Fundamentalists, Chartists and Asset Pricing Anomalies

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Abstract

This paper investigates whether serial correlations and excess volatility of asset prices may be explained through the interactions between fundamentalists and chartists. Fundamentalists are defined as agents who forecast future prices cum dividend through an adaptive learning rule. In contrast, chartists are defined as agents who forecast future prices based on the observation of past price movements. Numerical simulations reveal that the presence of both fundamentalists and chartists in the market generates trends in prices over short horizons and oscillations in prices over long horizons, as well as excess volatility of asset prices. Moreover, we find that the memory of the learning mechanism plays a key role in explaining predictability of returns as well as excess volatility. In particular, in the presence of chartists, (i.) short-run and long-run dependencies in financial time series can be explained by long memory in the learning mechanism of fundamentalists; (ii.) excess volatility of asset prices can be explained by short memory in the learning mechanism of fundamentalists.

Keywords: asset prices, returns correlation, bounded rationality, trading strategies, numerical simulations.

JEL Classification: C63, D83, D84, G12, G14.

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1 Introduction

This paper builds a heterogeneous agent model in order to investigate predictability and volatility of returns in financial markets. While under the efficient market hypothesis, excess returns should not be predictable and no sign of autocorrelation should be observed in financial time series, many studies have supported the fact that returns are predictable. Excess returns are negatively correlated over long horizons (e.g., Fama and French, 1988) and they are positively correlated over short horizons (e.g., Lo and MacKinlay, 1988). Besides, many works have suggested that stock prices exhibit excess volatility (e.g., LeRoy and Porter, 1981; Shiller, 1981, 1992) and that stock price movements may not coincide with fundamental news (Frankel and Froot, 1986; Cutler, Poterba, and Summers, 1989; Ofek and Richardson, 2003). These empirical “anomalies” are not fully explained by the classical asset pricing theory (Shiller, 1992). The agent-based approach to finance (see, for instance, LeBaron (2000) and Barberis and Thaler (2003) for extensive surveys of the literature) has however tried to overcome the weaknesses of the classical asset pricing theories in explaining anomalies in financial markets. In agent-based models, markets are populated by heterogeneous boundedly rational agents (e.g., Cutler, Poterba, and Summers, 1991; Lakonishok, Shleifer, and Vishny, 1994), using simple rules of thumb strategies.

This paper contributes to the ongoing debate about the explanation of the above-described anomalies by studying asset price dynamics in an agent-based model with heterogeneous trading strategies. Specifically, we investigate whether serial correlations in returns as well as excess volatility can be explained by the interplay of fundamentalists, who set their strategies from the inference of the
asset fundamentals, and chartists, who set their strategies on the observation of past price movements. The main novelty of our study consists in the assumption regarding the knowledge of fundamentals. In fact, most of the works based on such an approach have so far concentrated on the assumption that fundamentalists know the true value of the fundamentals (see, for instance, Zeeman, 1974; Frankel and Froot, 1986; Farmer and Joshi, 2002; Westerhoff, 2003). In our analysis, we depart from this benchmark, by assuming that fundamentalists do not have complete knowledge of the fundamentals, rather they can only try to predict the evolution of some related statistics, namely dividends. More precisely, we assume that fundamentalists update their expectations through a first-order autoregressive learning rule: today’s expectation of tomorrow’s price is a convex combination of yesterday’s expectation of today’s price and yesterday’s price (see Hommes, 1994; Barucci, 2000; Barucci, Monte, and Renò, 2004, for similar attempts in this direction).

The starting point of our study is the work by Barucci, Monte, and Renò (2004). In a framework similar to ours, they establish that the presence of boundedly rational fundamentalists is able to simultaneously generate positive correlations in returns over short horizons and negative ones over long horizons. In contrast, our work consists in investigating the induced price dynamics when chartists are present in the market as well. The aforementioned departure is actually supported by empirical evidence. Indeed, survey data on expectations have revealed that chartist strategies are also widely used among financial practitioners (Frankel and Froot, 1987b,a; Shiller, 1987; Allen and Taylor, 1990; Frankel and Froot, 1990a,b; Ito, 1990; Liu, 1996; Lui and Mole, 1998).

