The Impact of Dividends in an Investor Network

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Abstract. The behavior of financial markets has, and continues, to frustrate investors and academics. With the advent of new approaches, including a complex systems framework, the search for an explanation as to how and why markets behavior as they do has greatly expanded. The use of agent-based models (ABMs) and the inclusion of network science has played an important role in increasing the relevance of the complex systems framework. Through the use of an artificial stock market utilizing an Ising model based agent-based model, this paper provides significant insight into the mechanisms that drive the returns in financial markets, including periods of elevated prices and excess volatility. In particular, the paper demonstrates that the network topology that investors form and the dividend policy of firms significantly impacts the behavior of the market. However, if investors have a bias to following their neighbors then the topology becomes redundant. By successfully addressing these issues this paper helps refine and shape a variety of further research tasks for the use of ABMs in uncovering the dynamics of financial markets.

Keywords. Agent-based model; artificial stock market; networks; dividend policy.

1 Introduction

Financial markets commonly produce periods of extreme volatility. In an attempt to understand this behavior, the use of a complex systems framework has become increasingly popular. The complex system approach is consistent with the thoughts of [1], who concluded that to understand stock market returns, one must consider: imitation, herding, self-organized co-operativity and positive feedbacks. A further benefit of utilizing a complex systems framework is that it allows networks to be included, with their relevance to financial markets being their ability to explain investor trading decisions and portfolio performance [2]. The use of ABMs has been a primary tool is trying to understand the dynamics of a complex system and a large volume of work utilizing ABMs to create artificial stock markets has been developed. The key rationale for the use of ABMs is that they are not constrained to equilibrium conditions [1]. However, the utilization of network structures within these models has been limited. This paper implements an artificial stock market model that not only makes use of differing investor networks but also varies the dividend payout ratio of the risky asset traded in that market. This research produces multiple insights that management should consider when implementing a dividend policy and investors should consider in general.

2 The Model

2.1 Background

Utilizing the Ising based agent-based model (ABM) of [3] (H&S hereafter) as a foundation, various extensions were made to address the specific research questions. The model is implemented in NetLogo 5.3 [4]. The justification for utilizing the H&S model as a foundation comes from the key findings of the paper, which included:

- Price movements were impacted by how influenced investors were by their neighbors. Importantly, the authors suggest that when the initial bias to listening to one's neighbors reached a certain level, a positive feedback loop with regards to investors adapting the actions of their neighbors became material, that is, the investors 'herded' and bubbles and crashes appeared; and
- The asset returns matched the stylized facts of financial markets yet did not match the Gaussian distribution of the public and private information.

The basic premise of the H&S model is that boundedly rational investors have access to three sources of information; the expected actions of their neighbors ($E_{ij}[a_{ik}(t)]$), public ($pi_i(t)$) and private $\epsilon_{ij}(t)$ information, that they utilize to determine their propensity to invest (ω_{ij}) in a risky asset as per Equation 1. To determine the expected actions of their neighbors, each investor polls their neighbors' actions to see if they are buying, selling or holding their risky asset at each step. The other information sources are generated by a random draw from a normally distributed probability function.

$$\omega_{ij} = c_{1ij}\left(\sum_{k=1}^{K} nt_{jk}\,(t-1)E_{ij}[a_{ik}(t)]\right) + c_{2ij}pt_i(t-1)pi_i(t) + c_{3ij}\epsilon_{ij}(t) \qquad (1)$$

The level of influence of each information source is weighted by a combination of up to two variables. For the c_{1ij}, c_{2ij} and c_{3ij} variables, investors are initiated with a fixed value that is drawn randomly from a uniform distribution between 0 and a user defined value. With the variable being used to weight the information the investor generates from the particular information source, an acceptable interpretation is that a higher value (such as 4), indicates a higher initial bias to the particular information source. As investors have a different value for these variables it introduces a level of heterogeneity within the population. By altering the c_{1ij}, c_{2ij} and c_{3ij} coefficients, different dynamics were generated in the H&S model. In particular, when the upper limit for c_{1ij} is set at 4, bubbles in the risky asset's price appear. Hence, analyzing the impact of different levels for this variable and c_{2ij} forms a key component of this paper and the H&S paper.

