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Momentum effect in individual stocks and heterogeneous beliefs among fundamentalists

Sandrine Jacob Leal
CEREFIGE - ICN Business School, Nancy-Metz, France - GREDEG

Abstract

This paper investigates whether the observed momentum effect in individual stocks, caused by positive serial correlations in monthly returns over short horizons, can be explained by fundamentalists' heterogeneous beliefs when chartists are present in the market. To this end, we propose a heterogeneous agent model wherein agents follow different strategies and information about asset fundamentals diffuses slowly. On the one hand, fundamentalists predict future prices based on the observed discrepancy between the current stock price and its fundamental value. However, due to slow diffusion of firm-specific information, fundamentalists have heterogeneous beliefs about asset fundamentals. On the other hand, chartists predict future prices based on the observation of past price movements. Computer-based simulations reveal that the interplay of fundamentalists and chartists can robustly generate positive serial correlations in monthly returns over short horizons, stock price overreaction to news events and price misalignments. In particular, we find that (i.) slow diffusion of information does not suffice to explain the momentum effect in individual stocks; (ii.) the interplay of fundamentalists and chartists robustly generates short-term momentum in returns, which is mainly driven by the pervasive presence of chartists; (iii.) we find that, when trend followers dominate the market, stock price overreacts and subsequently corrects due to slow diffusion of firm-specific information.

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Contact: Sandrine Jacob Leal - sandrine.jacob-leal@icn-groupe.fr.
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1. Introduction

The momentum effect in individual stocks, caused by positive serial correlations in monthly returns at short-term horizons ranging from three to twelve months is a well-documented empirical evidence; see, for instance, Jegadeesh (1990); Chan, Jegadeesh, and Lakonishok (1996); Moskowitz, Ooi, and Pedersen (2012) for individual asset returns, and Poterba and Summers (1988); Cutler and Summers (1991); Bhojraj and Swaminathan (2006); Sewell (2012) for monthly stock index returns. Evidence of positive serial correlations of individual stock and equity index returns at monthly frequency is further supported by empirical studies on cross-sectional momentum. Empirical works suggest that momentum strategies are profitable over a period from one to twelve months as suggested, for instance, in Jegadeesh (1990); Jegadeesh and Titman (1993, 2001) for US equities, and Rouwenhorst (1998, 1999); Griffin, Ji, and Martin (2003); Doukas and McKnight (2005); Chui, Titman, and Wei (2010) for international stock markets. However, monthly return persistence is inconsistent with the classical asset pricing theory.[1] Indeed, the efficient market hypothesis (Fama, 1970, 1991) suggests that, at all time scales, no sign of autocorrelation should be observed in financial time series.

Several explanations have been proposed for the emergence of positive serial correlations in returns. First, a well-documented explanation relies on the tendency of stock prices to underreact to news events in the short run (*e.g.,* Shefrin and Statman, 1985; Barberis, Shleifer, and Vishny, 1998; Hong and Stein, 1999; Frazzini, 2006). Behavioral theories further support stock prices underreaction to new information relying on some form of investor irrationality.[2] In particular, such a persistence in stock returns arises from investor psychological biases. From this viewpoint, owing to biased self-attribution (*e.g.,* Daniel, Hirshleifer, and Subrahmanyam, 1998), representativeness heuristic and/or conservatism (*e.g.,* Tversky and Kahneman, 1974; Barberis, Shleifer, and Vishny, 1998), investors are kept from quickly adapting their beliefs to new and convincing information. Consequently, investors tend to underreact to news (see, for instance, Barberis, Shleifer, and Vishny, 1998; Daniel, Hirshleifer, and Subrahmanyam, 1998) and individual stock returns therefore exhibit positive short-lag autocorrelation. According to these works, the way investors interpret available information becomes crucial in explaining short-term momentum. Instead, earlier empirical and theoretical works have suggested that the key factor explaining the momentum effect in individual stocks is the diffusion of information. In this case, such a pattern arises because the market responds only gradually to new information (see, for instance, Chan, Jegadeesh, and Lakonishok, 1996; Hong and Stein, 1999; Hong, Lim, and Stein, 2000; Doukas and McKnight, 2005). Furthermore, behavioral explanations of the momentum effect in individual stocks also rely on overreaction to new information. Earlier works suggest that investor overconfidence causes stock price movements to persist in the short run (*i.e.,* positive serial correlation in returns). However, investor overconfidence generates both trends in prices (*i.e.,* positive serial correlation in returns) in the short run and subsequent price reversal (*i.e.,* negative serial correlation in returns) in the long run; as investors realize they were too optimistic

[1] It is worth stressing that stock return continuation does not hold at shorter time scales. Instead, it is well-known and -documented that autocorrelations of asset returns at weekly and daily frequency are insignificant (see, for instance, Cont, 2001; Bouchaud, 2002; Lux, 2009, and further references therein), except for very small intraday time scales (*e.g.,* Cont, 2001; Bianco and Reno, 2006).