Furthermore, contrary to most of the earlier heterogeneous agent models based
on the distinction between fundamentalists and chartists (e.g., Lux, 1995, 1998; Farmer and Joshi, 2002), we do not model the switching mechanism between different trading strategies. This departure is justified by empirical evidence on investors’ behaviors. Indeed, while chartist - both trend-following and contrarian - strategies are widespread among investors, the former usually use one or the other type of strategy, rather than switching between strategies (see, for instance, Goetzmann and Massa, 2002).

Numerical simulations reveal that the interplay of fundamentalists and chartists is able to robustly generate both trends in price over short horizons and oscillations in price over long horizons, as well as excess volatility of returns, hence reproducing the anomalies observed in financial data. First, short-run (long-run) dependencies in financial time series may be explained by the presence of trend followers (contrarian traders). Moreover, fundamentalists’ memory plays a significant role in explaining predictability of returns. Trends in prices tend to vanish when fundamentalists have short memory, and to be strengthened for higher memory values. It follows that, in the presence of chartists, fundamentalist trading strategies may weaken predictability of returns over short horizons when fundamentalists have short memory. Lastly, we find that excess volatility of returns tends to vanish when fundamentalists have long memory. This finding suggests that fundamentalists’ short memory can explain excess volatility of returns.

The paper is organized as follows. Section 2 presents the model. Section 3 analyzes the results of the simulations. Finally, Section 4 summarizes the main findings of this work and concludes.
2 The model

Consider a market in which there are two assets, namely, a risk-free asset and a risky one. The risk-free rate, which is assumed to be constant over time, is \( r_f \). The risky asset delivers dividends \( D_t \) that are modeled through a trend stationary AR(1) process:

\[
D_{t+1} = \theta + \beta(t + 1) + \gamma D_t + \sigma Z_{t+1}
\]

where \( \theta, \beta, \gamma \) and \( \sigma \) are constant parameters (\( \gamma < 1, \sigma > 0 \)) and \( (Z_t)_{t \geq 1} \) is a sequence of i.i.d. normal random variables with \( E[Z_t] = 0 \) and \( E[Z_t^2] = 1 \) for \( t \geq 0 \) (see Timmermann, 1996).

In the market, there are two types of boundedly rational agents, namely, fundamentalists and chartists. First, in order to derive fundamentalists’ behavioral rule, we closely follow Barucci, Monte, and Renò (2004). Accordingly, in a rational expectation environment, with risk neutral rational traders aiming at exploiting arbitrage opportunities, the no arbitrage condition implies that today’s price equals the discounted expectation of tomorrow’s price plus dividend. The expectation is given by the conditional expectation so that:

\[
S_t = \frac{1}{r_f} E\left[ S_{t+1} + D_{t+1} | F_t \right]
\]

Under full rationality, there is a unique rational expectation solution to (1) - (2)

\(^1\)The economy is not common knowledge, i.e., agents do not know the true dividend process as described in eq. (1). In this respect, agents are not fully rational.

\(^2\)The discount factor is given by the risk-free rate.
\[ S_t = \frac{\gamma}{r_f - \gamma} D_t + \frac{r_f}{(r_f - 1)(r_f - \gamma)} \left( \theta + \frac{r_f}{r_f - 1} \beta + \beta t \right) \]  \hspace{1cm} (3)

However, as mentioned above, fundamentalists are assumed to be boundedly rational. More precisely, they compute the expected price cum dividend, denoted \( X_t = S_t + D_t \) at time \( t \), according to an adaptive learning mechanism as a smoothed average of observed prices (see Barucci, 2000). Let \( \hat{X}_t \) denote the expectation at time \( t \) of the price cum dividend at time \( t + 1 \), so that:

\[ \hat{X}_t = \hat{X}_{t-1} + \alpha_t \left( X_{t-1} - \hat{X}_{t-1} \right) \]  \hspace{1cm} (4)

where \( \alpha_t \) is the learning coefficient (\( 0 \leq \alpha_t \leq 1 \)). In this work, the coefficient \( \alpha_t \) is assumed to be constant (\( \alpha \)). The coefficient \( \alpha \) describes the memory of the learning mechanism. When \( \alpha \) tends to 0, agents have a long memory since remote and recent observations are weighted almost the same way (\( 1/t \)). In contrast, when \( \alpha \) tends to 1, agents have a short memory since recent observations have a weight larger than remote ones. As a result, memory is decreasing in the value of \( \alpha \) i.e., agents have longer memory as \( \alpha \) decreases.

