UNIVERSITE DE DROIT, D'ECONOMIE ET DES SCIENCES D'AIX MARSEILLE
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**CENTRE D'ETUDES ET DE RECHERCHE
EN GESTION D'AIX MARSEILLE**

CHARTISTS AND FUNDAMENTALISTS IN AN AGENT BASED HERDING MODEL*

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W.P. n° 944 **June 2014**

***This paper was presented at the 9th Conference of the European Social Simulation Association (ESSA), Varsovie, 16-20 September 2013**

Acknowledgment
The author would like to thank Prof. Alan Kirman and Prof. Hanaki Nobuyuki for fruitful discussions, very helpful comments and suggestions. The author is particularly grateful to Prof. Younes Boujelbène et Prof. Pierre Batteau for their valuable comments.

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Chartists and fundamentalists in an agent based herding model

Abstract

We propose a model of an artificial asset market in which agents choose either a chartist or a fundamentalist forecasting rule and interact with each other. Agent' anticipations of prices depend on the past performance of investment strategies. The interactions between these two trader types may generate cyclical dynamics. Alternating dominance of both trader types is observed in the market according to the relative success of the strategies. The amplitude of the dynamics is affected by the noise included in these rules. The composition of the population of the competing forecasting strategies also depends on the confidence of fundamentalists in the return to fundamentals and on the amount of trust in past price movement for chartists. Moreover such dynamics generate substantial price fluctuations.

Key words*:*

forecasting strategies; interacting agents; herd behavior; agent based model.

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1. INTRODUCTION

More and more recent models have departed from the assumption of the representative agent[2]. These studies consider heterogeneous agent models by introducing some differences across the agents' expectations (De Long et al., 1990a, 1990b; Frankel and Froot, 1986). Heterogeneous agent' theory highlights the need to endogenously specify the interaction process between the agents. The advantage of the 'bottom up' approach is that it allows one to control the behavioral aspects of investors and hence to study the effects of various behavioral assumptions in complex financial markets. (For an overview of agent-based computational finance, see (LeBaron, 2000; LeBaron, 2006; Chen and Yeh, 2001; Ussher, 2008). The interaction and the contagion of opinions affect the market price and efficiency.

Robert Shiller (1984) emphasizes that imitation is a human behavior widespread in social life and more particularly in financial markets, and this was already observed by Poincaré (1908) where he argued that people have an intrinsic tendency to behave like sheep. When the information used is contained in others' choices, imitation represents a completely rational behavior. Theoretical works of Orléan (1989, 1986) and Bikhchandani et al. (1992) have contributed to the reintegration of imitation as a legitimate study in finance. As summarized and emphasized by Hirshleifer and Teoh (2009), taking into account thought and behavior contagion is an important issue in the study of price movements and trading behavior in financial markets. For these reasons, it is reasonable to examine imitation in the analysis of this topic.

The interplay of chartists and fundamentalists has been studied extensively replicating important stylized facts. (See Lux, 2009; Brock and Hommes, 1998a; Tedeschi et al., 2012; Kirman, 1991; Kirman and Teyssiere, 2002; Lux and Marchesi, 2000; Hommes, 2006)…) In this article, we employ the chartist-fundamentalist approach taking into account the influence of imitation in the interaction between these two traders types. In the simulation model, the agents switch their trading strategies and consequently their anticipations of prices based on their past performances according to two different mimicking strategies: One strategy is to imitate the most successful trader's current rule and we will refer to this as the most profitable

[2] See, for example, Kirman's criticisim of the representative agent. (Kirman, 1992)

rule and the other is to imitate the strategy that has yielded the highest average profit and we will refer to this as the average rule.

As individuals communicate with one another, this stochastic process generates alternating predominance of the two traders group. Our model revealed the existence of tranquil periods dominated by fundamentalists and unstable trading episodes when chartists dominate which we will refer to as a chartist regime. The behavior of market participants as well as the relative weight of each group may have an impact on price movements. Indeed, these dynamics depend on the traders' confidence in fundamentals and in past movements of the prices.