[2] Rational asset pricing theories instead propose risk-based models to explain such evidence (see, for instance, Berk, Green, and Naik, 1999; Johnson, 2002; Ahn, Conrad, and Dittmar, 2003; Avramov and Chordia, 2006; Sagi and Seasholes, 2007; Liu and Zhang, 2008).

and reverse their positions (*e.g.,* DeLong, Shleifer, Summers, and Waldmann, 1990a,b; Bikhchandani, Hirshleifer, and Welch, 1992; Barberis, Shleifer, and Vishny, 1998; Daniel, Hirshleifer, and Subrahmanyam, 1998; Hong and Stein, 1999; Daniel, Hirshleifer, and Subrahmanyam, 2001; Baker and Wurgler, 2007).
Overall, these works suggest that information - both the diffusion process and the way investors interpret it - is crucial for explaining the momentum effect in individual stocks. However, financial economists are still far from reaching a consensus on the source of this phenomenon.

This paper contributes to the ongoing debate on the explanation of the momentum effect in individual stocks at the monthly frequency by developing a heterogeneous agents model wherein fundamentalists have heterogeneous beliefs due to slow diffusion of firm-specific information. The above-mentioned works focus either on pervasive psychological biases which affect investors' decisions or on market statistics to explain the emergence of short-term momentum in real financial time series. We improve upon these works by showing how the momentum effect in individual stocks and its characteristics are determined by the interplay of common trading strategies. In particular, we investigate whether positive serial correlations in monthly returns over short horizons can be explained by the interplay of fundamentalists, who set their strategies from the inference of 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. Indeed, most of the works based on the explicit distinction between fundamentalists and chartists assume that fundamentalists know the fundamental value of the asset (*e.g.,* Beja and Goldman, 1980; Lux, 1995; Brock and Hommes, 1998; Lux, 1998; Lux and Marchesi, 2000; Farmer, 2002; Farmer and Joshi, 2002; Chiarella, He, and Hommes, 2006; He and Li, 2012). In this work, in line with earlier works which suggest that slow diffusion of information plays a key role in explaining momentum effect in individual stocks, we depart from the above assumption by allowing fundamentalists to be sequentially aware of any news about asset fundamentals (*e.g.,* Abreu and Brunnermeier, 2002, 2003). As a result, fundamentalists have, for some period of time, heterogeneous beliefs about asset fundamentals and they may not be able to recognize misalignments in asset prices.

Numerical simulations reveal that our model offers a qualitative description of asset prices dynamics. Furthermore, our parsimonious model is able to simultaneously explain the momentum effect in individual stocks, asset price overreaction to news events and price misalignments. First, we find that slow diffusion of information does not suffice to explain the momentum effect in individual stocks. Second, the interplay of fundamentalists and chartists robustly generates short-term momentum in monthly returns, which is mainly driven by the pervasive presence of chartists. Lastly, we find that, when trend followers dominate the market, asset price overreacts and subsequently corrects due to slow diffusion of firm-specific information.

This paper is organized as follows. In Section 2, we present the model of linear price formation rule with sequentially informed fundamentalists. In Section 3, we present and discuss the results of the computer-based simulations. Section 4 summarizes the main findings of this work and concludes.

2. The model

We consider a market in which there is a single risky asset with price P_t and fundamental value V_t. The fundamental value of the asset is based on the asset future payoffs *i.e.,* the prospects of future cash flows. The evolution of the asset fundamental value over time is formalized as follows:

$$V_t = V_{t-1} + \epsilon_t \tag{1}$$

where $\{\epsilon_t\}$ is a sequence of i.i.d. random variables with $E[\epsilon_t] = 0$, $var[\epsilon_t] = \sigma_\epsilon^2$ and $cov(\epsilon_t, \epsilon_{t-j}) = 0$ for $j \geq 0$, so that $E[V_t] = V_{t-1}$.