The model design is such that the price of the risky asset is endogenously determined through a market-making model after each investor makes their investment decision and submits their buy or sell orders. Investors then use the subsequent asset returns to reassess and adjust the trust they have in each of their information sources via the network trust (nt_{jk}) and public trust (pt_i) coefficients. These variables are initiated at 0, with the investor's trust based on the ability of the information source to predict an appropriate action. An appropriate action being when the information tells the investor to buy and the price subsequently increases (and vice versa for a sell signal).

2.2 Model Extensions - Networks

While there is a large volume of work of utilizing ABMs to simulate financial market returns (see [5] and [1] for extensive reviews of the application of ABMs to financial markets), the utilization of networks within the various frameworks has been limited. The rationale for utilizing networks, is that the behavior of a system can vary greatly depending on the network structure (the topology) the system takes. The benefits of adding networks to artificial stock markets has been demonstrated in papers such as; [6] who showed that network structures are capable of influencing the stability of, and the fluctuations of an asset's price and [3] who demonstrated how bubbles may emerge as a result of agents considering different information sources, including the expected actions of their neighbors. In addition, works have emerged that show how the topology of investor network impacts information efficiency [2] and demonstrate the role that centrality plays in determining the dynamics of a market [7] and [8].

Within network science literature there are four general types of network; regular/lattice, random, small world, and scale free networks. In high levels terms, the differences relate to how each agent is assigned their neighbors and the number of neighbors they have. The extended model has the flexibility to consider all of these network with a range of settings including; the number of neighbors an investor has and the probability of how the investors connect to each other.

In creating the various network topologies, the ability to have the average number of edges and the average number of neighbors consistent across the different network structures was a key consideration. This meant that any difference in the outcome across the networks was not influenced by the number of edges, but solely by the degree distribution of the network. The significance of the differing degree distribution is that if an investor only has one neighbor they will have an initial bias towards public and private information, as they collect less opinions and if they have a lot of neighbors there will be an initial bias to the information coming from their network as they collect more opinions. Consideration was given to normalizing the network information but this would have minimized the impact of the different network structures. With investors continually reassess their trust in each information source, it does not preclude a single neighbor becoming very persuasive. Conversely, an investor with a large number of neighbors may end up attributing very little trust in them.

2.3 Model Extension - Dividends and Earning Expectations

To remove a level of abstraction in the original model, a new source of public information along with dividends were introduced. To achieve this, earnings per share (EPS) for the risky asset was introduced as it reflects the income generating ability of the asset and is a key component in determining the fundamental value of an asset. The EPS value at each step is drawn from a Gaussian distribution, in a similar manner as the H&S model, but with the probability density function (PDF) having a mean equal to the initial price of the asset divided by the model's timeframe which is then further divided by an appropriate price earnings (PE) ratio. The extended model used a quarterly timeframe with an initial price and PE of 1 and 15. The standard deviation was set at 50 percent of the mean. A consensus earnings forecast is also included because according to [1] "in a given financial bubble, it is expectation of future earnings rather than present economic reality that motivates the average investor". The model computed the forecast by using a moving average of the asset's EPS history with an exponentially decreasing kernel, determined by a memory variable.

To determine the value of public information, the extended model has the investors assess the actual EPS for the asset at each tick against the consensus forecast, as per Equation 2, rather than the Gaussian process used in [3]. If the actual earnings exceed the consensus estimate ($pi_{ti} > 0$), this is considered an earnings surprise, resulting in a buy signal and vice versa for a miss. If earnings meet expectations, then the information adds no value because the investor assumes the information is already reflected in the price. Support for the extension comes from the volume of work that shows stock prices react positively to positive earnings news, yet it takes time for this information to be reflected in the price of the asset [9].

$$pi_{ti} = \frac{eps_i(t) - epsf_i(t)}{epsf_i(t)} \tag{2}$$

In a further extension, the risky asset returns a dividend (DPS) if the EPS for a period is greater than 0. The justification for introducing dividends is that they are a key component in the total return of a financial asset. For example, for the S&P 500, dividends are responsible for 42% of total returns [10]. Despite the role dividends play in supporting returns, it should be noted that the reason why firms pay a dividend is an area of ongoing discussion, with no decisive evidence supporting the argument they are used to signal favorable information to the market or to mitigate agency problems [11]. An alternative view has been provided by firstly [12], and supported by [11], with the proposed dividend catering theory Under the theory, investors' demand, and therefore any premium that dividend paying firms attract, is dependent on investors' appetite for dividends at any particular time, which in turn varies based on market conditions.

