Insights into the Market Impact of Different Investment Styles

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Abstract: Modern day equity markets are populated by investors pursuing a number of investment styles. In this paper we simulate the behaviour of investors pursuing various types of these styles in order to examine whether their interaction is a major contributing factor to inefficiencies within markets and particularly to the anomalous pricing behaviour identified in the literature. We found that small market fractions constituted by momentum and growth investors are very disruptive to markets, significantly increasing their volatility and causing mispricing for extended periods of time. They also induce an increase in both the risk and trading volume experienced by the other types of investors. We conclude that momentum and growth investing may be a source of the many market anomalies and serious thought should be given to policy, economic and social implications of equity pricing consistently not reflecting fundamental value.

JEL Codes: G12, G14

Key Words: Heterogeneous Agents; Market Efficiency; Mispricing

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Section 1: Introduction

Over the last half century, the growth of the managed fund industry has spawned the development and implementation of a myriad of investment styles[1]. Whereas at one stage equity markets were dominated by fundamental investors, who adopt information-driven strategies, today markets are populated by investors pursuing a multitude of styles many of which pay little or no attention to the available information that is commonly thought to drive stock prices. Examples of such styles include index and momentum investing. Index (passive) trading ignores all information other than the market weights of the stocks included in the index. As Lorie and Hamilton (1973) emphasised, a massive fly-to-passive investing has the effect of reducing the competition and the efficiency within markets. Likewise, momentum (technical) trading disregards any information other than the immediate past history of stock returns. It is significant that one important necessary condition to promote informational efficiency in market pricing is active competition between investors, who seek out all relevant information in their search for mispriced securities, trade on any perceived mispricings, and so ensure the existence of fully-revealing prices (Fama, 1965). The fact that a significant proportion of markets is now in the hands of investors who utilise a limited subset of information is suggestive of the possibility that security prices might depart from their fair value for extended periods of time.

In this paper we simulate an artificial market populated by investors pursuing different investment styles: fundamental, price momentum, contrarian, index and noise (random). Our focus is on the impact that different combinations of these strategies could exert on returns and risks experienced by each style of investor[2] and the consequent effect on the market price dynamics. Our proposition is that, nowadays, the composition of markets seems to depart quite radically from that assumed for an efficient pricing to take place. Therefore, we impound into our model proxies for investment styles commonly adopted in real markets with the aim to establish whether the resulting artificial market appears to display stylised characteristics similar to those commonly identified in the market anomalies literature. We will also provide evidence on the extent to which each particular style trader impacts on the returns, risks, and trading volumes realised by other traders. In Section 2 of the paper, we provide a brief review of the literature. In Section 3, we model the behaviour of each of the investment styles to be used in our simulations of the behaviour of markets composed of various combinations of these different style investors. We present and discuss the main findings in Section 4 paying special attention to the insights that they provide into the process of price formation and the extent to which they are in accord with the literature. Our discussion will highlight that it is price momentum and over-extrapolating fundamental investors contribute to generating a destabilising influence in trending markets. We conclude in Section 5 with a summary of our findings and a discussion of possible directions for future research.

Section 2: The Evidence on Market and Investment Style Behaviour

Although the initial tests of the informational efficiency of capital markets date back over a century, it was only with the writings of Fama in the 60's and early 70's that the empirical research in this area began to mushroom[3]. According to the Efficient Market Hypothesis (EMH), securities are "correctly'" priced to the extent that investors cannot formulate investment strategies, based upon information related to firm's characteristic (e.g. size), some

