Herd behaviour as a source of volatility in agent expectations

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Abstract

Herd Behaviour is often cited as one of the forces behind excess volatility of stock prices as well as speculative bubbles and crashes in financial markets. This paper examines if social interaction and herd behaviour, modelled within a multi-agent framework, can explain these characteristics. The core of the model is based on the social learning literature which takes place in a small world network. We find that when the network consists entirely of herd agents then expectations become locked in an information cascade. Herd agents receive a signal, compare it with those agents with whom they are connected, and then adopt the majority position. Adding one expert agent enables the population to break the cascade as information filters from that agent to all other agents through contagion. We also find that moving from an ordered to a small world network dramatically increases the level of volatility in agent expectations and it quickly reaches a higher level (at which point increasing the randomness of the network has little effect). Increasing the influence of the experts, by increasing the number of connections from these agents, also increases volatility in the aggregate level of expectations. Finally it is found that under certain network structures herd behaviour will lead to information cascades and potentially to the formation of speculative bubbles.
Keywords: social learning, herd behaviour, small world networks, information contagion, volatility, information cascades.

1 Introduction

Herd Behaviour is probably one of our most basic instincts and one we easily assume. Further when individuals are influenced by this it creates a first order effect [1]. Intuitively this results in herd behaviour having a potentially

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significant impact on economic variables whether it is voting patterns, crime, fashion or prices in financial markets. In this paper a multi-agent model of herd behaviour is constructed to analyse the dynamic process of expectation formation. In this model agent's expectations are formed from simple decision making rules within the self organisational framework [2, 3]. The core of the model is based on the social learning framework initially developed by Bikhchandani et al. [4] (here after referred to as BHW). The social learning takes place in a social network consistent with the work on small worlds by Watts [5].

The basic model consists entirely of herd agents who receive a signal, compare it with the expectations of other agents with whom they are connected and adopt the majority position. In the absence of heterogeneous decision making rules agents enter into an information cascade, learning stops and agents become fixed upon a given set of expectations. Heterogeneous decision making is introduced with the adding of expert agents, who are similar to the fashion leaders and experts discussed in BHW [4]. We find that the addition of one expert agent will be enough to enable the population to break the cascade, with information regarding changes in the state of the world filtering to the herd agents from the expert agents through contagion.

We also find that in an ordered network volatility in the aggregate level of agent expectations appears to increase linearly, but less than one to one, with the number of expert agents. Moving from an ordered to a small world network dramatically increases the level of volatility and it quickly reaches a higher level. At this point increasing the randomness of the network has little effect while increasing the number of experts has minimal effect. Increasing the number of connections has a significant effect independent of the small world properties. This provides some insight behind changes in the volatility in agent expectations over time.

Lastly we consider whether the structure of the social network can lead to instances when information cascades form in the presence of heterogeneous decision makers. We find that increasing the number of connections between herd agents creates an information cascade. This may explain the situation where agents continue to hold a view on the market (for example that the market remains in a bull run) despite evidence to the contrary. It can also provide a reason for their sudden collapse in confidence in a bull market where the state of the world had already changed but this information did not filter to herd agents until network connections decreased.

There are a number of approaches to modelling the process of expectation formation. For example Lux [6] and Brock et al. [7] use non linear dynamics to determine supply and demand and then close the model through an exogenous market maker. A second approach is through a Markov switching process [8]. A third approach introduces the concept of the social network whereby agents only communicate with, and see the actions and sometimes payoffs of, those agents in which they have a connection with. Therefore, in formulating their decision, agents use the experience of this subset of society, and possibly their own experiences, in updating their posterior using Bayes Law [9, 10]. The paper is also related to the literature on Word-of-Mouth particularly Banerjee and Fudenberg [11] and Ellison and Fudenberg [12].

Conceptually this paper uses a similar approach to [9, 10] in analysing the impact of network architecture on both the long run and dynamic properties of the agent expectations. The point of differentiation is this model introduces the concepts of small worlds, which is then extended to examine the implications and influence of expert agents by varying the number and strength of connections from expert to other agents.

The paper is organised as follows. Section two outlines the model. The third and fourth sections examine the long run equilibrium and dynamic properties. The fifth section draws some conclusions and suggests areas of further work.

