

where, G_t is the number of stocks the agent holds at time t, p_t is the price of the stock at time t and W_t denotes the cash.

3.3 Price Evolution

Many different methods are used in literature for determining prices in artificial financial markets. In this paper, the category that uses a slow price adjustment process is adopted. In this category the market is mostly never in equilibrium and the price of an asset basically depends on excess demand, which is the difference between demand and supply. It rises if more agents are willing to buy instead of sell and falls if the supply exceeds the demand. Assuming that price is adjusted according to the observed excess demand, the price movements can be viewed as the results of opinion dynamics in the market and the traders.

An early example of such approach is (Day and Huang 1990), where there is a market maker who broadcasts the price and agents submit their buy and sell orders for this price. The orders are then summed, and in the case of existence of excess demand (supply) the price is increased (decreased):

$$p_{t+1} = p_t * (1 + \alpha * (D_t - S_t)) + \delta, \tag{7}$$

where, α is a positive coefficient, which accounts for the sensitivity of price change with respect to excess demand. $D(p_t)$ is the number of buy and $S(p_t)$ is the number of sell orders. The random normal, IID noise process, δ (with zero mean and constant standard deviation σ_α) accounts for economic factors other than short-term excess demand that may influence the evolution of the asset price.

3.4 Interaction and Learning

The macro dynamics of the market as a whole is the result of endogenous switching between there groups of agents defined in the previous section. Switching or adaptive belief dynamics that enables agents to shift between different strategies is considered to be a necessary source for creation of many stylized facts observed in the real financial markets (Lux and Marchesi 2000). In the N-type models, learning is encapsulated in the switching method. The fitness measure that drives agents to change their opinion and switch to a new trading strategy is considered to be the temporal realized profits from each rule, which is formulated as follow:

$$S_t = \begin{cases} (1-m)*(p_{t+1}-p_t)+m*S_{t-1}, & \text{if agent was buyer} \\ (1-m)*(p_t-p_{t+1})+m*S_{t-1}, & \text{if agent was seller} \end{cases}$$

where, $m \in [0,1]$ is the normalization of memory parameter T, and is used to account for the past performance of each rule.

In this model, agents are able to switch between chartist and fundamentalist strategy as well as switching between optimist and pessimist within the chartist group. Since in the latter case agents can only choose between two rules, the switching process is modeled using the Logit binary choice model (Luce 2005). At the beginning of each trading day, each agent meets and exchanges information with its neighbors, taking the average utility associated with their trading rule. The probability that an agent chooses optimist over pessimist trading rule is:

$$P(X=o) = \frac{\exp[\lambda \bar{S}^o]}{\exp[\lambda \bar{S}^o] + \exp[\lambda \bar{S}^p]}, \tag{8}$$

where, $P(X=o)+P(X=p)=1$.

In the first case, where there is switching between fundamentalists, optimists and pessimists, the adaptation part of the switching mechanism is extended from the original Logit model (8) into the multinomial Logit model. Following is the probability that an agent chooses fundamental over optimist and pessimist trading rules:

$$P(X=f) = \frac{\exp[\lambda \bar{S}^f]}{\exp[\lambda \bar{S}^o] + \exp[\lambda \bar{S}^p] + \exp[\lambda \bar{S}^f]}, \tag{9}$$

where, $P(X=f)+P(X=o)+P(X=p)=1$. λ is the intensity of choice, which measures how quickly agents switch if there are additional profits gained from choosing fundamental over chartist trading rule. If $\lambda = 0$, there is no switching between strategies, while for $\lambda = +\infty$ all agents immediately switch to the most profitable strategy.

3.5 Herding

In the proposed model, herding is investigated from two different aspects. The first side lies in the agent based design portion of the work. A herding component is incorporated in the agents behavior and trading approach that enables them to follow the crowd to the extend that gives the most accurate results in macro level, with respect to empirical evidence. To model this process, an imitation threshold, γ is introduced that would allow all types of traders to change their action (buy/sell/hold) if less than γ percent of their neighbors chose the action similar to them.

Table 1: Parameters of the stock market model.

Parameter	Value
Number of traders (N)	1000
Price adjustment (a)	0.2×10^{-4}
Fundamentalists activation threshold (K)	[2%,5%]
Pareto exponent for wealth (power law) distribution (α)	1.5
Initial cash distribution	[30, 100]
Imitation switch threshold (γ)	10%
EWMA smoothing parameter (ϕ)	[0.3,0.99]
Standard deviation of random factor in price process (σ_δ)	0.025
Reaction coefficient (c_o)	$N(\mu_{c_o}:0.5,\sigma_{c_o}:0.1)$
Reaction coefficient (c_p)	$N(\mu_{c_p}:-0.5,\sigma_{c_p}:0.1)$
Reverting coefficient (f)	$N(\mu_f:0.4,\sigma_f:0.1)$
Standard deviation of random factor in fundamental price process (σ_η)	0.026
Standard deviation of random factor in price process (σ_δ)	0.025
Standard deviation of random factor in fundamental trading (σ_τ)	0.01
Standard deviation of random factor in optimistic trading (σ_{β_1})	0.05
Standard deviation of random factor in pessimistic trading (σ_{β_2})	0.05
Intensity of choice (λ)	100
Memory of traders (T)	U (1,50)
Normalized memory (m)	[0,1]