The no arbitrage condition described in eq. (2) applied to the current environment, with boundedly rational fundamentalists, gives us:

\[ \hat{S}_t = \frac{1}{r_f} \hat{X}_t \]  \hspace{1cm} (5)

Equation (5) indicates the asset price that would prevail in the market at time \( t \), if there were only boundedly rational fundamentalists in the market. As a result,
\( \hat{S}_t \) given in eq. (5) is a proxy of the asset fundamental value in each period \( t \).

Second, in this work, not all of the agents in the market try to predict dividends. Chartists rather merely base their trading strategies on the observation of past prices from which they try to predict future price movements. While most of the heterogeneous agent models based on the explicit distinction between fundamentalists and chartists (see, for instance, Lux, 1995; Lux and Marchesi, 2000; Farmer and Joshi, 2002; Westerhoff, 2003; De Grauwe and Grimaldi, 2005) essentially consider that the very figure of technical analysis is a trend follower, we depart from this hypothesis. We rather assume that there are two types of chartists, namely, trend followers and contrarian traders. Trend followers believe that any trend in past prices will repeat in the future. Contrarian traders instead believe that any trend in past prices will revert in the future. In fact, in line with earlier works (see, for instance, Odean, 1998, 1999; Lux, 1995, 1998; Lux and Marchesi, 1999, 2000), we assume that chartists may not only chase trends. Some investors could try to exploit such trends in prices or simply decide to go against the crowd i.e., contrarian traders. Empirical evidence gives further support to investment techniques that rest on a “contrarian” strategy. Indeed, there is extensive empirical works on the profitability of contrarian strategies (e.g., Lehmann, 1990; Jegadeesh, 1990; Jegadeesh and Titman, 1995b,a; Dechow and Sloan, 1997; Galariotis, 2004) which suggests that contrarian traders can survive in the long run.

At the beginning of each period, agents can place buy or sell orders in the

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3In the literature, an alternative terminology for contrarian traders is also used, namely, “pessimistic” (or bearish) chartists (as in Lux, 1995; Lux and Marchesi, 1999).
market. Fundamentalist orders at time $t$ are captured as:

$$d_t^F = \delta \left( \hat{S}_t - P_{t-1} \right)$$  \hspace{1cm} (6)

where $\delta$ is a positive reaction coefficient.

Trend follower orders at time $t$ are expressed as:

$$d_t^T = \phi \left( P_{t-1} - P_{t-2} \right)$$  \hspace{1cm} (7)

where $\phi$ is a positive reaction coefficient.

Lastly, contrarian trader orders at time $t$ are expressed as:

$$d_t^C = -\phi \left( P_{t-1} - P_{t-2} \right)$$  \hspace{1cm} (8)

where $\phi$ is a positive reaction coefficient.

Following Farmer and Joshi (2002), we assume that in each period, a market maker mediates all transactions and sets at the end of each period $t$ the price according to aggregate excess demand in the market:\footnote{A market maker based method of price formation enables one to study the price dynamics induced by each trading strategy as well as by the interplay of agents following different trading strategies.}

$$P_t = P_{t-1} + \mu (d_t^F q^F + d_t^T q^T + d_t^C q^C) + \varepsilon_t$$  \hspace{1cm} (9)

where $\mu$ is a positive price adjustment parameter. The terms $q^F$, $q^T$ and $q^C$ represent the portion of fundamentalists, trend followers and contrarian traders, respectively. These terms are parameters which values do not evolve over time.
This assumption enables us to investigate the effect of the whole range of market compositions on price dynamics, though discarding the modeling of the process through which a specific market composition emerges. It is worth mentioning that, in each period, the sum of the portion of each type of agents in the market (i.e., \( q^F \), \( q^T \) and \( q^C \)) is equal to 1. Lastly, the term \( \varepsilon_t \) captures any remaining random elements that may affect the market maker’s price setting decision.\(^5\)