The paper is organized as follows. Section 2 presents the model, the trading strategies and process of price formation. Section 3 is devoted to analyzing the cyclical dynamics generated by the interaction between chartists and fundamentalists. Section 4 discusses the impact of different values of the technical and fundamental trading rule parameter. Section 5 considers an example with information costs paid by agents using the fundamentalist strategy in order to determine how this change affects the market participants' dynamics and the adjustment of asset prices. The final section concludes.

2. THE MODEL

To investigate the variation of stock market prices in relation to the evolution of the relative proportions of different types of financial players, we test a model in a simulated agent based environment.

We consider a model of the stock market with a finite set of traders $\mathrm{N} = \{1,2,\dots,n\}$. Once investors form their expectations about the future price, their excess demands are computed and the market price is determined. Next, the profits of the agents are ascertained. Following that, the agents compare their payoffs with those of other players and then decide to change strategies or to stick with their current strategy. Finally, they form their expectations again in line with the chosen strategy and the cycle repeats. A detailed description of this process follows.

As already mentioned, we propose a model capturing the interaction between two different groups of investors using different trading strategies: Chartist and fundamentalist[3].

[3] In what follows, we refer to an investor who is using chartist strategy as a chartist and to one who is using fundamentalist strategy as a fundamentalist.

The chartists' strategy consists in exploiting the patterns observed in the past series. The chartists are assumed to anticipate the next period price using

$$\hat{s}^{n}_{t+1} = p_t + \alpha_C\,(p_t - p_{t-1}) \tag{1}$$

where p_t and p_{t-1} represent the stock price at period t and at period $t-1$. α_C is the chartist's current estimate of the speed of the trend-cycle. In fact, any rule based on an extrapolation of previous prices, however sophisticated could be used.

In our simple case the chartists' strategy is to buy stocks of which prices are increasing and sell stocks that have decreasing prices.

Fundamentalists are investors who hold the belief that market prices will return to their fundamental level. They anticipate the next period price using the following rule:

$$\hat{s}^{n}_{t+1} = p_t + \alpha_F\,(f - p_t) \tag{2}$$

where f denotes the fundamental value of the stock, α_F reflects the speed with which fundamentalists believe the price level will tend toward the fundamental value.

The fundamentalists' action consists in selling stocks when the price exceeds what they believe to be the fundamental value and buying stocks when the price is below that value.

We initialize the model by assigning trading strategies among agents so that half of the investors are fundamentalists and the remaining half are chartists. Each agent, first, forecasts his period price using his own strategy. Agents form their stochastic demand based on their forecast of the future price of the asset in question.

Thus, to summarize for a given price p, in a period of time t, each agent n has an excess demand function denoted by $e^{n}_{t}(p)$. We use the form of individual demand function proposed by Föllmer et al., (2005). On the basis of this formulation, the excess demand of agent n in period t is defined by

$$e^{n}_{t}(p) = (\log \hat{s}^{n}_{t} - \log p_t) + \eta^{n}_{t} \tag{3}$$

where $\hat{s}^{n}_{t}$ is the expected price for agent n in period t, p_t is the asset price and η^{n}_{t} is an exogenous random liquidity demand.

Thus, once investors form their expectations about the future price, their excess demands are computed based on this anticipated price to which a stochastic liquidity demand is added. Then each individual places an order (to buy or to sell) based on his price forecast and the liquidity demand which, in sum, determines his excess demand. Prices are then determined as those, which equilibrate agents' purchase or selling decisions, or, in other words as the prices necessary for aggregate excess demand.

The analysis of price evolution is the principle focus of our study. Hence, the price evolution is given by the sequence of temporary equilibria just described. At each point in time, the equilibrium price is that which makes current total excess demand zero. The market price p_t at time t is then the price for which $\sum_{n \in N} e_t^n(P_t) = 0$.

The logarithmic equilibrium price is then

$$\log p_t = \frac{1}{N} * \sum_{n \in N} \log \hat{s}_t^n + \eta_t \tag{4}$$

where $\eta_t = \frac{1}{N} * \sum_{n \in N} \eta_t^n$.