2 The model

The centrepiece of a model of herd behaviour is the coordination mechanism. It comprises of an observable signal, a social network and decision making rules. Consider the following. There are $i \in I = \{1,...,N\}$ agents. At the beginning of each round $t \in [1,,...,T]$ each agent receive a private binary signal $x \in X = \{0,1\}$ on the state of the world where 0 (1) represents an expectation that the stock that will fall (rise) in price in the next period. As an example this signal could take the form of a private belief based on learning from prices. Each agent *i* would then undertake a process to establish a view on how the market will perform in the next period. They do this by considering the signal they receive, as well as the most recent view taken by each of the other agents with which they have a connection. Agent *i*'s signal is then adjusted in light of the discussions with connected agents and this becomes their view. It is this view that is presented to the market with the private signal never released.

2.1 Generating the signal

Agents do not know the true state of the world. Instead they form a posterior belief through a Bayesian learning process. Agents receive a private binary signal with a probability dependent on the state of the world $v \in V = \{0,1\}$. The agent's posterior probability that the true state of the world is $V = 1$ is given by:

$$P(V=1|X=1) = \frac{P(X=1|V=1) \cdot P(V=1)}{P(X=1|V=1) \cdot P(V=1) + P(X=1|V=0) \cdot P(V=0)} \tag{1}$$

The value of both the conditional likelihood function and the prior will need to be determined. There would be a variety of factors that would be considered in formulating a view on the future direction of an individual security (or even a market as represented by an index). It is also likely that these factors will differ between agents. Take the extreme positions of a fundamental verse a herd trader. For the former V is likely to represent if a stock is over or undervalued according to fundamental value, while for the latter V is more likely to represent whether the market is in a bull or bear run. To complicate matters agents may not follow their own beliefs. For example agents may believe that stocks are overpriced but that the price will continue to rise in the next period [13].

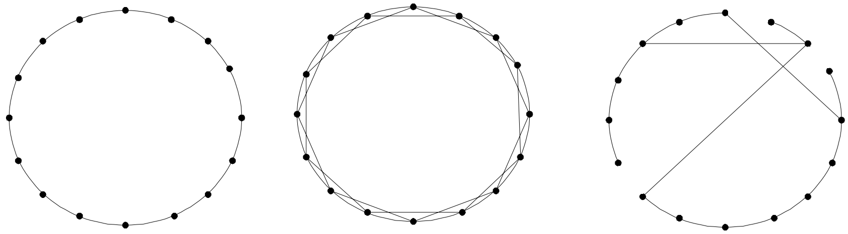
In order to focus on the effects of social learning and network structure, rather than the Bayesian learning process a simplified framework is employed whereby agents have the following conditional likelihood functions and priors:

$$P(X=1|V=1)=P(X=1|V=0)=q>0.5 \tag{2}$$
$$P(X=0|V=0)=P(X=0|V=1)=1-q \tag{3}$$
$$P(V=1)=P(V=0)=0.5 \tag{4}$$

2.2 The social network

The network consists of: a population of agents I in some finite social space; and a list of connections between agents initially defined as either 1 or 0. For any two individuals i and j a connection exists if $X(i,j)=1$, otherwise $X(i,j)=0$. In latter sections the strength between certain agents will be varied to replicate the case where the views of these agents (such as experts) hold more sway than other agents (thereby introducing the concept of 'social distance').

To develop the small world network each agent i is selected in turn along with the edge to the nearest neighbour in a clockwise sense. The connection is deleted and replaced with a random connection with a pre-determined probability p. Each agent goes thought this process until all agents have been assessed. The process then repeats itself for the next nearest neighbour if k = 4 and so on (see fig. 1 which is based on the work by Watts [5]). There is no social justification for a model that replaces one connection with another connection at random. However, in the world of stock market trading agents are just as likely to source information from unknown analysts via the web as to talk to neighbours, so the random approach may not be far from reality.



k = 2 and p = 0 k = 4 and p = 0 k = 2 and p > 0

Figure 1: Ring, small world and random graphs.

2.3 Decision making rule

In the first round each agent receives a signal according to eqn (1) and follows that signal. Therefore, the network does not impact on the expectations of agents in the first round. This is justified as the focus is on the stability of long run equilibria and the dynamics of steady state. At the end of the first round $t = 1$ agents have adopted an expectation x_i. Let $\boldsymbol{X_i}$ be the set of opinions of those agents connected to i. In the case of a ring lattice with $k = 2$ $\boldsymbol{X_i} = (x_{i-1}, x_i, x_{i+1})$, where: x_{i-1} represents the expectation formed by I - 1 at time t, x_i represents the signal received by i at time t and x_{i+1} represents the expectation formed by i + 1 at time t - 1. The prior probability of V can now be updated by forming the posterior of V given the knowledge gained through conversation according to:

$$P_i\left(V \middle| \boldsymbol{X_i}\right) = \frac{P\left(\boldsymbol{X_i} \middle| V\right) \cdot P(V)}{P(\boldsymbol{X_i})} \tag{5}$$