In the market, there are N agents, who are assumed to be of two types, namely, fundamentalists and chartists. The number of fundamentalists and chartists in the market is denoted n_f and n_c respectively, with $n_f + n_c = N$. The portion of fundamentalists is denoted $\eta \equiv n_f/N$.

Most of the earlier heterogeneous agent models consider that the very figure of technical analysis is a trend follower. Instead in this work, we depart from this assumption by assuming that the chartist population is composed of both trend followers and contrarian traders as, for instance, in Lux (1995); Lux and Marchesi (2000); Mannaro, Marchesi, and Setzu (2008); He and Li (2012). The respective number of these subgroups are denoted n_{TF} and n_{CT} with $n_{TF} + n_{CT} = n_c$. The portion of trend followers among the chartist population is denoted $z \equiv n_{TF}/n_c$.

In each period, agents can place buy or sell orders in the market. First, fundamentalists base their trading strategy upon any differential between the observed asset price and its fundamental value. Fundamentalists' orders are captured as follows:

$$X_{t+1}^F = \beta(E[V_t] - P_t) \tag{2}$$

where the term β is a positive reaction coefficient.

Second, chartists set their trading strategies based on the observation of past prices. Trend followers believe that any observed trend in prices will persist in the future. Their orders are as follows:

$$X_{t+1}^{TF} = \varphi(P_t - P_{t-1}) \tag{3}$$

where the term φ is a positive reaction coefficient.

Contrarian traders rather believe that any observed trend in prices will revert in the future. Their orders are therefore expressed as:

$$X_{t+1}^{CT} = -\varphi(P_t - P_{t-1}) \tag{4}$$

Furthermore, in this work, the price-setting mechanism is based on the existence of a market maker (as in Beja and Goldman, 1980; Day and Huang, 1990; Chiarella, 1992; Lux, 1995, 1998; Farmer, 2002; Farmer and Joshi, 2002; Chiarella and He, 2003; Hommes, Huang, and Wang, 2005; Chiarella, He, and Hommes, 2006; He and Li, 2012). While some theoretical works use the classical market clearing method (*e.g.,* Brock and Hommes, 1998; LeBaron, Arthur, and Palmer, 1999; Chiarella and He, 2002; Anufriev and Bottazzi, 2005, 2006), a market-maker price setting mechanism allow for a better representation of real financial markets.[3] Furthermore, this method of price formation enables us to study the price dynamics generated by each trading strategy because the market maker is assumed to provide, in any instant, the required liquidity. We therefore

[3]For detailed discussions and further references on the use of a market clearing method *versus* a market maker to set market prices see, for instance, Goldman and Beja (1979); LeBaron (1999); Hommes (2006); LeBaron (2006).

assume that in each period, the market maker mediates all transactions by matching agents' demand and supply and sets the end-of-period price according to aggregate excess demand in the market as follows:

$$P_{t+1} = P_t + \mu(n_f X^F_{t+1} + n_{TF} X^{TF}_{t+1} + n_{CT} X^{CT}_{t+1}) \tag{5}$$

where the term μ is a positive price adjustment parameter.
Substituting eq. (2), eq. (3) and eq. (4) into eq. (5) yields:

$$P_{t+1} = \mu n_f \beta V_{t-1} + (1 - n_f \mu\beta + \mu\varphi(n_{TF} - n_{CT}))P_t + \mu\varphi(n_{CT} - n_{TF})P_{t-1} \tag{6}$$

which constitutes our stochastic law of motion driving the price dynamics in the model.

Lastly, at some point in time, t_0, there is a positive shock on the asset fundamental value.[4] This shock captures any good news events which will markedly alter future cash flows of the asset and as a consequence its intrinsic value. However, we assume that information about the asset fundamentals diffuses slowly.[5] Consequently, fundamentalists are only sequentially aware of the true fundamentals. In each period, instead, an additional fraction of fundamentalists (n_{inc}) is informed of the true asset fundamentals. All fundamentalists are therefore not immediately able to recognize that the asset fundamentals have markedly changed. For a while, fundamentalists with heterogeneous beliefs about asset future payoffs coexist in the market. This is explained by the fact that the perceived asset fundamental value by some fundamentalists does not immediately coincide with the true one. More precisely, after t_0, some fundamentalists know the true asset fundamental value and they are immediately able to recognize that the asset is mispriced *i.e.,* it is undervalued. In contrast, others stick to the previous asset fundamental value, so that they are not able to identify the price misalignment.