The realized profit according to orders placed by both chartists and fundamentalists is then

$$\Pi_t^n = (P_t - P_{t-1}) \times e_{t-1}^n(P_{t-1}) \tag{5}$$

Information about individuals' performance is available for all traders. Given the profits and the actual price, traders can change their strategy according to the performance of others. They may follow one of the following mimicking rules, the most profitable rule or the average rule. The most profitable rule (Selten and Ostmann, 2001) prescribes the imitation of the forecasting strategy used by the most successful trader while the average rule (Ellison and Fudenberg, 1995; Schlag, 1998) proposes to imitate the strategy that generated the highest average profit.

3. CYCLICAL BEHAVIOR

We consider a market in which 1000 agents interact with one another. A total of 100 of simulations were conducted, each with 1000 periods of trading. A deterministic interaction process between agents of our model leads to the market being "locked into" a one trading strategy. Indeed, in the case of the most profitable rule, as with the average rule, everybody will make the same choice because there is only one best performing strategy for everyone. Each agent is connected to everybody else. Since they simultaneously make their expectations, then everybody switches in the same direction all the time.

However, with the noise in the copying process, a small fraction of agents may do the opposite of what the rule predicts. We therefore get waves of alternation. The results are shown in the following figure.

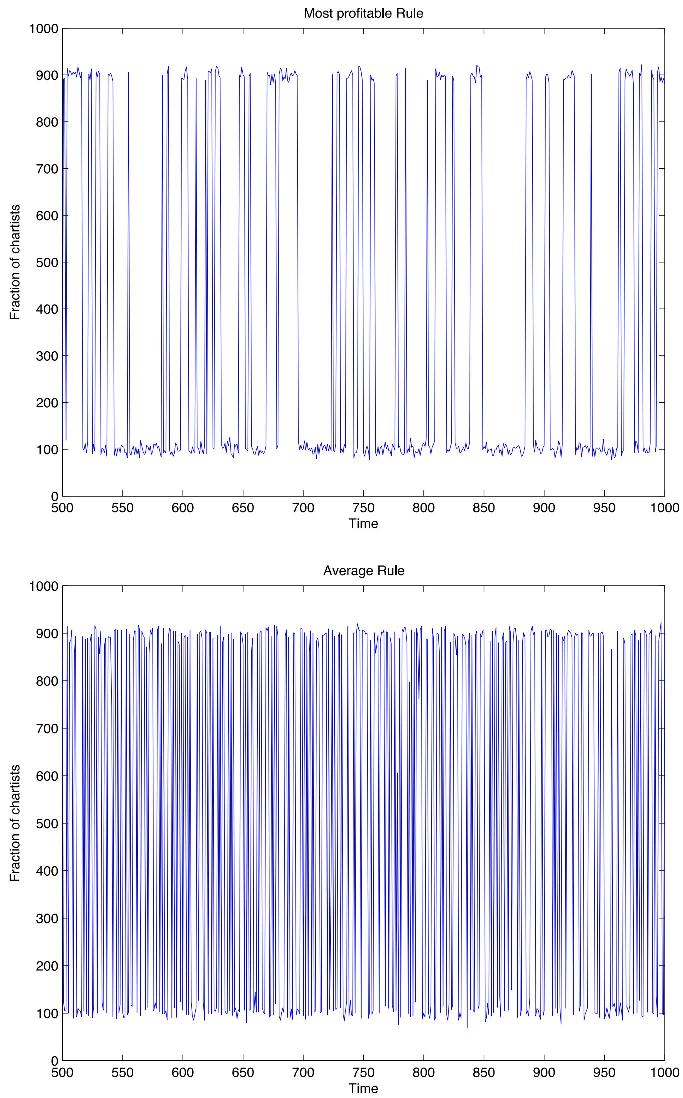


Fig.1. A simulated time series of the evolution of chartists' fraction with alterating phases of dominance of one or the other strategy. $\alpha_C = \alpha_F = 0.1$, noise=0.1. Left: Most profitable rule. Right: The average rule.

For the most profitable and average rules, the mean number of chartists is not far from one-half the number of agents $(N/2)$ but it is achieved because the system spends essentially half of its time in the two extremes of the distribution, for each simulation, eventually over time. Nevertheless, with one of the rules the system spends more time in one extreme than the other but the dominance of chartists is still inevitably followed by dominance of fundamentalists and so forth.