[1] By style we mean the strategy or process by which an investor chooses the stocks to be included in his portfolio.
[2] In results not reported here we also examined the impact of each type of investor on trading volume.
[3] Fama (1970)

valuation multiple (e.g. book-to-market) and/or some corporate announcement (e.g. a new share issue), that consistently generate returns over and above the level necessary to reward the investor for the inherent risks of the investments. There are three general conditions that must exist within markets for efficient pricing to be established in the sense outlined above. First, information flows costlessly to the market within a short time of it being generated. Second, investors immediately analyse the implications of new information for a stock's valuation and trade where they believe that a stock is incorrectly priced. The final condition being that transaction costs should not inhibit the profitability from trading to exploit any perceived mispricings. Where these conditions hold, efficient pricing should be established as investors will quickly compete away any profitable opportunities. In this paper, we concentrate our attention on the second of the previous conditions, namely the presumption that the market is populated with investors whose decisions (based upon their analysis of all available information) are geared to exploiting any mispricing opportunity. We adopt this as our working definition of the age-old style commonly referred to as *fundamental investing.* Indeed**,** the potential for fundamental investors to add value depends on both the magnitude of inefficiencies in markets and their ability to accurately identify and exploit them in a timely fashion. We will specifically consider two types of fundamental investors: (i) "accurate" fundamental investors, who are always able to identify the true (fair) value of a stock; and (ii) "biased" fundamental investors who significantly over-extrapolate the most recently released earnings growth. We will refer to the latter as "growth" investors.

The empirical evidence on the disappointing performance of active investment managers, dating back to the early work of Treynor (1965), Sharpe (1966) and Jensen (1968), provided the stimulus for many investors to turn to *index investing* (Malkiel, 2003). This drift has resulted in upwards of 25% of the investible funds in many of the developed equity markets being in the hands of passive investors. Moreover, clients' mandatory guidelines (e.g. benchmark selection for measuring managers' risk and return) have made active managers more accountable for their performance. This process has resulted in many managers moving to being closet indexers (or *quasi-indexers*) with respect to a significant portion of their active portfolios. It would not be unreasonable, hence, to assume approximately a third or more of managed funds in the major world equity markets being subject to either overt or covert passive investing[4]. This phenomenon generated a liquidity drag, with a significant proportion of investible funds "out of the market" as a result of index investor totally ignoring all information releases when determining their portfolio index weightings (Woolley and Bird, 2003).

The remaining portion of equity investment is separated between what is known as contrarian and momentum investing. The origin of *contrarian investing* dates back over 70 years to the publication of the text *Security Analysis* authored by Graham and Dodd (1934), even though the interest from the academic community has largely been restricted to the last 15 years (Fama and French, 1992, Lakonishok *et al.*, 1994). One of the explanations for the existence of a value premium (value stocks outperform growth stocks) is that investors tend to over-extrapolate the current poor (good) performance of an under- (over-) valued stock (judgemental mistakes), with the consequence of a reversion in the performance in the following one to 3 years. Hence, a contrarian strategy consists of buying (selling) cheap (expensive) stocks, in order to profit from expected subsequent mean reversion. Contrarian investors typically rely upon simple valuation multiples (e.g. price-to-book, price-to-earnings, and dividend-yield) in order to identify cheap or expensive securities. Therefore, although they utilise information in their decision process, it is only a narrower subset than is the case with fundamental investors. The similarity between contrarian and fundamental investors is that both try to identify cheap and expensive stocks, though basing their assessment on

[4] Except where otherwise referenced, such estimates made in this paper represent a consensus from information gathered from a survey of the major international asset consultants.

different information signals and, hence, timing. Indeed, contrarians tend to react slower to new information as in most cases there will be a time delay before new information is impounded into valuation metrics used to separate the cross-section. Moreover, as emphasised by Asness (1997), these valuation multiples provide only a very crude measure as to whether a particular stock is mispriced[5]. For example, a contrarian investor might regard a particular stock as being cheap based upon its valuation multiples when in fact it is fairly priced when one considers a wider set of information that typically does not enter into their decision process. Despite these deficiencies, the empirical evidence supports the existence of a positive value premium which suggests that the disciplined implementation of a contrarian investment style will on average outperform the market[6].

Momentum investing is an investment style that has only achieved prominence in recent years in the academic literature, though it was undoubtedly being practiced well before index investing achieved any form of popularity. The most common form of price (return) momentum investing involves purchasing (selling) winner (loser) stocks whose recent market performance has been good (poor). Jegadeesh and Titman (1993, 2001) examined various implementations of this form of investment and found evidence to suggest that the best of them significantly outperformed the market. Several other writers have confirmed these findings suggesting a market inefficiency which has proved difficult to explain in the light of traditional models (Fama, 1996, 2006). Although not many investors actually represent themselves as momentum investors, there is clear evidence that momentum constitutes a significant part of many investment strategies and is reinforced by the herding behaviour of both institutional and individual investors[7]. As momentum investors base their investing solely on past price movements they have the potential to be a destabilising force by exacerbating trends that already exist in market and making it more difficult for mean reversion to occur even in the face of changing fundamentals[8].