The extended model determines the asset's dividend as per Equation 3. The justification for the use of a payout ratio, as opposed to an absolute dividend, is summarized by [13], who suggest a firm's payout ratio is dependent on a combination of various accounting metrics including; profitability, cash flow and debt to equity ratio.

$$d_i(t) = eps_i(t) * pay\_out\_ratio_i \tag{3}$$

The presence of the dividend will boost returns for investors. Therefore, when investors reassess their trust based on the returns of the asset if the price increased the level by which the trust is reassessed is amplified due to the dividend. However, if the price declines after negative news the signal is suppressed due to the dividend. Therefore, investors will tend to revise upwards their trust at a faster rate than they revise it downwards. The impacts of this are assessed in Section 3.

Despite receiving a dividend investors do not have access to those funds for the purpose of further investing. This ensures that the extended model remained consistent with original model, which was closed to new funds.

3 Results

The extended model was utilized to assess the impact of changing the source of public information and varying the payout ratio along with how investors were connected (either a lattice or scale free network). The lattice network is used as it allows for a direct comparison with the H&S paper, while the use of the scale free network resulted in the most contrasting results. The initial levels of network (c_{1ij} or c1) and public bias (c_{2ij} or c2) are varied to explore the dynamics of the model in a similar fashion to the H&S paper. The justification for varying c1 is to see if a bubble or excitable movements still result when the investors have a higher initial bias to the information from their network. The increase in c2 is designed to test whether investors having a higher initial faith in the value of public information is capable of preventing the positive feedback loop that results in investors blindly following their neighbors' behavior.

A summary of how the prices (and therefore returns) varied for the various networks scenarios is provided in the boxplots in Fig. 1. (all figures have been produced using [14]). The data for the plots comes from determining the mean price from the 30 runs of 2,500 ticks for each of the particular settings in the parameter sweep. The remaining settings for the experiments are consistent with those of the H&S paper, including there being 2,500 investors with the average number of neighbors being 4. The degree distribution of neighbors is constant for the lattice network while the scale free network has a power law like degree distribution.

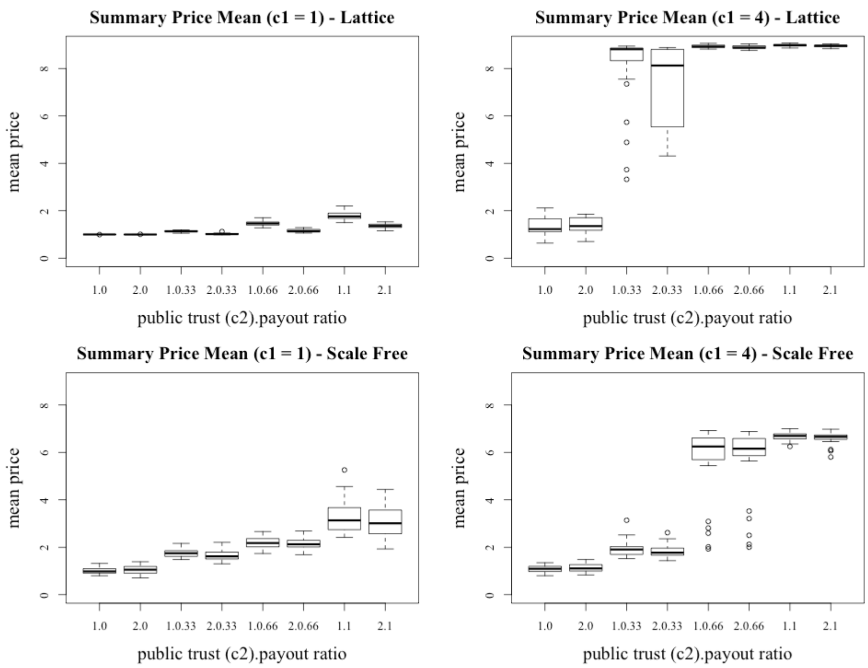

Fig. 1. Boxplots of the mean prices from varying networks, payout ratios and public information bias