The fully connected network that links the agents leads to only one best performing investor, and also only one best average performing strategy that all the agents follow with a high probability. The market share of the agents who adopt the most profitable strategy or the strategy that recorded the highest average profit increases. If the observed profitability of one of the strategies is greater than that of the other strategy, more investors will act in the same way as the one that generates the highest profitability. This is known as positive feedback or to use Soros' term, "reflexivity". However, the noise in the system will eventually lead to some of the participants deviating together to the other strategy and this will trigger a mass move to that strategy. Thus, the two sets of agents dominate alternatively.

This is a reasonable result and is derived from the Kirman ants' model (1993) that also has endogenously led to swings. Hans Follmer proved, for that model, that in the limit when the number of agents becomes large and the noise goes to zero, the distribution of the shares of the two types is a symmetric beta distribution. However, without the noise, the system gets absorbed straight away in one of the two extremes. If the noise is big, the process yields shares which stay around one half of the number of agents. Again, noise plays a subtle role here, it should not be thought of as akin to the aggregate exogenous shocks commonly assumed in macroeconomic models.

Thus, the distribution of opinion is directly affected by the noise in the mimicking behavior. Fig. 2 illustrates the behavior of chartists' fraction for different values of the noise.

Another important observation is that the alternation between the two strategies is more rapid in the average rule than in the most profitable rule. If the most profitable rule is adopted, the agents follow the best investor. Since the fundamentalist strategy seems to perform better than the chartist's strategy, most of the time4, fundamentalists dominate in most cases but from time to time the chartists may dominate. When the chartists are more profitable, as everybody predicts, the future price direction at the same time and as individuals are connected to each other; they all become chartists. On the other hand, if the average rule is followed, on average, chartists perform as well as fundamentalists because of the randomness. This in turn led to more rapid fluctuations in the evolution of the fraction of chartists.

[4] Without the noise in the mimicking rule, the market contains only one type of traders. Fundamentalists are more likely to dominate the market than chartists. It is noted that there is a heightened probability (60%) that fundamentalists dominate the market.