In the second phase of studying herding, a simple function is defined to capture herding phenomena and its intensity at each time-step:

$$Herding_t = |D_t - S_t|/N. \tag{10}$$

When $Herding_t$ is close to zero, the number of buy and sell orders are close and no herding is taking place in the market and vice versa for $Herding_t$ gets closer to one. The relationship of herding parameter with other market parameters and phenomena will be investigated in Section 4.

4 SIMULATIONS AND RESULTS

In this section, the relationships between different market phenomena and parameters (herding, investment return, volatility, number of different trader types and bullish/bearish markets) are investigated. Granger causality has been utilized to discover the causation relationships present in model generated time series.

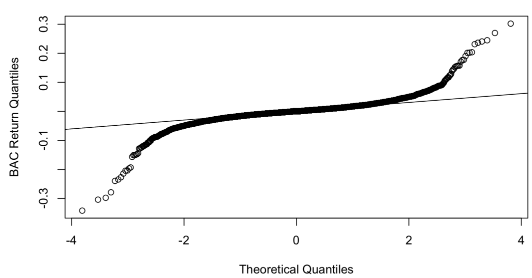
4.1 Model Validation

The first step to the process of analyzing model generated time-series is to calibrate and validate it with respect to empirical findings and a benchmark, in this case the Bank of America stock (BAC). The closing prices of the BAC from 30 May 1986 to 3 February 2015 is used, which includes 7231 cases and is collected from Yahoo Finance website . After calibrating the model, the values of the market parameters that result to produce time series close to empirical findings is presented in Table 1.

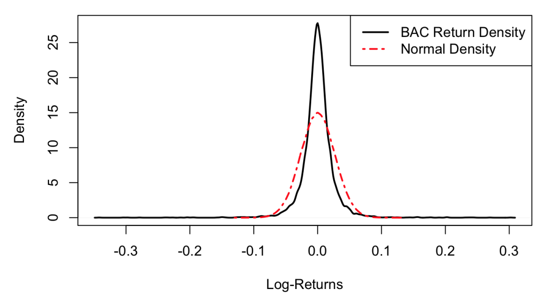
Time series of financial markets exhibit many statistical features that are mostly common to a wide range of markets and time periods (Cont 2001). These properties are known as ”stylize facts” and are used to calibrate and validate the financial market models. In this paper, we use the three important stylized facts observed in financial time series: *heavy-tails in distribution of stock returns*, *absence of autocorrelation in raw returns* and *volatility clustering*. The distribution of high frequency returns in most cases is not normal and exhibits a heavy tail with positive excess kurtosis, meaning there is higher density on the tails of the distribution in comparison to the tails density under the normal distribution. The second characteristic is about the fact that the autocorrelation coefficients of raw returns are basically zero for all lags in real world financial time series. The third feature describes the fact that high-volatile events tend to cluster in time. Different measures of volatility display a positive autocorrelation over several days (Cont 2001) and a common proxy for volatility is the absolute return.

The fat-tail property of stock returns in the model and BAC time series is explored by the kurtosis measure and the two normality plots on the top panels of Figure 2 and Figure 3. As it can be observed, the non-Gaussian character of both distributions is clear in q-q and normality plots, and the proposed model was successful in replicating such phenomena. Table 2 demonstrates the basic statistics of simulation and BAC time series. Both series have positive means and are slightly skewed. The kurtosis of model is not as big as the BAC, but still shows the existence of heavy tail in the returns.

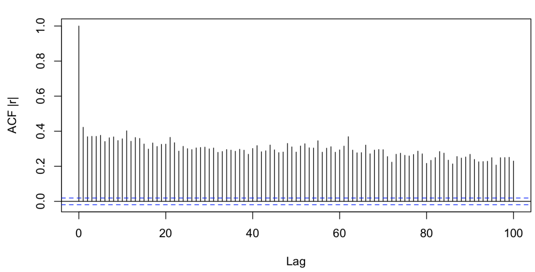
The bottom two panels of Figure 2 and Figure 3 examine the autocorrelation of raw and absolute returns in BAC and model. The dotted blue lines indicate the 95 percent confidence intervals. As it is demonstrated, the absolute returns exhibit a slow decay of the autocorrelation and stay positive for more than 100 lags, whereas the raw returns in both cases show no autocorrelation past the first few lags. This is the evidence of existence of volatility clustering, which can be observed in many real world financial markets as well as the model generated time series.