Substituting eq. (6), eq. (7) and eq. (8) into eq. (9) yields:

\[
P_t = \mu \delta q^F \hat{S}_t + (1 - \mu (\delta q^F + \varphi(q^C - q^T))) P_{t-1} + \mu \varphi(q^C - q^T) P_{t-2} + \varepsilon_t \tag{10}
\]

which constitutes our stochastic model driving the price dynamics.

### 3 Numerical analysis

We consider the above-described model and seek to investigate whether such a simple framework - with linear behavioral rules and linear price formation rule - based on the bounded-rationality hypothesis may reproduce some empirical regularities that are not fully explained within the classical asset pricing theory based on rational expectations, namely, serial correlations of returns and excess volatility of asset prices. In a framework similar to ours, Barucci, Monte, and Renò (2004) establishes that the presence of boundedly rational fundamentalists with short memory is able to simultaneously generate positive serial correlations in returns over short horizons and negative ones over long horizons. Our work rather consists in investigating the induced price dynamics when chartists are also present in the.

\(^5\)The term \( \varepsilon_t \) may also represent the activity of noise traders in the market.
The model presented in Section 2 does not have analytical solution. Thus, in order to study it, we use computer simulations. We simulate the model by using Monte Carlo simulations with the following parameter values as estimated in Timmermann (1996) on the Standard & Poor 500 time series for the period (1873-1992): $\theta = 0.47, \gamma = 0.9$ and $\sigma^2 = 0.25$. As in Barucci, Monte, and Renò (2004), we set $\beta = 0$ in order to have a stationary time series. In addition, we set $r_f = 1.05$. The remaining parameter values used in the simulations are reported in Table 1.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fundamentalist reaction coefficient ($\delta$)</td>
<td>1</td>
</tr>
<tr>
<td>Chartist reaction coefficient ($\varphi$)</td>
<td>1</td>
</tr>
<tr>
<td>Market maker price adjustment parameter ($\mu$)</td>
<td>1</td>
</tr>
<tr>
<td>Memory of the learning mechanism ($\alpha$)</td>
<td>From 0 to 1</td>
</tr>
</tbody>
</table>

Table 1: Parameters for the simulations.

A preliminary study of the deterministic version of the model provides the required background to set the appropriate parameter values used in computer simulations. This study enables us to present results when the price time series are stationary and preclude findings that would be due to non-stationary price time series, which are beyond the scope of this work.

Our investigation of the statistical properties of artificially generated series is presented in the following two subsections. We begin by presenting results regard-

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6The code, written in MATLAB, is available from the author upon request.
7This study is available from the author upon request.
8Results are robust to changes in initial conditions.
ing return predictability. In this regard, we are interested in evaluating whether (i.) significant autocorrelation values are detected and (ii.) autocorrelation patterns of returns emerge at different horizons. Next, we move to study excess volatility of asset prices. There, we assess whether excess volatility of asset prices emerges in the market when both fundamentalists and chartists are present. This is done by comparing the asset price bounded-rationality dynamics with the one obtained under rational expectations.