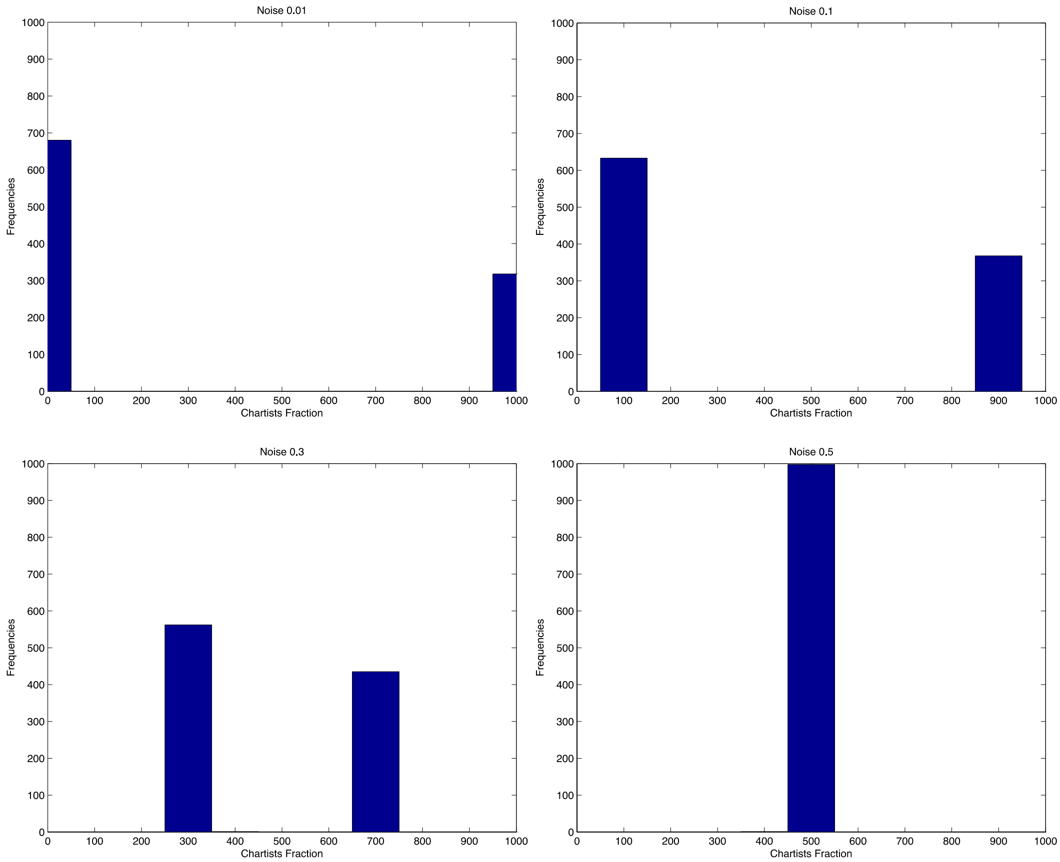


Fig. 2. Different possibilities for the distribution of the population type for different values of the noise: 0.01 (Top-Left). 0.1 (Top-Right), 0.3 (Bottom-Left), 0.5 (Bottom-Right).

These two mimicking rules show chartists and fundamentalists' waves as depicted in the Fig. 3, which give rise to price fluctuations. Asset price movements reveal that prices increase rapidly followed by a rapid decline, giving rise to repetitive bubbles. We assume, for simplicity, that the fundamental value is at all times constant and equal to 25. We note that the higher the proportion of chartists in the market, the greater the remoteness of the asset's price from the fundamental solution.

One of the most frequently explanations given to explain the difference between the fundamental value and the price, in particular the formation of financial bubbles, is that is due to the mimetic behavior of the agents in the market (Orléan, 1989). They are copying each other in their investment choices and this either selling or buying at the same time. Their expectations are no longer based on fundamental information, but on the behavior of other agents. This results in a disconnection of the stock prices compared to the real economic sphere.

If the portion of chartists is very large, their presence destabilizes prices and causes them to diverge from the fundamental value. Occasionally, due to the noise, it happens that a trader following the fundamentalist strategy makes higher profits than chartists. As a result, the number of fundamentalists increases because the imitation process can only amplify. Most agents will change their trading strategy to a fundamentalist one and thus prices will join again the fundamental value.

The interaction between the two types of investors involving endogenous modification of strategies according to their performance leads to unstable prices.

This would suggest that the relevant asset returns follow a chaotic dynamic. The asset prices may sustainably move away from fundamentals and then forcefully return toward it. This is due to the non-linearity that stems from the link between profitability and fraction of the different strategies, which implies a self-reinforcing contagion process.

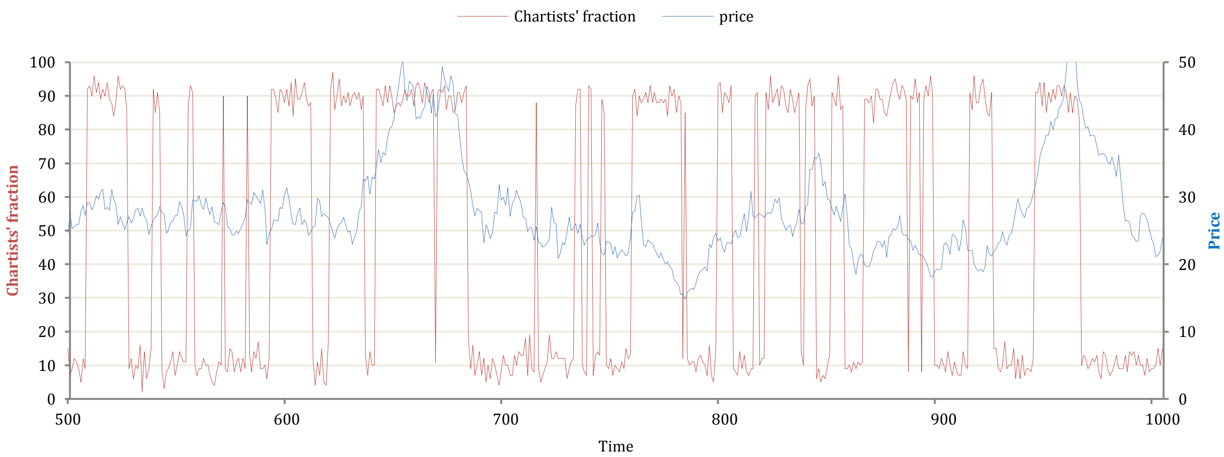


Fig. 3. Time series of price Pt and the corresponding fraction of chartists.