From Fig. 1. it can be seen that there is both a large variation within and between the various networks and the payout ratios. In terms of the lattice network it can be seen that once the initial bias to listening to your neighbors (the c1 variable) is set at 4 then the mean price is greater than 8 once the dividend payout ratio is increased to 33%. For the scale free-network, it can be seen that the c1 variable does not need to be increased to 4 for the mean to move away from 1. The other point of note is that the scale free networks maintains a higher degree of variability in general across the various settings.

The impact on the price of the asset for the two network topologies through varying levels of c_{1ij}, c_{2ij} (detailed in the heading by the c1 value) and the payout ratio results are illustrated in the fan plots [15] in Fig. 2. through Fig. 5. The lattice results are seen in Fig. 2. and Fig. 3. and the scale free network in Fig. 4. and Fig. 5.. The fan plots were formed from 30 runs for each parameter setting and the reader should note that the x-axis in these charts is time as determined by the tick/step number of the experiment. The plots have the median price for the sample marked with the line marked with 50%.

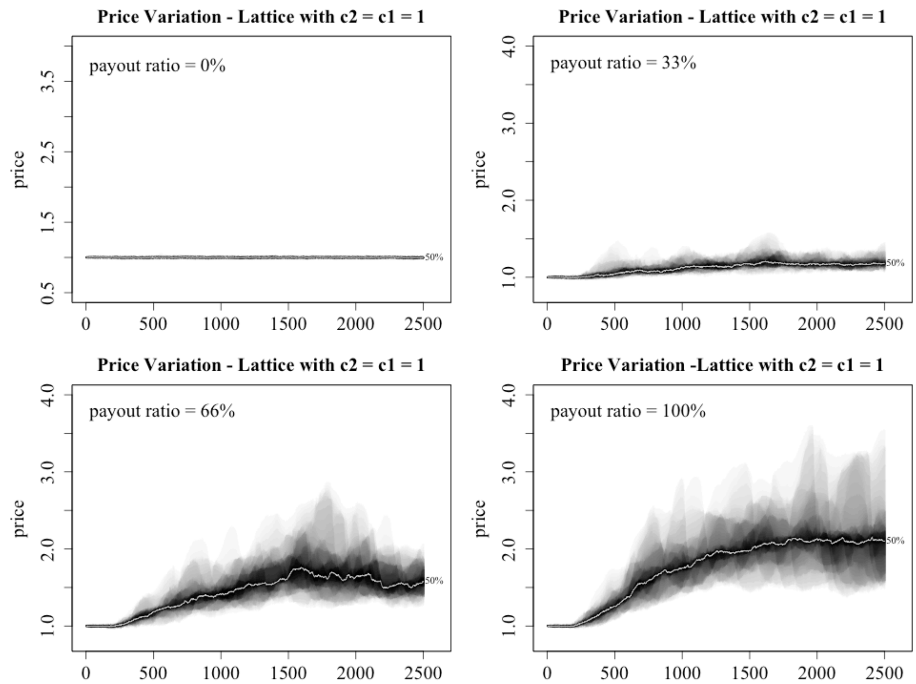

Fig. 2. The impact of varying payout ratios with c1 = c2 =1 over time for the lattice network

The upper left hand corner of Fig. 2., shows the setting of c1 = c2 = 1 and no dividend. These settings see no volatile price movements with the price series confined to a narrow bound around 1. This result effectively replicates the results from the H&S model with similar settings thus supporting the use of the extended model. While the price band is narrower than the H&S model, tests confirmed that the distribution of returns did not fit a Gaussian distribution, which is consistent with the H&S model. Further verification of the extended model is illustrated in the top left hand corner of Fig. 3, where the settings are changed to c1 = 4 with no dividend. Now bubbles and crashes, comparable size to the original model appear, albeit they appear with greater regularity.