3.1 Explaining serial correlations in returns

In this section, we try to assess whether first, returns from the simulated time series are serially correlated; second, our model is able to generate autocorrelation patterns over differing horizons which are often observed in real time series. For this purpose, we calculate the sample autocorrelation functions of the returns. Since the risky asset pays dividend, as described in eq. (1), the definition of asset returns used in this work is as follows:

\[ r_t = \ln(P_t + D_t) - \ln(P_{t-1}) \] (11)

In this section, we focus on the effect of the memory in the learning mechanism of fundamentalists \( i.e., \alpha \) on price dynamics of the simulated time series. For this purpose, we study the price dynamics that emerge in the market for different values of \( \alpha \). This is done by varying the value of \( \alpha \) from 0 to 1 with step 0.1.\(^9\)

As a first step in our investigation, it is worth mentioning that a careful ex-

\(^9\)As a preliminary step in this work, we studied the stationarity of the deterministic version of the above-described model. We found that the price time series is stationary for \( 0 \leq \alpha < 1 \). This work is available from the author upon request.
amination of the above-described model, in particular eq. (6), eq. (7) and eq. (8), enables us to stress that, in line with earlier works (see, for instance, Sentana and Wadhwani, 1992; Farmer and Joshi, 2002), trend following strategies induce short-term trends in prices, while fundamentalists and contrarian strategies induce long-term price mean-reversion.

With this in mind, we now examine the price dynamics that emerge when fundamentalists, with differing learning coefficients, as well as chartists are present in the market. Fig. 1 shows the sample autocorrelation function of returns from the simulated time series for differing values of $\alpha$\textsuperscript{10}. Fig. 1 reveals that trends in prices over short horizons as well as oscillations in prices over long horizons tend to vanish as fundamentalists have short memory (i.e., $\alpha$ tends to 1) (see Fig. 1a and Fig. 1b). Indeed, positive (negative) coefficients over small (large) lags are both smaller and less persistent as $\alpha$ increases. Consequently, when chartists are present in the market, fundamentalist strategies tend to weaken return predictability over differing horizons, when fundamentalists have short memory.

In contrast, when fundamentalists have long memory (i.e., $\alpha$ tends to 0), returns exhibit both stronger and more persistent positive as well as negative serial correlations over short horizons and long horizons, respectively (see Fig. 1c and Fig. 1d). As a result, contrary to (Barucci, Monte, and Renò, 2004), when chartists are present in the market, returns from the simulated price time series are both positively serially correlated over short horizons and negatively autocorrelated over long horizons when fundamentalists have long memory.

This finding is mainly explained by the adaptative learning rule of fundamental-

\textsuperscript{10}For this purpose, it is particularly enlightening to present the findings from settings wherein fundamentalists dominate the market. However, it is worth stressing that simulation results do not crucially differ from the aforementioned ones, for other values of $q^F$.\n
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Figure 1: Sample autocorrelation functions of returns for differing values of $\alpha$.

Indeed, since fundamentalist strategies induce long-run mean-reversion in prices, when fundamentalists have long memory, the former effect on price dynamics is amplified. As described in eq. (4), when fundamentalists have long memory (i.e., $\alpha$ tends to 0), remote observations are weighted the same as more recent prices. Consequently, observed remote price trends strongly influence future price movements. In this case, returns are more negatively autocorrelated over long horizons.

From the above considerations, we can ascertain that our model is able to
simultaneously bring about positive serial correlations in returns over short horizons and negative ones over long horizons. Furthermore, our results suggest that trends in prices over short horizons and oscillations in prices over long horizons can be simultaneously explained by long memory in the learning mechanism of fundamentalists. Our model therefore offers a valid framework in order to explain the predictability of returns often observed in financial time series.

3.2 Explaining excess volatility of asset prices

In the previous section, the investigation of the statistical properties of artificially generated time series was focused on autocorrelation patterns of returns. We now turn to focus on the emergence of excess volatility of asset prices when fundamentalists and chartists are present in the market. More precisely, we assess whether excess volatility of asset prices, which is often detected in financial time series (LeRoy and Porter, 1981; Shiller, 1981; Timmermann, 1996), can emerge in our framework.

For this purpose, we compare the asset price bounded rationality evolution as described in eq. (10) to the one obtained under rational expectations as given in eq. (3). In particular, we use the ratio of the sample standard deviation of the simulated asset price time series $P_t$ from eq. (10) and the rational expectation price time series ($RE\ price$ henceforth) $S_t$ as described in eq. (3), i.e.,:

$$\sigma(P_t)/\sigma(S_t)$$

According to eq. (12), when the simulated asset price varies less than the RE price, then the ratio of the sample standard deviation of $P_t$ and $S_t$ (volatility ratio
henceforth) is lower than one. However, when the simulated asset price varies more wildly than the RE price, then the volatility ratio, in eq. (12), is greater than one. The simulated asset price therefore exhibits excess volatility.