Returning to the case of a ring lattice with $k = 2$, if both agents I - 1 and i + 1 formed an expectation that $V=0$ and i receives a signal $x = 1$ then:

$$P_i\left(V = 1 \middle| x_{i-1} = 0; x_i = 1; x_{i+1} = 0\right) = \frac{P\left(\boldsymbol{X_i} \middle| V\right) \cdot P(V)}{P\left(\middle| \boldsymbol{X_i}\right)} \tag{6}$$

$$= \frac{P(x_i = 1|V = 1) \cdot P(V = 1|x_{i-1} = 0; x_{i+1} = 0)}{P(x_i = 1|V = 1) \cdot P(V = 1|x_{i-1} = 0; x_{i+1} = 0) + P(x_i = 1|V = 0) \cdot P(V = 0|x_{i-1} = 0; x_{i+1} = 0)} \tag{7}$$

Faced with this scenario and assuming that agents give equal weight to all $\boldsymbol{X_i}$ then, as $P(x_i = 1|V = 0) \cdot P(V = 0|x_{i-1} = 0; x_{i+1} = 0) > P(x_i = 1|V = 1) \cdot P(V = 1|x_{i-1} = 0; x_{i+1} = 0)$, they will ignore their own signal and update their prior so that the true state of the world is 0. The dynamic model becomes:

$$P_{i,t}\left(V_t \middle| \boldsymbol{X}_{i,t}\right) = \frac{P(\boldsymbol{X}_{i,t}|V_t) \cdot P(V_t)}{P(\boldsymbol{X}_{i,t})} \qquad \boldsymbol{X}_{i,t} \subset \boldsymbol{X_t} \tag{8}$$

where $\boldsymbol{X_t} = \{x_{1,t}; \ldots; x_{i-1,t}; x_{i,t}; x_{i+1,t-1}; \ldots; x_{n,t-1}\}$

Agents update their decision sequentially but make repeated decisions. Further, in updating their prior, herd agents do not take into account their expectation formed in the previous round only the signals they receive from other agents. Essentially the agent starts each time period with a blank sheet of paper and a new signal. This can be justified in instances where the past does not matter (such as fads or fashion) or is captured in the state of the world and consequently in the signal obtained by the agents. For example, stock market prices incorporate past information with the only concern to agents being the future direction of the price.

This process does not mimic the types of conversations, and social learning, that occurs when individuals meet (for example there will be an element of joint decision making rather than agent i conferring with agent $I + 1$ prior to formulating a decision, then in turn $I + 1$ confers with i). However, what this approach does do is emphasise the effects of 'Chinese Whispers' where, because the communication is by word of mouth, hard evidence is not always provided [12]. The decision process also incorporates a form of 'public weighting' appropriate to such models.

3 Long run equilibrium

Consistent with the results of BHW [4] when the network consists entirely of herd agents, information becomes blocked and all learning ceases. For the purpose of undertaking the numerical analysis the following parameter values are used unless specified otherwise: $N = 200$, $q = 0.7$ and $k = 2$. In order to test the robustness of these results simulations are also run with $N = 100$ and $q = 0.6$ and 80 with no noticeable changes to the results.

We now examine the probability that a network consisting of 200 agents can avoid an information cascade after 900 rounds. 100 trials were run for each increment of q (noting that $q = 50$ represents the case where agents are following a random walk).

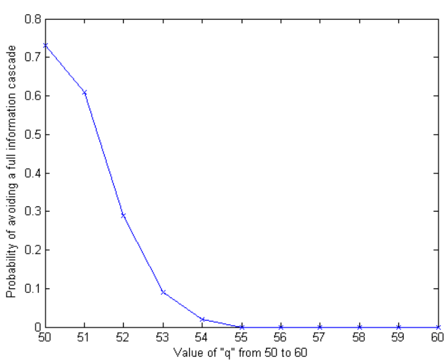


Figure 2: Probability of avoiding cascades.

It confirms that an information cascade forms with a probability of one even for low q (i.e. $q = 50 + \varepsilon$). As agents follow their own signal in the first round the probability that agents cascade on the wrong state of the world is negligible. This is consistent with the results of Ellison and Fudenberg [12] which also adopts an exogenous initial state with agents making repeated decisions.