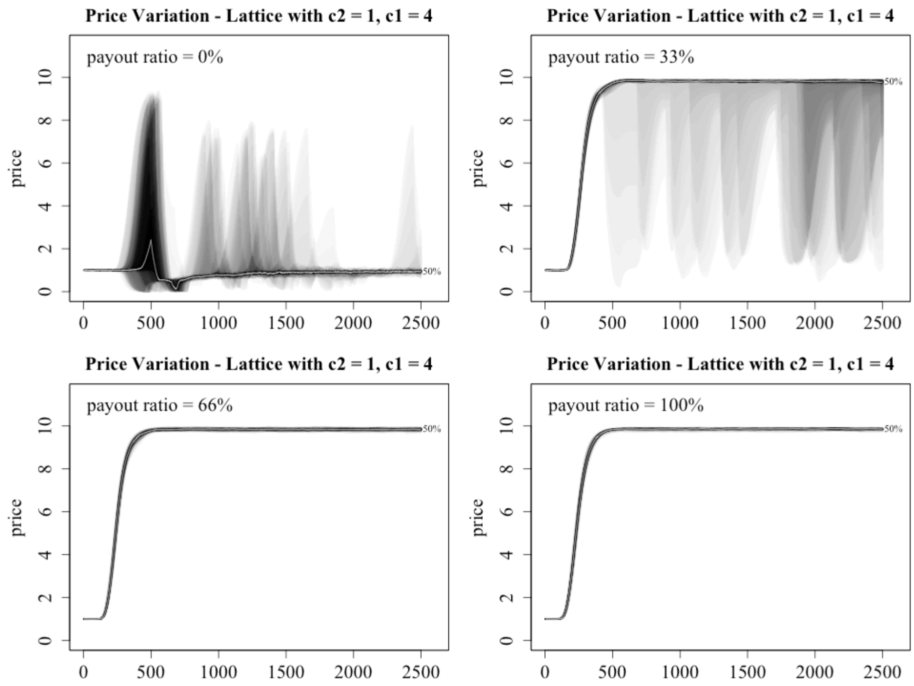

Fig. 3. The impact of varying payout ratios with c1 = 4 and c2 =1 over time for the lattice network

The introduction of a dividend impacts the price series in a number of ways. Firstly, from Fig. 2. it can be seen that as the payout ratio is increased from 0 to 1, the median and the volatility of the price series increases. At this point it is worth remembering the key characteristic of the model, namely that a dividend is only paid when the EPS for a period is greater than 0 and the investors cannot reinvest the proceeds. Also a sell signal is generated when the EPS result for the asset is less than the consensus forecast for the asset. which occurs approximately 50% of the time. In the instance that EPS < 0 and the result is below the consensus, the sell signal will not be diluted by the payment of the dividend. However, if the EPS result is positive, a dividend is paid which will boost the returns thus reducing the power of the sell signal, which in turn may limit the growth in trust for the public information. The likely impact of this being that the trust that investors generate in the information from their network is likely to go unchecked by the public information. This in turn will result in the formation of more herds as investors tend to follow the actions of their neighbors rather than acting on public information or even their private information. The consequence of the formation of more herds is that the price will increase in range and volatility based on the size of the herd.

It was seen in Fig. 2. that the introduction of a dividend under a regime where there was no initial bias to any information source had a mild impact. However, the results in Fig. 3., which illustrate the outcome of setting c1 to 4 (a setting that is responsible for the creation of a bubble in the H&S model), are far more explosive. The most telling result is that once the dividend is introduced the behavior post the inflation of the bubble is very different. In particular, the bubble does not deflate once the payout ratio is greater than 33%. Even with a payout ratio of 33%, the median price remains in bubble territory, but the investors can experience a high degree of volatility but it is not sufficient to move the median price materially from its' upper limit. When the payout ratio is 66% or greater, the median does not move once the bubble is formed.