4. PARAMETERS OF THE CHARTIST AND THE FUNDAMENTAL TRADING RULE

For each period, the expected price is determined as compared with price for the preceding period as in (1) and (2) for chartists and fundamentalists, respectively. The coefficient α_F reflects the speed with which fundamentalists believe the price level will tend toward the fundamental value. There are cases in which the participants believe that prices tend to return to the fundamentals very quickly and cases in which agents think that it takes a considerable time to return to reach this level. When α_F tends towards 0, the return to the fundamentals is estimated to be slow. In contrast, when α_F tends towards 1, this means that fundamentalists have more confidence in the return to the fundamentals.

On the other hand, α_C is the chartist's current estimate of the speed of the trend-cycle. Let us assume that a large gap exists between yesterday and today's price. If today's price is much greater with a sharply increasing slope, chartists estimate that prices will continue to rise. As a result, this difference is fed into tomorrow's price. If α_C has a zero value, tomorrow's anticipated price will equal today's price. A higher value of α_C means more confidence in the market momentum. α_C may be negative; this means that agents are contrarians. The contrarian trading opportunities implies a belief in the inverse dynamics of the market. If the market shows a persistent upward trend, contrarian traders expect that, at some point, it will go down. For simplicity, we will restrict our attention to examining cases of positive values of α.

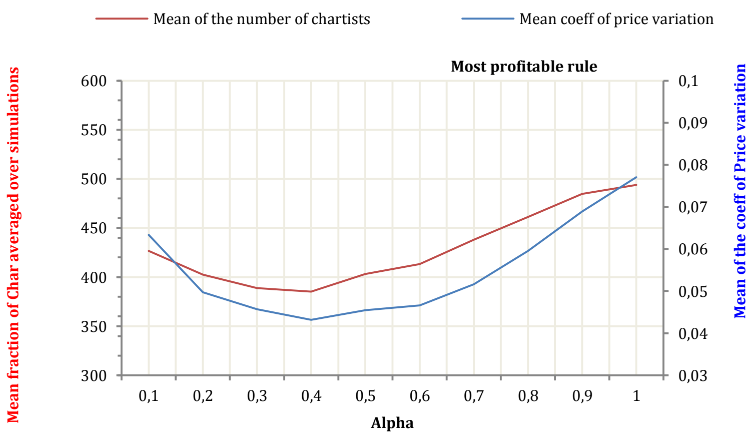
In this subsection, we assume that the chartists and fundamentalists have the same parameter α ($\alpha_F = \alpha_C = \alpha$) and we perform a sensitivity analysis over the parameter range [0.1;1].

Fig. 4 shows the behavior of price volatility for the different values of α. When α is very small, the belief in the price adjustment is very weak. This reflects a considerable slowness of price adjustment. In this sense, fundamentalists and chartists are really not that different from one other. They make the same anticipations. Fundamentalists have little confidence in a quick return to fundamentals. Prices may move away from the fundamental level and, as a consequence, prices will exhibit considerable volatility.

The higher the value of α is, the further is the behavior predicted by the two strategies. At the limit, when α is high, fundamentalists put their expectation of the price at the fundamental value.

However the rapid alternative dominance of trading strategies results in a higher degree of the price volatility. Fundamentalists are more active when the most profitable rule is adopted as discussed above.

The price adjustment process is not only guided by exogenous factors; but also driven by endogenous agents' communication.