Finally, we also include in our analysis those investors who do not trade on the basis of available information in any disciplined way: the *noise traders*. Noise trading is not a style that any investors claim to follow although it is likely to provide a reasonable representation of the trading behaviour of many individual and, possibly some, institutional investors. The issue of the impact of such investors on markets has been debated for the last 50 years with Friedman (1953) suggesting that they would tend to buy high and sell low and consequently have no significant impact on pricing as their trading would effectively be offset by arbitrageurs. De Long et al. (1990), instead, argued that arbitrage may not be as effective as Friedman might surmise, and raising the possibility of noise traders being quite disruptive in markets, possibly experiencing good returns over extended period of time and not necessarily underperforming in the long-term.

In our study, we adopt computational heterogeneous agent-based models (hereafter, HAM), which have become a common approach in the analysis of the implications of the interactions between traders with different beliefs and different investment strategies. In the recent literature, many HAM have been investigated through numerical simulation, given the complex analytical tractability of the traders' interactions. In the next section, we will briefly turn to considering the evidence on market anomalies as we are particularly interested in

[5] Bird and Casavecchia (2007).

[6] For evidence on the magnitude of the value premium across markets and across time, see Capaul et al (1993), Fama and French (1998) and Dimson et al (2003).

[7] For evidence on investor herding, see Grinblatt et al (1995), Wermers (1999) and Wylie (2000)

[8] Earnings momentum is another momentum investment strategy that involves trading stocks based upon signals generated by either their actual or forecasted earnings. One example being to purchase (sell) stocks whose current earning is grater (less) than the average earnings over the previous *n* quarters. This phenomenon has been extensively investigated in the literature with the evidence suggesting that prices are only slow to adjust to earnings announcements (Foster et al 1984, Bernard and Thomas, 1990). We have modelled earnings momentum and evaluated its impact on markets and investors pursuing other investment styles and found that investors pursuing this style have little or no deleterious impact on markets and other traders. We do not include them in the simulated markets reported in this study as their inclusion would only further extend the test cases considered without providing any additional insights in pricing bahaviour within markets.

whether the patterns of price behaviour observed by many previous authors can be at least partially explained by the impact of one or more of these styles on the price formation process.

Evidence on Market Anomalies

Over the most recent 30 years, we have seen a mounting volume of empirical evidence which has brought into question the EMH at all levels and fuelled the debate as to whether even the most developed and regulated markets can really be assumed as being efficient[9].

It is not our intention to provide a review of the evidence on market efficiency but rather to outline two of the more important pricing implications that many have drawn from the existing evidence on market anomalies[10]:

(i) *Prices will under-react to individual pieces of information but over-react to an aggregation of information*: many studies have highlighted a slow reaction in prices to information releases which in some instances would appear to extend over a number of years (Foster et al [1984]. In contrast the work of DeBondt and Thaler [1985] and others would suggest that prices often eventually move to unsustainable levels from which they correct. A number of studies have attempted to provide an explanation for the simultaneous existence of both under- and over-reaction with Hong and Stein [1999] being most in the spirit of this study by suggesting that it is a direct result of the market interaction of two types of investors: news followers (fundamental) and trend followers (momentum)[11].

(ii) *There are extended periods of time when a stock's price is removed, at some time excessively, from its fair value*: the evidence suggests possible departures from efficient pricings both at the relative and absolute level and that these departures can be large in magnitude and persist for extended periods of time. At the stock level (relative distortions) we have evidence to suggest that it can sometimes take up to five years for a market to adjust to certain corporate events (e.g. Harris, 2004; Lakonishok et al, 1994). At the market level (absolute mispricing), we have recently experienced the longest market cycle ever in many countries resulting in the "bubble" of the late 90's followed by a major correction (Siegel, 2003].