From eq. (6), it is worth briefly discussing the special case in which there are only fundamentalists in the market, *i.e.,* $n_f = 1$. In this case, although fundamentalists sequential awareness of the shock on V_t prevents fundamentalists from instantaneously correcting the stock price, stock returns are not serially correlated. As a result, when there are only fundamentalists in the market, slow diffusion of information does not suffice to explain the momentum effect in individual stocks, caused by positive serial correlations in returns. This is explained by the fact that the effect of fundamentalists strategies on price dynamics is not enough pronounced (or the convergence process too smooth) to markedly generate trends in prices over short horizons.[6]

3. Numerical analysis

We now turn to investigate whether the model presented in Section 2 is able to generate the momentum effect in individual stocks, caused by positive serial correlations in monthly returns over short horizons, when fundamentalists and chartists coexist in the market.

[4]Similar results of the model would be derived if a *negative* shock on V_t were considered.

[5]The foregoing assumption may also capture situations in which there is asymmetric information or differential interpretation of such an information among fundamentalists.

[6]Instead, when there are only chartists in the market (*i.e.,* $n_f = 0$), according to eq. (6), the stock price follows a deterministic autoregressive process which is not affected by the fundamental value. In this case, shocks to the fundamental value (the only shocks considered in this model) cannot affect price dynamics. Given that chartists are activated only when they observe any price change (see eq. (3) and eq. (4)), after the stock on V_t, P_t will remain constant and the stock remains mispriced (*i.e.,* $P_t \neq V_t$).

We analyze the model through numerical simulations due to the stochasticity of the model driving price dynamics and agents' heterogeneity. In our study, we focus on autocorrelation patterns in returns from the simulated price time series. In particular, we simulate the model with 500 time steps and we check the robustness of the simulation results by implementing Monte Carlo simulations over 50 runs.[7] The parameter values used in simulations are reported in Table I. The main criterion for choosing parameter

Table I: Parameters used in the simulations.

Parameters	**Values**
Number of periods (t)	500
Number of agents (N)	1000
Date of the shock (t_0)	10
Date at which all fundamentalists are informed (t_i)	20
Additional number of informed fundamentalists in each period (n_{inc})	$N/(t_i - t_0)$
Portion of fundamentalists (η)	from 0 to 1
Portion of trend followers (z)	from 0 to 1
Fundamentalist reaction coefficient (β)	1
Chartist reaction coefficient (φ)	1
Market maker price adjustment parameter (μ)	$1/N$
Initial price (P_0)	100
Initial fundamental value (V_0)	100
Size of the shock (b)	0.1

values was to match one of the crucial efficient market hypothesis prediction according to which stock prices should reflect asset fundamentals and arbitrage does work. To this end, we first identified the parameter values (i.e., β and μ) so that the asset price reflects its fundamentals when there are only well-informed and well-funded fundamentalists in the market. Second, we studied the stability conditions of the equilibrium from the deterministic version of the model,[8] described in eq. (6), in order to identify the parameter values (*i.e.,* φ, η and z) which ensure that the system is stable. In this way, numerical simulations are implemented using parameter values so that the deterministic model generates stationary price time series.[9] Furthermore, we pointed out that the $\{P_t\}$ sequence is stable for a wide range of parameter values.[10] Lastly, given the stability conditions on parameter values, we showed that the $\{P_t\}$ sequence is stable whatever the composition of the population (*i.e.,* η and z).

With this in mind, we now move to investigate the statistical properties of artificially generated price time series in order to identify under which conditions the momentum effect in individual stocks emerges when fundamentalists and chartists - both trend followers and contrarian traders - are present in the market. This is done by varying the portion of fundamentalists (*i.e.,* η) from 0 to 1 and the portion of trend followers (*i.e.,* z) from 0 to 1.