### 3.2.1 The role of market composition

As a first step in our investigation, we examine the price dynamics induced by each trading strategy as well as by the interplay of fundamentalists and chartists. For this purpose, the value of the parameter $\alpha$ is held constant at the benchmark level i.e., $\alpha = 0.5$.

First, it is worth focusing on the effect of fundamentalist strategies on the price dynamics, while chartists are present in the market. Simulations reveal that fundamentalist strategies play a key role in explaining the emergence of asset price excessive volatility. Fig. (2) presents the volatility ratio values as a function of the portion of fundamentalists in the market, for different compositions of the chartist population.

![Figure 2: Volatility ratio values as a function of the portion of fundamentalists ($q_F$), for differing compositions of the chartist population.](image)

(a) When $q^T = 0.2$.  
(b) When $q^T = 0.3$.  

Figure 2: Volatility ratio values as a function of the portion of fundamentalists ($q_F$), for differing compositions of the chartist population.
Fig. (2) shows that volatility ratio values are increasing in the portion of fundamentalists in the market. In other words, the greater is the portion of fundamentalists in the market, the larger the volatility ratio is. Furthermore, simulations unveil that when fundamentalists dominate the market, fundamentalist strategies can explain asset price excessive volatility. Indeed, from Fig. (2), the ratio in eq. (12) is greater than one, when \( q^F \) tends to 1. It is worth mentioning that results do not significantly depend on the portions of trend followers and contrarian traders mainly because \( \alpha \) is constant (i.e., \( \alpha = 0.5 \)).

Second, in order to further understand the role of the interplay between fundamentalists and chartists on the emergence of excess volatility, we now turn to focus on the effect of chartist strategies, both trend-following and contrarian ones, on price dynamics. In this case, it is particularly enlightening to focus on a setting wherein chartists dominate the market. Table (2) shows the volatility ratio values for differing compositions of the chartist population.

<table>
<thead>
<tr>
<th>( q^T )</th>
<th>( q^C )</th>
<th>volatility ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.2</td>
<td>0.6</td>
<td>0.88109</td>
</tr>
<tr>
<td>0.3</td>
<td>0.5</td>
<td>0.90788</td>
</tr>
<tr>
<td>0.4</td>
<td>0.4</td>
<td>0.94517</td>
</tr>
</tbody>
</table>

Table 2: Volatility ratio values for differing \( q^T \) and \( q^C \), when \( \alpha = 0.5 \) and \( q^F = 0.2 \).

Figures in Table (2) clearly show that, whatever is the composition of the chartist population, since the portion of fundamentalists is low, the simulated asset price varies less than the RE price does. This finding further stresses the fact that fundamentalist strategies play a key role in explaining excess volatility of asset prices.
Furthermore, even though excess volatility of the simulated asset price is not detected for such a market composition, it is worth stressing that the volatility ratio of $P_t$ and $S_t$ is increasing (decreasing) in the portion of trend followers (contrarian traders).

Overall, the above investigation highlights that market composition can help explaining the emergence of asset price excessive volatility. In particular, both fundamentalist and chartist strategies influence the emergence asset price excess volatility often observed in financial time series.

3.2.2 The role of fundamentalists’ memory

With $\alpha = 0.5$, we have seen that the market composition plays a key role in explaining the emergence of asset prices excessive volatility. In order to complete our investigation, we now turn to examine the effect of fundamentalists’ memory on simulated price dynamics.\(^{11}\)

As mentioned in Section 2, fundamentalists and chartists - both trend followers and contrarian traders - coexist in the market. In order to understand the effect of the memory in the learning mechanism of fundamentalists on the emergence of excess volatility, it is particularly enlightening to focus on a setting where fundamentalists dominate the market (i.e., $q^F \geq 0.5$). Indeed, in this case, price dynamics are mainly influenced by fundamentalist strategies which therefore enables us to fully grasp the influence of the learning coefficient on simulated price dynamics.