We will treat these as stylised facts against which to evaluate the pricing behaviour that we generate in our simulations within markets populated by various combinations of the several investment styles that we will discuss in more detail in the next section.

Section 3: Methodology

Initial Set Up

Our aim is to create a market with just sufficient complexity to provide us with interesting insights into pricing behaviour and this is achieved by restricting our analysis to a market with one risky asset (which could be an index) with quarterly return r, and one risk-free asset with quarterly return r_f[12]. The risk free asset is perfectly elastically supplied at a gross return of $R_f = 1 + r_f/K$, where K stands for the frequency of trading period per quarter which is assumed to be weekly (thus K= 13 periods per quarter). The sole source of information that affects prices is quarterly earnings announcements where the quarterly growth in earnings is:

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[9] This literature dates back to the June-September 1978 volume of *Journal of Financial Economics* totally devoted to what became known as market anomalies.

[10] Brief reviews of the literature on market efficiency are to be found in Dimson and Mussavian (1998) and Srivastava (2004).

[11] There are also noticeable similarities to the paper of De Long et al (1990)

[12] This could be modeled to follow some stochastic process.

- either *randomly drawn* (each quarter from a distribution with an assumed mean and standard deviation of 1 per cent), or
- *serially correlated*, oscillating around a long-term growth rate of 1% per quarter, where the complete cycle takes three years (i.e. 12 quarters), each composed of a upward drift in earnings growth for six quarters followed by a mean reversion in earnings growth (i.e. mean reversion) over the subsequent six quarters. This 12-quarter cycle is then repeated[13].

After each quarterly earnings announcement, a new fundamental value for the stock is determined by applying a dividend discount model as described below and a new round of weekly trading is generated.

Determination of Fundamental Price

The fundamental value for the stock, which also could be referred to as its fair value or intrinsic value, is determined immediately after each earnings announcement by extrapolating out the earnings growth for the next 12 quarters (the time length of the earnings growth rate) at the average earnings growth rate for the current and the previous three quarters. Beyond these 12 quarters, it is assumed that earnings will grow at the long-run quarterly growth rate for earnings. These projected earnings figures are then discounted in a dividend discount model at a risk-adjusted rate to determine the fundamental price. The fundamental price P_t^* can be expressed as follows:

$$P_T^* = \lambda E_T \left(\sum_{i=1}^{12} \left[\frac{1+\bar{g}_T}{1+r} \right]^i + \sum_{i=13}^{\infty} \left[\frac{1+g_o}{1+r} \right]^i \right) = \lambda E_T \left(\frac{1+\bar{g}_T}{r-\bar{g}_T} \left[1 - \left(\frac{1+\bar{g}_T}{1+r} \right)^{12} \right] + \frac{1+r}{r-g_0} \left(\frac{1+g_o}{1+r} \right)^{13} \right), \quad (1)$$

where E_T represents the earning per share of the stock over the quarter T, g_0 constitutes the long-term growth rate of 1% per quarter, λ is the payout ratio (assumed equal to 0.8), and $\bar{g}_T$ is an average growth rate calculated each quarter on the assumption that earnings will grow over the next 12 quarters at the average of the earnings growth rates over the current quarter and the last three quarters ($\bar{g}_T$).

As a special case when $\bar{g}_T = g_0$, we obtain the Gordon valuation formula:

$$P_T^* = \lambda \frac{1+g_0}{r-g_0} E_T . \quad (2)$$

Heterogeneous Trading Strategies

As mentioned previously, we assume that there are seven different types of investors pursuing five different types of investment styles: two fundamental investors (one who forecasts accurately and the other, referred to as a growth investor, who over-extrapolates past earnings growth), two momentum investors (one whose implementation is much shorter term than the other), contrarian investor, index trader, and noise trader. In the following discussion, we outline the nature of the demand function of each type of investor.

The *fundamental investors* make the following assumptions. They believe that the market price is mean reverting to their perceived fundamental price. Consequently, they purchase

[13] This pattern is consistent with the findings of Soffer and Walther (2000) for US stocks.