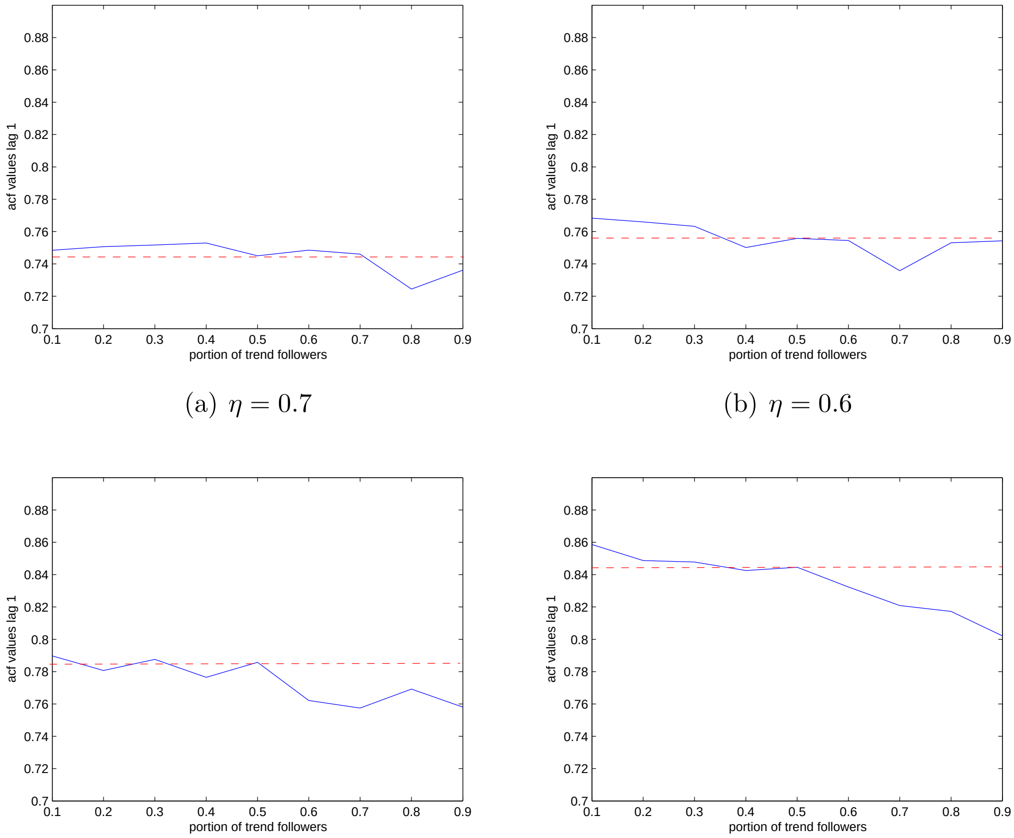
[7] The code, written in Java and Matlab, is available from the author upon request.

[8] In the deterministic model, we relax the sequential awareness assumption by assuming that fundamentalists know the asset fundamental value in each period.

[9] As a result, non-stationary behavior of the $\{P_t\}$ sequence is precluded from this study.

[10] The study of the stability of the solution of the deterministic version of the model is available from the author upon request.

First, simulations reveal that trend following (*contrarian*) strategies quicken (*slow down*) mispricing correction. Fig. 1 shows the relationship between the autocorrelation coefficient at lag 1 of mispricing duration and the portion of trend followers in the market ($0 < z < 1$) for differing portions of fundamentalists ($\eta = 0.2, 0.5, 0.6, 0.7$). This figure

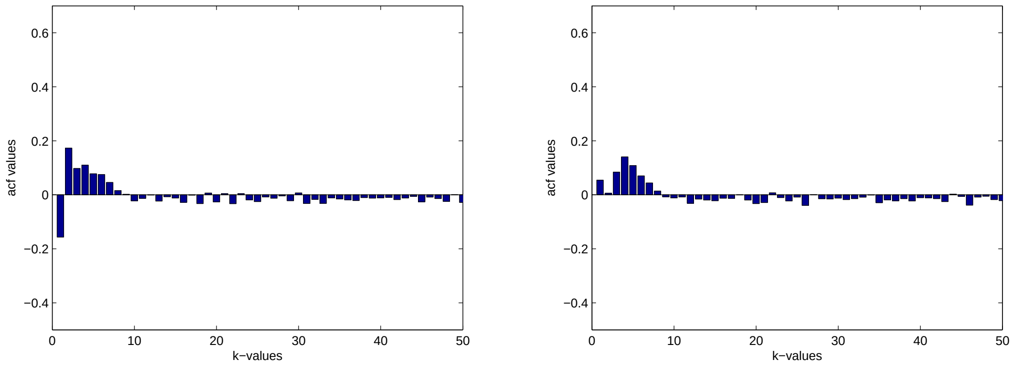


(a) $\eta = 0.7$ (b) $\eta = 0.6$

(c) $\eta = 0.5$ (d) $\eta = 0.2$

Figure 1: Relationship between mispricing duration and z for differing values of η. The *dash line* represents ACF(1) of mispricing duration when $z = 0.5$.