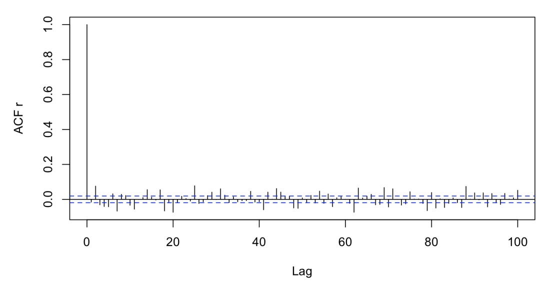
(a) The q-q plot for normality comparison.



(b) The normality plot.



(c) The autocorrelation plot for absolute returns.



(d) The autocorrelation plot for raw returns.

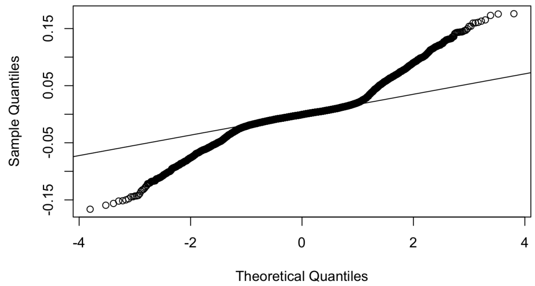
Figure 2: Normality and autocorrelation test results for BAC returns.

Table 2: Basic statistics of stock returns for model and BAC.

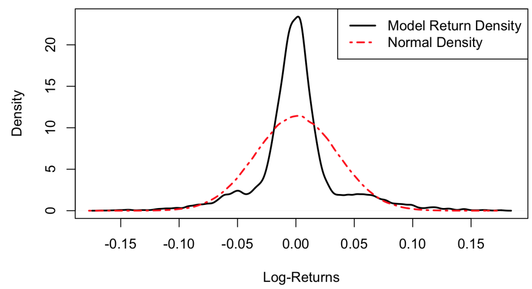
	Mean	Variance	Skewness	Excess Kurtosis
Model	0.0.000727	0.001226972	0.4132471	3.509046
BAC	0.000115	0.000711	-0.359977	26.81

4.2 Stationarity Test

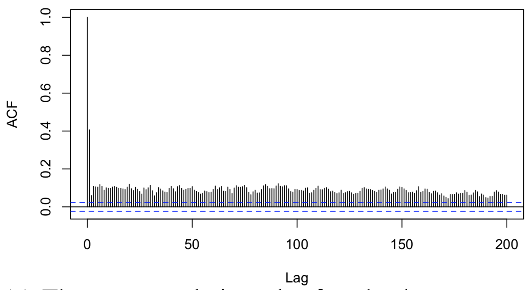
Having obtained a validated model, the extent of effects of different market phenomena on each other can now be investigated. To explore these relationships, the first step (as in standard econometric procedure)



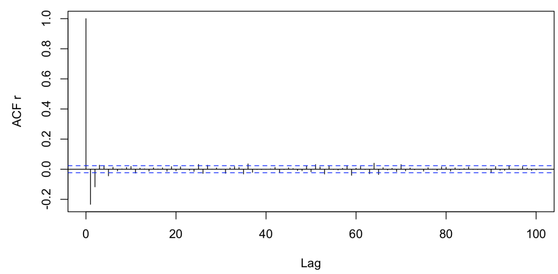
(a) The q-q plot for normality comparison.



(b) The normality plot.



(c) The autocorrelation plot for absolute returns.



(d) The autocorrelation plot for raw returns.

Figure 3: Normality and autocorrelation test results for model returns.

is to conduct the augmented Dickey-Fuller unit root test to examine their stationarity. Non-stationary time series cannot give meaningful sample statistics and correlations with other variables. They are unpredictable and in the case of Granger causality test, the problem of spurious correlation can arise, where the variables that are not related seem to have correlation with each other. The test is ran on all the parameters that are going to be explored (e.g. price, return, volatility and herding). The results of the Dickey-Fuller test can be found in Table 3.

The null hypothesis of the test is non-stationarity. The test statistics along with corresponding p-values indicate that the null hypothesis is rejected in all cases, except the price. Meaning that the price generated by the model is in fact non-stationary, which is in agreement with the real financial time series. As it can be seen, all the variables expect price are stationary in their levels.

Table 3: Augmented Dickey-Fuller unit root tests.