(sell) the stocks when the market price is below (above) this perceived fundamental price. The fundamental investors determine their perceived fundamental price by applying a dividend discount approach as in equation 1. We model two types of fundamental investors: one type that "correctly" forecasts future earnings growth and so effectively always knows the fundamental price and a growth investor who over-extrapolates past earnings growth which is a judgmental error that is commonly reflected in stock prices (Lakonishok et al, 1994). In both cases it is assumed that beyond an initial period earnings will grow at the long-term earnings growth rate. We also assume that each of the two types of investors only trade when the deviation of the current price from their perceived price $P_t - P_{t,i}^*$ is either above or below a certain percent, say $\overline{\alpha}_s \in [0, 1]$, of the current price level in recognition of the risks, and various trading and financing costs, associated with the investment. Moreover, given their role in stabilising the market, their demand is proportional to the deviation of the market price from the fundamental price. Therefore, we can express the demand of the fundamental investors ($z_{s,t}$) at time t as follows:

$$z_{s,t} = \begin{cases} \alpha_s \left[P_{t,i}^* - (1+\overline{\alpha}_s)P_t\right] & \text{if} \quad P_{t,i}^* > (1+\overline{\alpha}_s)P_t \\ 0 & \text{if} \quad \left|P_{t,i}^* - P_t\right| < \overline{\alpha}_s P_t \\ \alpha_s \left[P_{t,i}^* - (1-\overline{\alpha}_s)P_t\right] & \text{if} \quad P_{t,i}^* < (1-\overline{\alpha}_s)P_t \end{cases} \qquad (3)$$

where, α_s (greater than zero) measures the demand intensity, $\overline{\alpha}_s$ (greater than zero) measures required premium that incorporates both transactions costs and a compensation for the risks associated with the investment. The demand function expressed in units of shares indicates that the fundamental traders only purchase (sell) stocks when they believe that the potential gain (loss) is above (below) $\overline{\alpha}_s$. $P_{t,i}^*$ represents the perceived fundamental price, with i equal to the length of the extrapolation of the fundamental trader considered. In the case of the accurate fundamental investors i is equal to 12 quarters (as in the case of P_t^*) whereas for the growth investors i equals 40 quarters. It should be noted that the perception of the fundamental price by the accurate fundamental investors is, by construction, always correct and as such they provide a useful benchmark. Indeed, a market composed 100% of these investors is always efficient.

As aforementioned, we also simulate the trading of two price *momentum investors*. In our formulation, momentum investor purchases (sells) stocks that have changed in price over the previous f weeks (formation period) at a rate greater (less) than g_0, which is the average growth rate per quarter, and to hold the position created for h weeks before reversing the transaction. This is akin to the trading strategies set out in Jegadeesh and Titman [1993, 2001] who evaluated the performance of momentum strategies implemented with various combinations of formation periods (f) and holding periods (h). The two such implementations considered in this paper include a short term version, with a formation period of 13 weeks and a holding period of 6 weeks (or f = 13, h =6), and a longer term version with a formation period of 26-weeks and a holding period of 26-weeks (or f = 26, h = 26)[14]. More precisely, for the momentum investors, we assume that: (i) their trading signals are generated by the difference between the current price and the price accumulated in the previous f weeks at the rate g_0; (ii) they are risk averse, namely they increase their (long/short) positions initially

[14] Given the periodicity of the pricing cycle produced in our simulations, the shorter-term momentum investor is somewhat akin to the early-stage momentum investor identified in Lee and Swaminathan (2000) while the longer-term momentum trader is more akin to the late-stage momentum investor.

when the trading signals generated are strong enough, but they are cautious when such signals are too strong (their demand function is a nonlinear increasing function of the trading signals while the marginal demand is decreasing); and (iii) they hold their positions for h weeks and then reverse them.