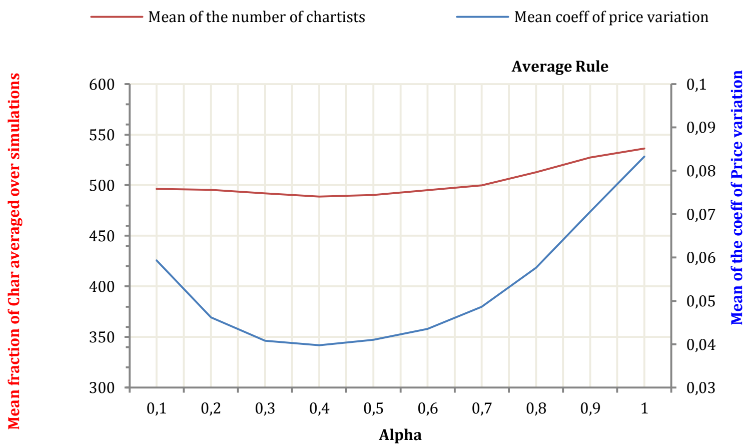
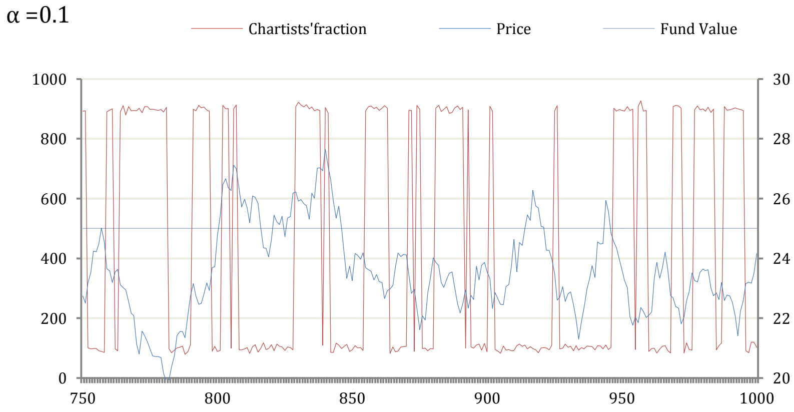


Fig. 4. The behavior of price volatility and the mean number of chartists for different values of α. Left: Most profitable rule. Right: The average rule.

To clarify further, let us take the case of the most profitable rule and consider one simulated time series of prices and its corresponding distribution of chartist fraction. We ignore the first 750 periods and plot the population dynamics and the corresponding price behavior for the last 250 periods. We study two extreme cases ($\alpha = 0.1$; $\alpha = 1$). The results are shown in Fig. 5.

We find out that the relative importance of the competing strategies varies more rapidly with a higher parameter of the technical and fundamental trading rule. Asset prices move more quickly and more sharply in response. This result clearly shows the determining role of the individuals' interaction in price formation. In part this reflects the price sensitivity of the market to these interactions.



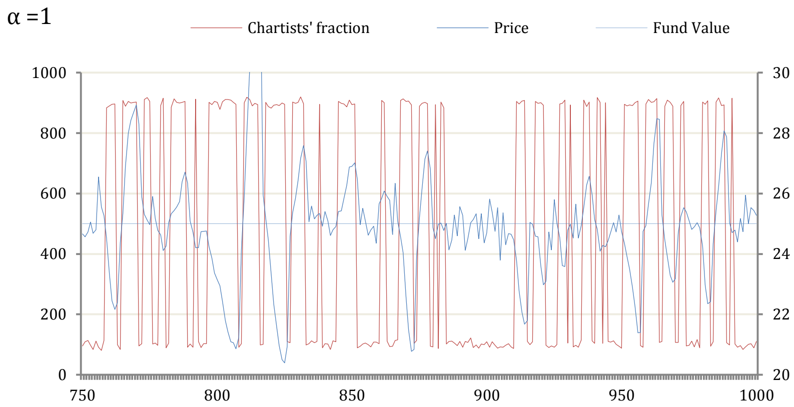


Fig. 5. Simulated time series of prices and its corresponding distributions of chartist fraction when the most profitable rule is adopted. Above: $\alpha = 0.1$. Below: $\alpha = 1$.

5. COSTLY FUNDAMENTALISTS VERSUS FREE CHARTISTS STRATEGY

In this section, we consider an example with information costs paid by agents using fundamentalist strategy. Since it is costly to analyze the various data to discover the "fundamental" value, there is a cost of obtaining the access.