The significance of these findings are that if there is a high initial bias amongst investors to listening to your neighbors (c1 = 4), the introduction of a dividend sees investors form a buying herd and they can never be persuaded to switch (by analyzing the intentions of the population this process was confirmed). The herding occurs regardless of what the investors' public and private information sources are telling them, including the fact that the EPS of the asset will miss consensus on average 50% of the time, thus creating a negative score for public information and providing a sell signal. This phenomenon occurs because the trust the investors place in the actions of their neighbors dominates the decision making process and the trust does not subside nor can the trust in the other sources build sufficiently to displace it.

To confirm the previous observations, a Kruskal-Wallis rank sum test was used to test the null hypothesis that dividends have no impact on price. This test was used because the distributions of the prices violated the assumptions for a one-way ANOVA test. The null was rejected for all combinations of initial public (c2) and network bias (c1). The inference to be drawn is that increasing the payout ratio has a positive impact on the price for an asset despite the earnings profile remaining similar.

The results of the utilization of a scale free network are shown in Fig. 4. and Fig. 5., and confirm the initial findings seen in Fig. 1, that is the scale free network generates results that a significantly different to the lattice network. The key difference, as seen in the top left of Fig. 4. is that a bubble is generated despite their being no dividend and the investors having no initial bias for listening to their neighbors (c1 = 1). A similar result is also generated when the original source of public information is utilized in combination with a scale free network. This provides another key finding of the extended model, that is if investors are linked in a scale free network, the market will be more volatile, regardless of the bias that the investors may or may not have towards the information coming from their neighbors.

The work of [2] provides a possible explanation for this result, where they proposed that price volatility will be highest in markets with an intermediate level of connectedness yet lower in markets with higher or lower connectedness. Indeed, while the scale free network does have a lower average betweenness measure than the other topologies, it does have intermediate clustering when compared to other network topologies. Interestingly, this finding appears to become somewhat irrelevant once the initial bias to listening to one's neighbors increases.

Returning to Fig. 4., we can see that as the dividend payout ratio is increased, two points of interest appear. The first is that the median price is greater than 1 in the earlier time periods and the second being that the volatility of the system appears to increase. The median price series also behaves in a contrasting manner to the lattice network, as it appears to revert to 1 (or at least trend down) in all cases except the 100% pay out scanerio. Interestingly, in the 0% payout case, the median price drops well below 1 following the initial crash of the bubble, before trending up to 1. This occurs because the investors continue to sell all the way to the bottom as they remain in a selling herd. The other scenarios still experience the initial crash but the dividend cushions the fall and the selling herd dissipates earlier. Given the contrasting findings to the lattice network, it appears that the effectiveness of a company's management to support their share price will be influenced by the network that their investors have formed.