Expert agents add another dimension to the decision making process. Experts tend to be high precision individuals that are more inclined to use their own information rather than those that they come into contact with [4]. For the purpose of numerical analysis the expert agents are spaced evenly within the network (so if there is one expert agent and N = 200, the 100^{th} agent is an expert). Within the framework of BWH [4] this is equivalent to high precision individuals that make their decision later in the sequence. It is shown that, with the inclusion of one expert, agents always herd around the correct state of the world.

For t < 300, v is set exogenously to 0. As can be seen from fig. 3 agents quickly herd around x = 0. At t = 301 v is changed to 1 representing a structural change in the system. Within a short period of time agents switch their belief of v to 1 (i.e. all but a few agents hold that x = 1 at any point in time). At t = 601 v is again changed and the same result occurs.

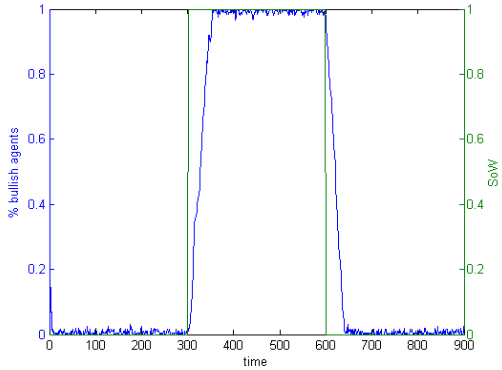


Figure 3: One expert agent.

This outcome of the model has some similarity with that of BWH [4], in that the presence of an expert, when they appear later in the sequence, has the potential to break information cascades. In our model experts always break cascades, with the herd switching to the correct state of the world in finite time. Experts ensure that information always flows to all agents through contagion as they make decisions over time. Therefore, when the average number of connections are low (k = 2), the presence of expert agents means that there is no long term mispricing. There is some delay between the change in the state of the world and the ensuing shift in agent expectations. This may result in overshooting of prices. Nevertheless the agents' response to changes in the state of the world is quite rapid. Our simulations have shown that increasing the number of expert agents only shortens this lag. These results are consistent with Banerjee and Fudenberg [11] and Bala and Goyal [9].

4 Dynamic properties

4.1 Small world properties of the social network

Firstly we consider the level of volatility as you increase the level of randomness p and the number of expert agents. Volatility is measured as the standard deviation with $\sigma = 1$. As can be seen from fig. 4, when p is approximately equal to 0 the number of experts affects the level of volatility in a linear fashion; steadily increasing from 0.1 when one expert is present to 0.05 when 10 expert agents are present. As the level of p increases the level of volatility rises sharply before reaching a plateau for $p > 1$ (as emphasised in fig. 4b which focuses on the range in p from 0 to 3). At this point, increases in either the number of expert agents, or the level of randomness (but holding k constant and equal to 2) has very little effect on the level of volatility. Assuming that $p > 1$ for all social networks then there is an inherent level of volatility in agent expectations. If individuals trading decisions are influenced by their expectations then this inherent level of volatility may in turn induce volatility in financial prices.

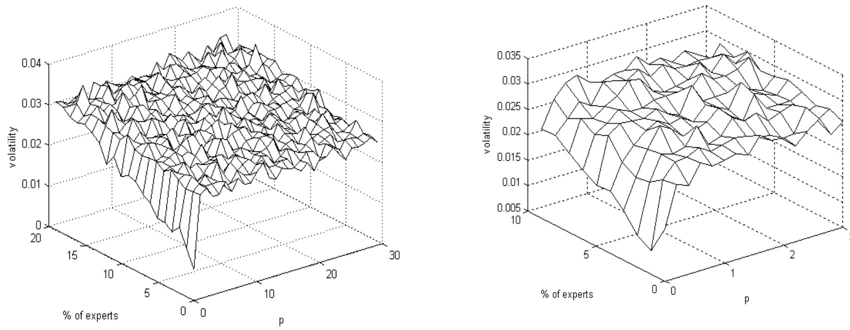


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Figure 4: Volatility vs. the number of experts and p.

4.2 The power of expert agents

As noted earlier expert agents are high precision individuals that tend to use their own information. However, experts also tend to have an increased influence over other agents. Experts are important because they provide valuable information particularly where that information is difficult to obtain or process or drawing conclusions is subjective. Two types of experts are considered in this paper. The first are experts that are well respected in the general community and are connected to many other agents in the network, such as Warren Buffet or Allan Greenspan. These are represented in the model as agents who have one way connections with many agents. The second type of agent is one whom is recognised locally as an expert. A good example of such an expert might be the local financial planner. In the model these agents have the same number of connections as the herd agent but the strength of their connections is increased.