Simulations bring out that, when fundamentalists dominate the market,\(^{12}\) excess

\(^{11}\)From the preliminary study of the deterministic version of the model, price dynamics is stationary for a wide range of $q^F$ values: $0.1 < q^F < 0.8$.

\(^{12}\)According to the findings from our study of the stationarity of the deterministic version of
volatility of asset prices emerges in any composition of the market. Fig. 3 presents
the volatility ratio from the simulated time series for differing values of the learning
coefficient $\alpha$, when fundamentalists dominate the market.

Figure 3: Volatility ratio values as a function of the learning coefficient ($\alpha$), for differing market compositions. The top panel exhibits volatility ratio values when the portion of trend followers is high. The bottom panel exhibits volatility ratio values when the portion of trend followers is low.

Fig. 3 clearly shows that, when fundamentalists dominate the market, first, volatil-
the model, this analysis is implemented for $0.5 \leq q^F \leq 0.8$. 

(a) Volatility ratio values when $q^F = 0.5$ and $q^T = 0.3$.
(b) Volatility ratio values when $q^F = 0.6$ and $q^T = 0.2$.
(c) Volatility ratio values when $q^F = 0.5$ and $q^C = 0.4$.
(d) Volatility ratio values when $q^F = 0.6$ and $q^C = 0.3$. 

Fig. 3 clearly shows that, when fundamentalists dominate the market, first, volatil-
the model, this analysis is implemented for $0.5 \leq q^F \leq 0.8$. 

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ity ratio values are increasing in $\alpha$. That is, the shorter is the memory of fundamentalists, the larger is the value of the volatility ratio.

Second, the simulated asset price varies more than the RE price \(i.e.,\) the ratio of the sample standard deviation of $P_t$ and $S_t$ is greater than 1) when fundamentalists have short memory \(i.e.,\) $\alpha$ tends to 1). In other words, when fundamentalists dominate the market, fundamentalists’ short memory explains the emergence of excess volatility of asset prices. These findings are mainly explained by the fact that, when fundamentalists have short memory, according to eq. (4), fundamentalists account more heavily on more recent prices in order to form their expectations of the price cum dividend. As a result, recent trends in prices influence more strongly future price movements. Furthermore, since fundamentalist strategies induce oscillations in prices, fundamentalists’ activity may favor asset price excessive volatility.

Lastly, simulations reveal that the composition of the chartist population also plays a crucial role in explaining the emergence of asset price excessive volatility. In particular, Fig. (3) suggests that contrarian strategies dampen excessive volatility. When the portion of contrarian traders is higher than the portion of trend followers in the market, excess volatility of the asset price is detected for high values of $\alpha$ (see Fig. (3)c and Fig. (3)d). This is mainly explained by the interaction between fundamentalists, which induce long-term oscillations in prices, and trend followers, which induce short-term trends in prices. So that overall, simulated price varies more wildly than the RE price.

In contrast, when chartists dominate the market \(i.e.,\) $q^F < 0.5$, simulations

\footnote{According to the findings from the preliminary study of the stationarity of the deterministic version of our model, this analysis is implemented for $0.1 \leq q^F \leq 0.4$.}
reveal that contrarian strategies may prevent the occurrence of asset price excessive volatility, even when fundamentalists have short memory. Fig. (4) presents the values of the volatility ratios as a function of the learning coefficient ($\alpha$), when chartists dominate the market.

![Volatility ratio graphs](image)

(a) Volatility ratio values when $q^F = 0.2$ and $q^T = 0.5$.  
(b) Volatility ratio values when $q^F = 0.3$ and $q^T = 0.4$.  
(c) Volatility ratio values when $q^F = 0.2$ and $q^C = 0.6$.  
(d) Volatility ratio values when $q^F = 0.3$ and $q^C = 0.6$.