clearly shows that, on the one hand, when chartists mainly use trend-following strategies ($z > 0.5$), mispricing duration is markedly shortened. It is worth stressing that the lower the portion of fundamentalists in the market, the greater the extent of mispricing correction driven by trend-following strategies. So, in contrast to earlier results (see, for instance, Lux, 1995, 1998; Farmer and Joshi, 2002; De Grauwe and Grimaldi, 2005), we find that, when trend followers dominate the market, trend-following strategies facilitate market efficiency thanks to slow diffusion of information. This result is explained by the fact that trend-following strategies tend to amplify trends in prices triggered by fundamentalists who sequentially trade against the mispricing. As a result, price correction is fastened. On the other hand, contrarian strategies (*i.e.,* when $z < 0.5$) lengthen mispricing duration, especially when the portion of fundamentalists is large ($\eta > 0.5$). Consequently, we suggest that contrarian strategies prevent fundamentalists from efficiently trading against the mispricing, even when the latter widely dominate the market. Nevertheless, simulations unveil that, when fundamentalists dominate the market ($\eta \geq 0.5$), whatever the portion of trend followers in the chartist population, positive serial correlations in returns over short horizons are not statistically significant. Fig. 2 shows the sample autocorrelation functions of returns from the simulated time series for high and low portion of trend followers ($z = 0.7$ and $z = 0.3$, respectively). We therefore



(a) $z = 0.3$ (b) $z = 0.7$

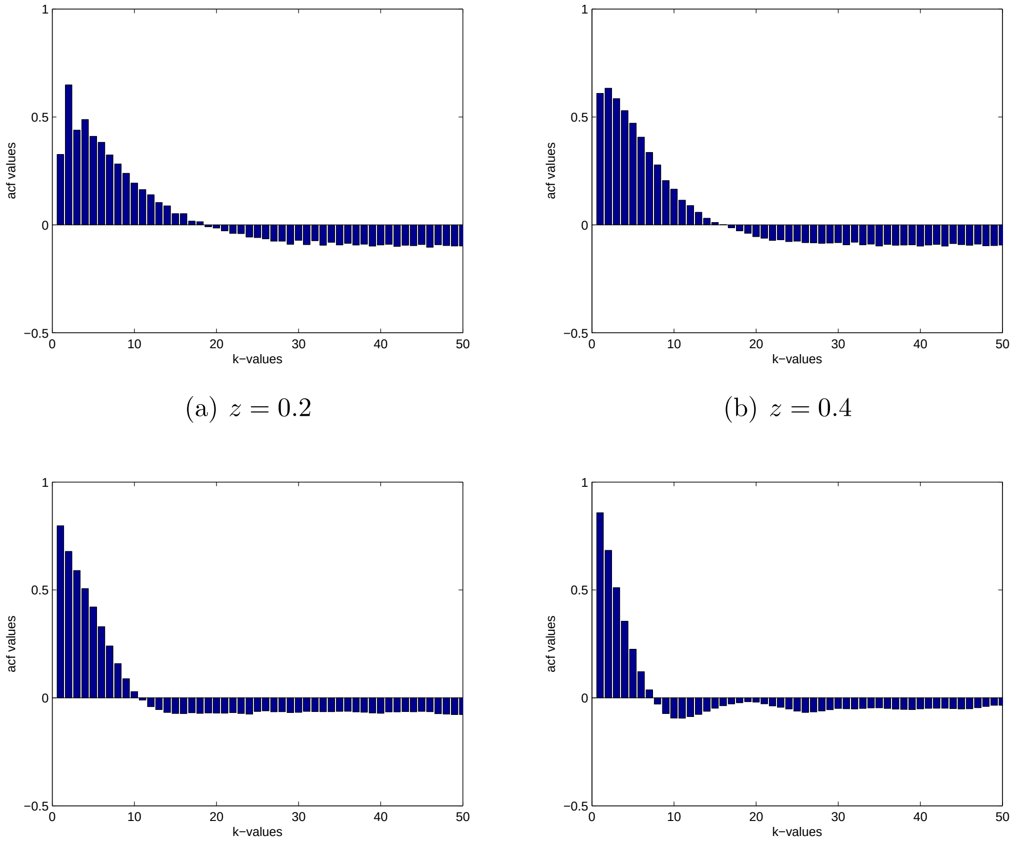
Figure 2: Sample autocorrelation functions of returns when $\eta = 0.7$ and for differing values of z.