As can be seen from fig. 5, as you increase the number of connections from the experts volatility dramatically increases (three percent of agents are experts). Unlike the previous case where the number of expert agents is increased, the effect of increasing the number of connections persists for $p > 1$. Further the volatility associated with this increases is in addition to the volatility due to the small world effect. These results suggest that volatility will be highest at times when experts are having the greatest effect, as measured by the number of connections, even though the average number of connections between all agents is not high. Doubling the strength of the connections from these experts increases the level of volatility, however, further increases have little effect (results not shown here). Therefore, any variation in the volatility of expectations can only be coming from an increase in the number of connections from expert agents.

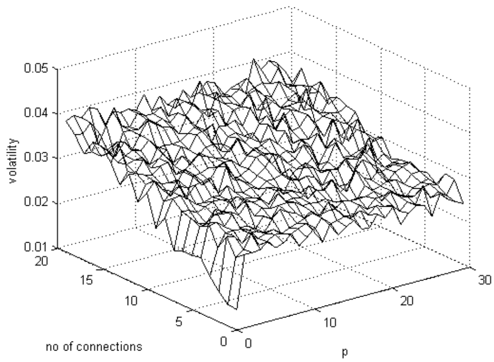

Figure 5: Volatility as you increase the number of connections from expert agents.

A number of questions arise from this result: when is the influence of experts strongest and is volatility high during these periods? Intuitively, connections from experts are high (low) when faith in the market is strong (weak). At this point agents are at their most receptive to news about the stock market. If this is the case then prices might be most volatile when markets are rising.

4.3 Information cascades and bubbles

In the scenarios considered thus far herd behaviour increases the level of volatility in the market but does not lead to long run and significant mispricing. In what follows the number of connections between herd agents k is increased from two to four. Five percent of all agents are expert agents. It is found that when the network is ordered, agents enter into an information cascade (see fig. 6a). However, for $p \geq 1$ the cascade is broken and volatility decreases significantly (fig. 6b). When k is greater than four agents are always in an information cascade with a result similar to fig. 6a (not shown here).

It is therefore possible that under certain network structures herd behaviour can lead to information cascades. This locking of expectations could lead to the formation of speculative bubbles. Intuitively, as long as the average number of connections between agents is low information can flow within the social network. As the number of connections increase information flows become congested as the actions of other agents dominate their own private signal. The surprising result here is that the number of connections per agent does not need to be large before information becomes blocked.

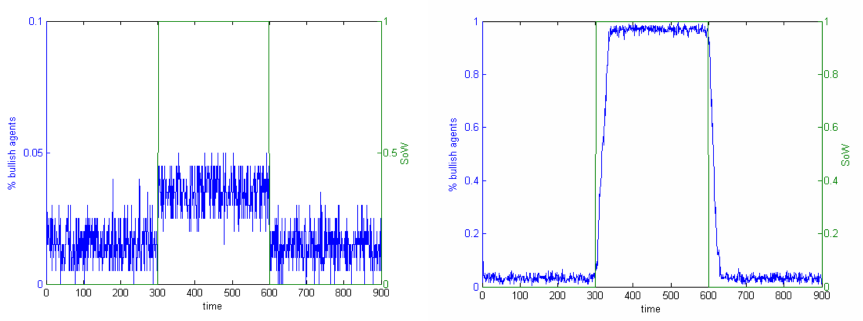

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Figure 6: Emergence of an information cascade.

Interestingly speculative bubbles in financial markets are characterised by excessive reporting in the media. It also dominates social discussions between neighbours or within the workplace. This could also explain the "bandwagon effect", where people exhibit herd behaviour out of fear of missing out on opportunities.

5 Conclusion

In this paper it is found that social interaction and herd behaviour, modelled in a multi-agent based framework, can explain the underlying volatility in agent expectations. It can also explain the variation in the level of volatility over time. Herd behaviour is often cited as one of the forces behind speculative price bubbles and crashes in stock markets. It is found that under certain network structures, where the number of connections between agents is increased, herd behaviour will lead to information cascades that have the potential to provide an explanation for the formation of speculative bubbles.

There are a number of potentially testable theories which arise from the work in this paper. Does volatility in agent expectations increase when communication from experts rises? Also, do bubbles occur during times when the number of connections between agents is high and is volatility high or low during these periods? There are also a number of extensions to the model including determining the impact of changing expectations on prices by incorporating a pricing mechanism. There is also growing empirical evidence that analysts herd in their recommendations, particularly inexperienced analysts [14, 15]. It would be useful to analyse this behaviour within the framework of a social network by linking the experts together in their own sub network.

Acknowledgement

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