Figure 4: Volatility ratio values as a function of the learning coefficient ($\alpha$), for differing market compositions. The top panel exhibits volatility ratio values when the portion of trend followers is high. The bottom panel exhibits volatility ratio values when the portion of trend followers is low.

Indeed, Fig. (4)c and Fig. (4)d clearly show that, when contrarian traders domi-
nate the market, whatever is the value of the learning coefficient \(\alpha\), the simulated asset price varies less wildly than the RE price (i.e., the volatility ratio is lower than 1). Nevertheless, when trend followers dominate within the chartist population, as previously discussed, excess volatility of the asset price emerges when fundamentalists have short memory. It is however worth mentioning that with respect to the setting wherein fundamentalists dominate the market, the extent of asset price excessive volatility is smaller.

To sum up, simulations reveal that excess volatility of asset prices tends to emerge when both of the following conditions are fulfilled:

(i.) fundamentalists dominate the market i.e., \(0.5 < q^F < 1\).

(ii.) fundamentalists have short memory i.e., the value of the learning coefficient \(\alpha\) tends to 1;

Lastly, while it has often been suggested that chartist strategies, especially trend following ones, tend to destabilize market prices (see Lux, 1995; Brock and Hommes, 1998; Lux and Marchesi, 2000; Farmer and Joshi, 2002), in our setting, chartist strategies could also, under some circumstances, stabilize market prices.

4 Conclusions

By assuming that boundedly rational agents follow differing trading strategies, namely, fundamentalist and chartist; and that fundamentalists update their expectations of future prices through a first-order autoregressive learning rule, we show that first returns can be predictable. Indeed, returns from the artificially generated time series exhibit simultaneously positive serial correlations over short horizons and negative ones over long horizons. Second, asset prices exhibit excess
In line with most of the works which account for fundamentalist and chartist strategies, we have shown that chartists tend to destabilize market prices (De-Long, Shleifer, and Summers, 1990; Chiarella, 1992; Lux, 1998; Westerhoff, 2003; De Grauwe and Grimaldi, 2005). In fact, when fundamentalists as well as chartists are present in the market, short-run dependencies in time series can be explained by the presence of trend followers.

Second, as suggested in Barucci, Monte, and Renò (2004), we found that the memory of the learning mechanism plays a crucial role. However, while Barucci, Monte, and Renò (2004) found that fundamentalists' longer memory induces a smaller degree of dependency when the horizon of the returns is long (i.e., weaker mean-reversion effect), in our setting, when fundamentalists as well as chartists are present in the market, fundamentalist strategies may weaken predictability of returns over short horizons, when fundamentalists have short memory. In contrast, longer memory values tend to induce both trends in prices over short horizons and oscillations in prices over long horizons.

Third, while excess volatility of returns may be explained by the presence of trend followers (see for instance Lux, 1995; Brock and Hommes, 1998; Lux and Marchesi, 2000; Farmer and Joshi, 2002), in our setting, when fundamentalists as well as chartists - both trend followers and contrarian traders - are present in the market, (i) excess volatility of returns tends to vanish when the portion of chartists, including trend followers, is large. The presence of chartists rather stabilize market prices. (ii) excess volatility of returns tends to emerge when fundamentalists have short memory (i.e., \( \alpha \) tends to 1). Longer memory values rather tend to stabilize market prices. Excess volatility of returns can hence be
explained by short memory in the learning mechanism of fundamentalists.

Overall, while we do not attempt to reproduce stylized facts, our frame offers a qualitative description of asset price behavior and help explaining some of the anomalies often observed in real financial markets.

Extensions of this work can be conducted along the following lines. First, in this work the market maker based method of price formation is quite simple. Market makers may instead adapt their price adjustment according to their positions. This would enable us to account for inventories as well as order flow signals. Westerhoff (2003), for instance, finds that inventory control may actually limit the positions of market markers and may cause markets to be less efficient. Second, in this work, the memory of the learning mechanism is assumed to be constant over time. However, fundamentalists may have different time horizons and the learning mechanism could be determined endogenously, which would lead to more complex price dynamics. We leave these extensions for further research.

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