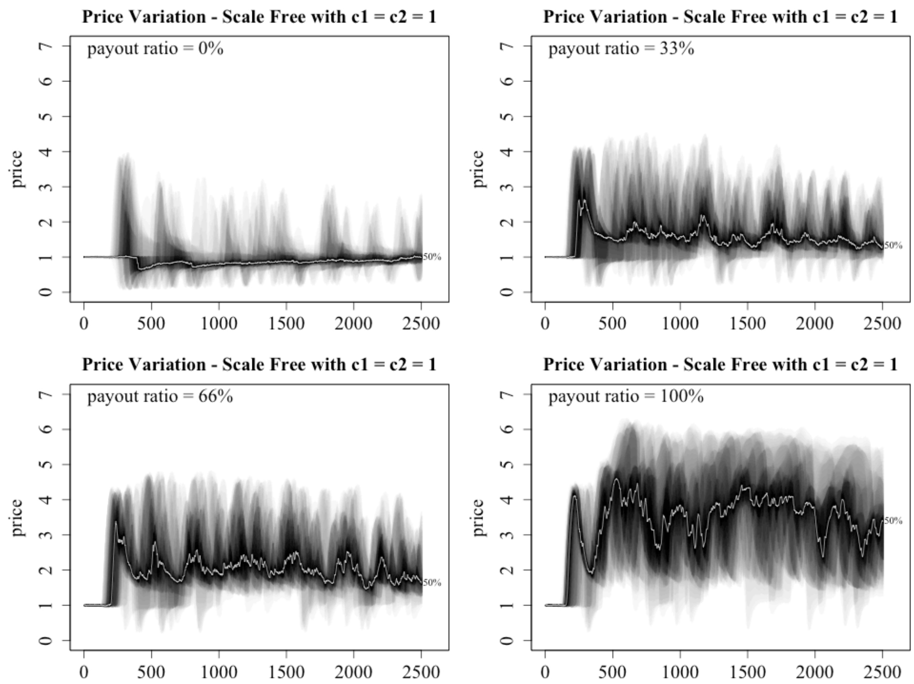

Fig. 4. The impact of varying payout ratios with c1 = c2 =1 over time for the scale free network

The result of increasing c1 to 4 as per Fig. 5., produce a diverse set of findings in comparison to the lattice network. Firstly, the median price only remains in bubble territory once the payout ratio is 66% or greater. For anything less the bubble will deflate and the price returns to its fundamental level. Even at the 66% payout ratio, while the median price remains high, there is far more volatility in the series. The other point is that the bubbles do not reach the same level as the lattice network and there appears a minor downward trend overtime, something not seen in the lattice model.

The impact of increasing c2 (the initial bias to public information) provided a number of interesting insights. From Fig. 1. the initial impression is that while the movement of the median price away from 1 still occurs, it is more gradual and does not reach the same level achieved by c1 = c2 = 1. A possible explanation, that is explored latter, is that the impact of higher initial bias to public information is to slow the growth in the trust among neighbors, which in turn diminishes the probability of a herd forming. This occurs because under this regime the influence of fundamental analysis is not diluted to the same extend in the decision making process. Therefore, this result identifies a mechanism that can prevent the inflation of a bubble, namely investors having a stronger initial faith in their public information source. The implication being that the use of fundamental information must remain in the population if excessive price movements are to be avoided.

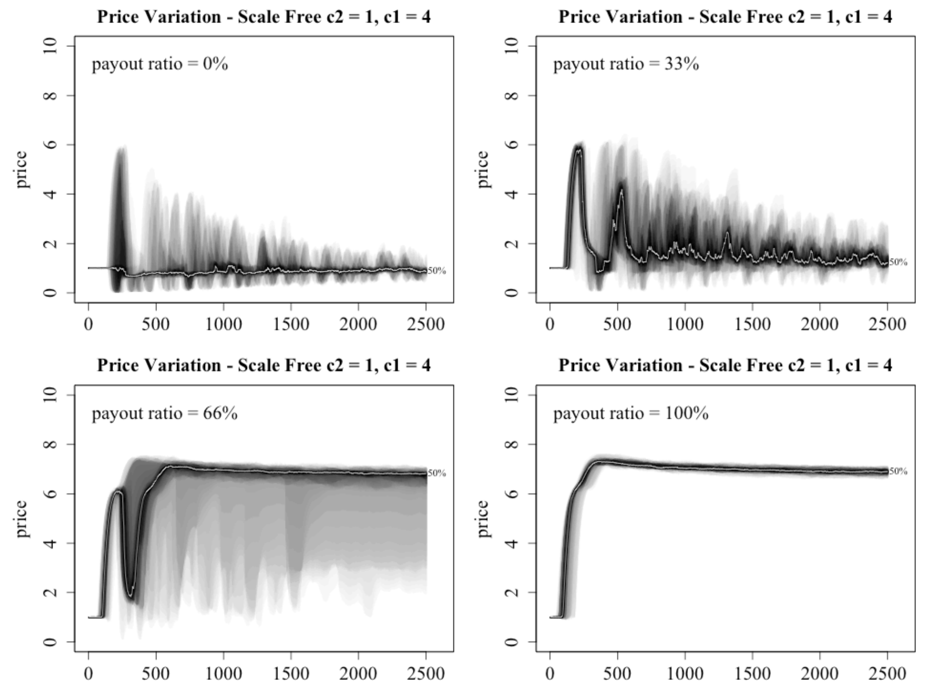

Fig. 5. The impact of varying payout ratios with c1 = 4 and c2 =1 for the scale free network

To answer the questions as to why the different network topologies and payout ratio create such different results, one needs to look at the dynamics regarding the trust that the investors have in the information coming from their neighbors. Noting that bubbles result when the positive feedback mechanism with regards to investors adapting the actions of their neighbors becomes material, Fig. 6. provides boxplots for the average network trust, in the same manner that Fig. 1. did for prices.