Zero Mean	Lags	Rho	P $<$ Rho	Tau	P $<$ Tau
Price	0	0.6700	0.8487	1.32	0.9531
	1	0.7432	0.8650	2.16	0.9930
Return	0	-9594.86	0.0001	-123.49	$<$.0001
	1	-15608.2	0.0001	-88.34	$<$.0001
Herding	0	-2065.32	0.0001	-34.81	$<$.0001
	1	-1743.28	0.0001	-29.55	$<$.0001
Volatility	0	-2433.32	0.0001	-38.38	$<$.0001
	1	-2241.32	0.0001	-33.48	$<$.0001

The first difference transformation of the price was taken to achieve stationary in the time series:

$$r_t = \ln[p_t] - \ln[p_{t-1}], \tag{11}$$

where, r_t is known as the stock returns and plays a critical role in the analysis of the market and validation of the model. The same measure was used in Section 4.1 to validate the model.

Table 4: Results of regressions (model).

	Independent variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	VI
Herding	Intercept	1	-0.02653	0.00286	-9.27	<.0001	0
	bull	1	-0.01534	0.00357	-4.29	<.0001	1.00248
	Volatility	1	9.40205	0.06661	141.16	<.0001	1.00248
Volatility	Intercept	1	0.00761	0.00024739	30.77	<.0001	0
	bull	1	0.00190	0.00032650	5.82	<.0001	1.00028
	Herding	1	0.07872	0.00055766	141.16	<.0001	1.00028

4.3 Effects of Bull and Bear Markets

In this part the relationship between different market states with herding and volatility is investigated. One of the common descriptions of bull and bear market is that they correspond to the periods of increasing and decreasing stock prices, respectively (Pagan and Sossounov 2003). In this analysis, a dummy variable, $bull_t$, is created. It takes the value of 1 if the return on day t is positive and market is bullish, and 0 when the return is negative, meaning that the market is bearish. The effects of these two states of the market can be estimated by running following regression models:

$$Volatility_t = X_1 + \Delta_1 bull_t + \Theta_1 Herding_t. \tag{12}$$

$$Herding_t = X_2 + \Delta_2 bull_t + \Theta_2 Volatility_t. \tag{13}$$

The number of fundamentalists, optimists and pessimists was also included in both models, and since it resulted in statistically insignificant parameter estimations, they were removed from the regressions. The results of the regressions are presented in Table 4. Both models have R-Squares and Adjusted R-Squares of around 0.74, showing that the majority of variation in the dependent are explained with the independent variables and since they are close to each other, the models are not over-fitted. As it is demonstrated in Table 4, the t-scores along with corresponding p-values indicate that both herding and volatility have significant positive effect on each other. This reveals that the level of herding intensity increases as the volatility goes up in the market, and vice versa, which seems to be in agreement with actual markets (Cont and Bouchaud 2000). On the other hand, bullish market has opposite effects on volatility and herding in our model. It has significantly positive effect on volatility while herding seems to go up in bearish markets.

4.4 Herding and Volatility

By detecting statistically significant relationships between herding and volatility, the causal relationships between the two time series is further tested. This method is based on prediction used to identify causal relationship between variables, and believes that what happens today is the function of the past. In this work, a simple approach of the autoregressive specification of a bivariate vector autoregression is adopted to test for Granger causality (Clements and Hendry 1998). Following is a least squares equation using a lag length of l for the causal relationship between herding and volatility:

$$H_t = \alpha + \sum_j^l \beta_j H_{t-j} + \sum_j^l \delta_j V_{t-j} + \varepsilon_t, \tag{14}$$

where, H_t and V_t are vectors of time series variables of herding and volatility, δ and β are coefficient matrices, and ε is an unobservable zero mean white noise vector process. The test performed here is an F-test on the coefficient of lagged values of V_t, the independent variable and is based on the following null hypothesis:

$$H_0 : \sum_{j=0}^l \delta_j = 0. \tag{15}$$

Table 5: Causality test between Volatility and Herding.

Null Hypothesis	DF	Chi-Square	Pr > ChiSq
Herding does not GC Volatility	4	683.80	<.0001
Volatility does not GC Herding	4	258.38	<.0001

The results of Granger causality Wald tests at 5% significance level with the null hypothesis of no causality are reported in Table 5. As it can be seen by the test statistics and p-values, the null hypothesis in both directions can be rejected, which proves that the four lag causal relationship is significant and both herding and volatility Granger cause each other. This means the past values of volatility help improving the prediction of current values of herding beyond the past values of herding alone, and vice versa.

5 CONCLUSION

In this work, an agent-based model of stock market is proposed to study the relationships between different market phenomena (e.g. bull/bear markets, herding, volatility). The key features of this model were local interactions and heterogeneity that allow for global market protocols and behavioral norms to arise from the bottom up. The behavior of the market as a whole, such as the dynamics of asset prices and herding, is an emergent property of the agents' behavior. The model was able to explain and reproduce some of the most important stylized facts observed in financial time series and was in agreement with empirical observations. This study suggested that the bullish and bearish states of the market have statistically significant effect on generated herding and volatility. Also, a significant bidirectional causal relationship was detected between herding and volatility in the market.

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