find that first fundamentalist strategies prevent monthly returns from being predictable. Second, in contrast with earlier works which suggest that the momentum effect in individual stocks can be explained by stock price underreaction (*e.g.,* Barberis, Shleifer, and Vishny, 1998; Hong and Stein, 1999; Frazzini, 2006), we suggest that slow diffusion of firm-specific information is not a sufficient condition to explain this phenomenon.

Second, simulations unveil that when chartists widely dominate the market (*i.e.,* $\eta \leq 0.2$), trend-following (*contrarian*) strategies amplify (*reduce*) short-term momentum. Fig. 3 shows the sample autocorrelation functions of returns when $\eta = 0.2$, for differing portions of trend followers (*i.e.,* $0 < z < 1$). The returns from the simulated time series exhibit positive serial correlations over short horizons, whatever the portion of trend followers versus contrarian traders in the chartist population. However, on the one hand, when contrarian traders dominate the chartist population ($z < 0.5$), positive coefficients over short lags are smaller but slow decaying. Consequently, we find that the greater the portion of contrarian traders, the longer mispricing duration is. In other words, we point out that contrarian strategies increase mispricing duration. On the other hand, when trend followers dominate the chartist population ($z > 0.5$), we find that positive coefficients over short lags are larger but fast decaying. This implies a positive relationship between the portion of trend followers and short-term positive serial correlations in returns. Trend-following strategies therefore amplify short-term momentum which, in this case, fasten mispricing correction.

Overall, while earlier works suggest that the momentum effect in individual stocks is mainly explained by slow diffusion of information (*e.g.,* Chan, Jegadeesh, and Lakonishok, 1996; Hong and Stein, 1999), we point out that this is not a sufficient condition and that the composition of the market population plays a key role. In particular, we find that, when information diffuses slowly, chartist strategies generate positive serial correlations in returns over short horizons.

Lastly, we further investigate the role of market composition on price dynamics by excluding contrarian traders. Simulations bring out that when there are only trend followers within the chartist population (*i.e.,* $z = 1$), the asset price overshoots before

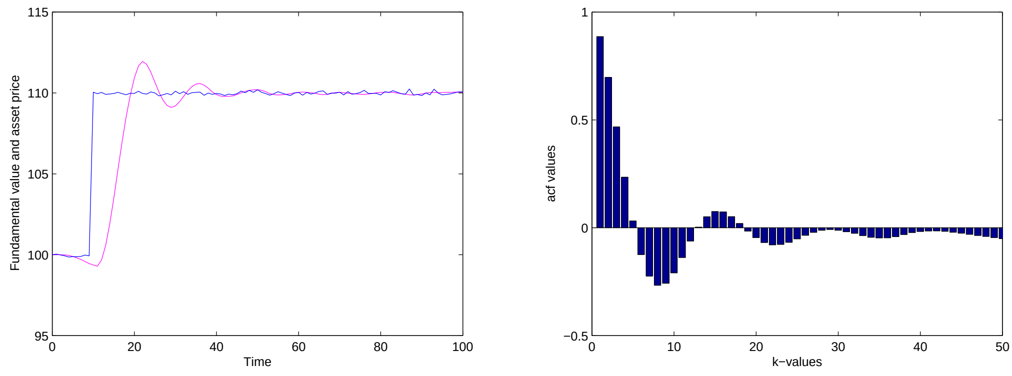


(a) $z = 0.2$ (b) $z = 0.4$

(c) $z = 0.7$ (d) $z = 0.9$

Figure 3: Sample autocorrelation function of returns when $\eta = 0.2$ for differing values of z.

converging towards the asset fundamental value. Fig. 4 shows the simulated time series as well as the sample autocorrelation function of returns from the simulated time series when $\eta = 0.2$ and $z = 1$.