What becomes apparent is that the level and deviation of network trust in each of scenarios matches the price series, thus providing support to the argument that it is the level of trust investors have in their neighbors that is primarily responsible for driving market volatility. Of particular note is the lattice network where c1 is set to 4. This scenario, which is responsible for a bubble remaining inflated (when the payout ratio was greater that 33%), has the highest level of trust and a lower deviation in trust once the payout ratio increases above 33%. In summary from Fig. 6., it is apparent that the level of trust can be impacted by the network topology that investors form, the dividend that companies pay or the level of bias investors have to public information.

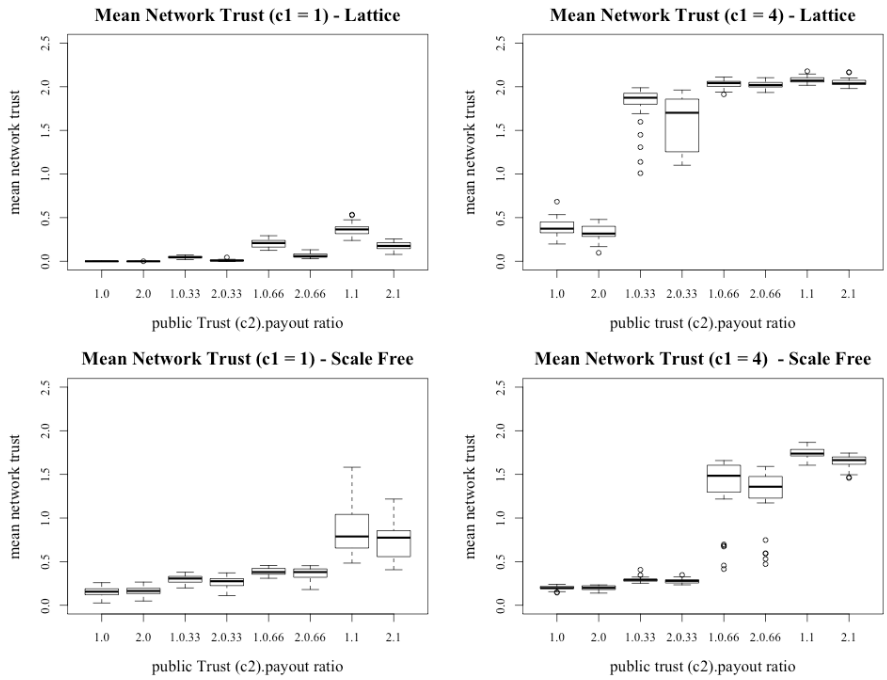

Fig. 6. Boxplots of the mean network trust from varying networks, payout ratios and public information bias.

4 Summary and Conclusion

The conclusion drawn from this paper is that dividends play an important part in supporting a bullish sentiment amongst investors as they underwrite returns, which in turn supports the positive feedback process of investors imitating their neighbors. Therefore, providing management with the ability to influence their share price through their dividend policy. This result contrasts with the capital structure irrelevance principle of [16], which states that the market value of an asset is a combination of the earnings power and the underlying risk of a firm's assets, leaving the dividend policy as irrelevant. In reality this may be a short-term view because increasing the payout ratio comes at a cost, namely a lack of investment in future growth. Therefore, the earnings profile of the company will quite possibly be unsustainable.

To be fully effective in managing their share price, management will need to understand how and if their shareholders are connected and whether they have a particular bias to an information source. As for the impact of investors being more susceptible to following their neighbor it was observed by [17], who suggested that markets had tended to be more efficient when professional investors using fundamental analysis controlled them. It had been the result of "uneducated" investors, who tended to follow the crowd, entering the market that created the greater volatility.

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