We pursue the issue of chartists versus fundamentalists and capture their interaction. The question is to know which regime is dominant and examine whether the price dynamic becomes very complex. The net-recorded profit in period t by fundamentalists is $\Pi_t^F - C$, where $\boldsymbol{\Pi_t^F}$ is the realized profit in period t for investors using the fundamental costly rule, and C represents the cost paid by fundamentalists to obtain an accurate estimation of the fundamental value.

The analysis focuses on the case when agents mimic according to the average performance. If there are no costs of being fundamentalist, the two strategies alternatively and equally dominate the market. When the cost is greater than or equal to the average loss of agents, the distribution of agents using each strategy changes according to the relative average success of the two strategies. The fraction of chartists goes up until most fundamentalists leave the market leading to lasting deviations of the asset prices from fundamentals. This makes sense because, given the information costs that fundamentalists pay to obtain the fundamental value, their profits decrease and agents will change their trading strategy to chartist. Chartists appear to dominate the market on most trading periods (83,46%). Our results are consistent with those of (Brock and Hommes, 1998b; Evans and Ramey, 1992; Sethi and Franke, 1995).

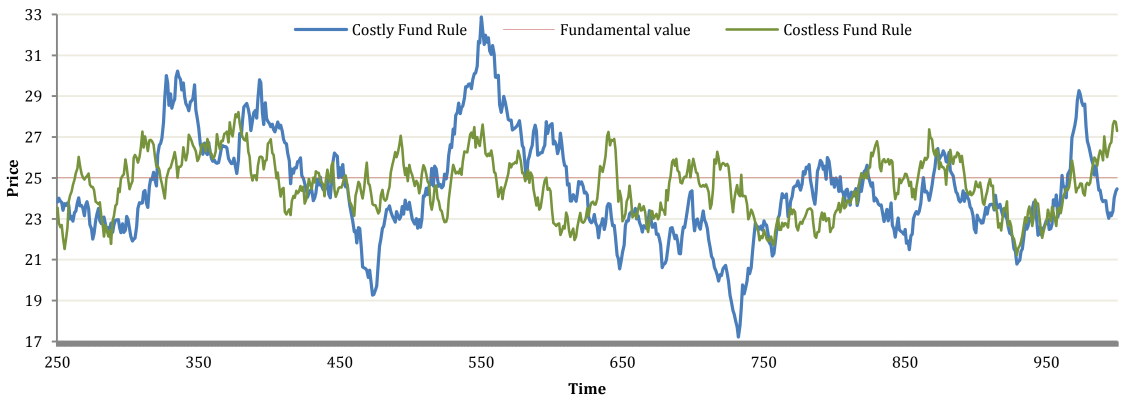


Fig. 6. Time series of prices with a costly and costless fundamental strategy.

In this case, the overwhelmingly presence of the chartist investors destabilizes the prices and thus, the latter diverge from the fundamental value as shown in Fig. 6. Brock and Hommes (Brock and Hommes, 1998a), show numerically the existence of chaotic price fluctuations when the intensity of choice to change prediction strategies increases.

In contrast, when the average loss exceeds the cost of being fundamentalist, both types of strategies co-evolve over time.

6. CONCLUSION

Stock markets are composed of heterogeneous agents, and in our simple model we characterised these as chartists and fundamentalists. Such market participants have different behavior and use distinct strategies reflecting heterogeneous expectations. Taking into consideration the interpersonal influence and the interaction between the heterogeneous agents gives results that are very different from those that would be predicted by standard equilibrium theory.

We employ the chartist-fundamentalist approach taking into account the influence and the interaction between the two types of trader. Agent’s price expectations depend on the past performance of investment strategies.

As individuals interact with one another, our model exhibited the existence of tranquil periods dominated by fundamentalists and unstable trading periods when in the chartist regime. An alternative dominance of both trader types is observed in the market according to the relative success of the strategies. The magnitude of this dynamics is affected by the noise included in these rules.

The price adjustment process is not only guided by exogenous factors; but also driven by endogenous agents’ interaction. The behavior of market participants weighted by the relative share of each group has an impact on price movements. The heterogeneity of the agents’ expectations led to prices dynamics that are governed by alternating periods of convergence and divergence from fundamentals. Moreover, these dynamics depend on the traders’ confidence in fundamentals and in past movements of the prices.

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