(a) Simulated time series. (b) Sample autocorrelation function of returns

Figure 4: Price dynamics when $\eta = 0.2$ and $z = 1$. In panel (a), the *blue line* represents the evolution of the asset fundamental value. The *red line* represents the evolution of the asset price over time.

In Fig. 4a, convergence towards the asset fundamentals occurs through dampened os-

cillations and the asset price clearly overreacts then corrects. As a result, when trend followers dominate the market, positive as well as negative serial correlations in returns over differing horizons emerge, as shown in Fig. 4b. Price misalignments therefore persist longer in the market. In fact, when fundamentalists are present in the market, trend following strategies, which according to eq. (3) (see also Fig. 3) primarily induce trends in prices, amplify the foremost trend in prices triggered by fundamentalists and cause asset price overreaction.
Under some circumstances, our model is therefore able to simultaneously generate short-term positive serial correlations in returns (*i.e.,* price trends) and long-term negative serial correlations in returns (*i.e.,* asset price reversals). Although the time horizon of the patterns generated by the simulations does not exactly coincide with the time horizon indicated by empirical evidence, these results are consistent with earlier works which suggest that the momentum effect in individual stocks is explained by price overreaction to news events and subsequent correction (see, for instance, De Bondt and Thaler, 1985, 1987; DeLong, Shleifer, Summers, and Waldmann, 1990b; Doukas and McKnight, 2005). However instead of relying on some form of investor irrationality, we suggest that market composition plays a key role in explaining the momentum effect in individual stocks.

4. Conclusion

The aim of this work is to assess whether the momentum effect in individual stocks, due to positive serial correlations in monthly returns, can be explained by the interplay of fundamentalists and chartists - both trend followers and contrarian traders - when firm-specific information diffuses slowly. For this purpose, in this paper, we build a heterogeneous agent model of financial stock market wherein, in line with earlier works, fundamentalists have heterogeneous beliefs owing to slow diffusion of firm-specific information (*i.e.,* sequential awareness, as for instance in Abreu and Brunnermeier (2002, 2003)).

We find that our parsimonious model offers a qualitative description of asset prices dynamics and enables us to simultaneously explain the momentum effect in individual stocks, asset price overreaction and price misalignments.
First, in contrast with earlier works (*e.g.,* Chan, Jegadeesh, and Lakonishok, 1996; Hong and Stein, 1999), we show that slow diffusion of information does not suffice to explain the momentum effect in individual stocks, caused by positive serial correlations in monthly returns. Second, consistent with the explanation of the momentum effect relying on stock price underreaction to news events (*e.g.,* Jegadeesh and Titman, 1993; Chan, Jegadeesh, and Lakonishok, 1996; Hong, Lim, and Stein, 2000; Jegadeesh and Titman, 2001), we suggest that, when firm-specific information diffuses slowly, short-term momentum arises from chartist strategies. In particular, trend-following strategies play a key role in explaining the momentum effect in individual stocks, when there is slow diffusion of information. Lastly, consistent with earlier empirical works which suggest that the momentum effect in individual stocks is better characterized as a stock price overreaction, as for instance in De Bondt and Thaler (1985, 1987); Doukas and McKnight (2005), we find that trends in stock returns reverse over long horizons. Our findings reveal that market composition plays a key role in interpreting the momentum effect in individual stocks. Indeed, when trend followers dominate the market and firm-specific information diffuses slowly, we show that asset price overreacts then corrects. Indeed, returns from the simulated time series therefore exhibit both positive serial correlations in returns over short horizons and negative serial correlations in returns over long horizons. Such a price behavior also explains persistent price misalignments, often observed in real financial time series.

Extensions of this work can be conducted along the following lines. First, in this work, we assume that agents are well-funded. Instead, in real world, agents are likely to face financial constraints which would limit their trading strategies. With this new assumption, we could also account for the evolution of agents' wealth and of the market composition over time, which is likely to lead to more complex price dynamics. Second, in this work, the learning process is quite simple. Indeed, in each period, a constant fraction of fundamentalists is assumed to be aware of the true asset fundamental value. However, the diffusion of firm-specific information is likely to be better approximated by a more complex rule. This refinement would enable us to further understand the effect of the information diffusion process on price dynamics.

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