Based on the above assumptions, the demand function of the momentum investors $z_{m,t}$ at time t may thus be defined by the following piece-wise nonlinear function:

$$z_{m,t} = \begin{cases} \alpha_m \tanh\left(\frac{\beta_m}{\sigma^2}\left[P_t - (1+\overline{\alpha}_m)(1+g_0)P_{t-f}\right]\right) & \text{if } P_t > (1+\overline{\alpha}_m)(1+g_0)P_{t-f} \\ 0 & \text{if } \left|P_t - (1+g_0)P_{t-f}\right| < \alpha_m(1+g_0)P_{t-f} \\ \alpha_m \tanh\left(\frac{\beta_m}{\sigma^2}\left[P_t - (1-\overline{\alpha}_m)(1+g_0)P_{t-f}\right]\right) & \text{if } P_t < (1-\overline{\alpha}_m)(1+g_0)P_{t-f} \end{cases} \quad (4)$$

where, $\alpha_m > 0$ measures the demand intensity, $\sigma^2 > 0$ measures the volatility of the market price, which is assumed to be a constant, $\overline{\alpha}_m > 0$ measures the trading cost, and β_m measures how quickly the traders adjust their demand when the trading signals are small.

The *contrarian investors* purchase (sell) stocks that are undervalued (overvalued) as indicated by the stock's (yearly) earnings-yield ($\overline{E}_{T,t}/P_t$). The level of under- (over-) valuation is defined relative to the (yearly) long-term earning-yield $(1/P_t)$, calculated as the inverse of the perpetual Gordon constant growth rate model. Again, they trade on this signal only when the difference is above (below) a certain transaction cost $\overline{\alpha}_c \in [0,1]$, As a result, the demand of a contrarian investor ($z_{c,t}$) is expressed by the following function:

$$z_{c,t} = \begin{cases} \alpha_c\left(\frac{\beta_c}{\sigma^2}\left[\frac{\overline{E}_{T,t}}{P_t} - (1+\overline{\alpha}_c)\frac{1}{P_t}\right]\right) & \text{if } \frac{\overline{E}_{T,t}}{P_t} > (1+\overline{\alpha}_c)\frac{1}{P_t} \\ 0 & \text{if } \left|\frac{\overline{E}_{T,t}}{P_t}\right| < (1+\overline{\alpha}_c)\frac{1}{P_t} \\ \alpha_c\left(\frac{\beta_c}{\sigma^2}\left[\frac{\overline{E}_{T,t}}{P_t} - (1-\overline{\alpha}_c)\frac{1}{P_t}\right]\right) & \text{if } \frac{\overline{E}_{T,t}}{P_t} < (1-\overline{\alpha}_c)\frac{1}{P_t} \end{cases} \quad (5)$$

where, again $\alpha_c > 0$ measures the demand intensity, $\sigma^2>0$ measures the volatility of the market price, assumed to be a constant, β_c measures how quickly the traders adjust their demand when the trading signals are small, and $\overline{E}_{T,t}$ is the current yearly earnings calculated as the sum of the earnings released in the most recent four quarters. A stock whose current earning yield is above (below) the long-term earnings-yield (the initial earnings are equal to 1), is designated as an under- (over-) valued stock.

Consistent with other authors, we formulate the *noise traders* as investors whose demand are randomly determined. In this framework, the noise trader is a particular category of those investors who trade on "noise [as]… they [were] trading on information" (Fisher, 1986). Their demand is expressed as a random draw from a normal distribution:

$$z_{n,t} \sim N(0, 3). \quad (6)$$

The noise traders, hence, trade on random perceptions rather than some heuristic trading strategy as in the case of the momentum or contrarian investors[15].

Finally we have the index investors as always 100% invested in the risky asset. Hence, the demand of the *index investors* $z_{i,t}$ is always zero.

Wealth function

In our model each investor has a choice between holding his wealth in either shares (risky asset) or a risk-free asset (which we will refer to as cash). It is possible for him to hold a short position in stocks and to borrow (i.e. negative cash). The wealth position of an investor at any point in time can be is calculated as follows[16]:

$$W_{p,t} = N_{p,t}P_t + \lfloor (W_{p,t-1} - N_{p,t-1}P_{t-1})(1 + r_f/13) - \Delta N_{p,t}P_t \rfloor \quad (7)$$

where W_{pt} denotes the wealth of the p^{th} investor at time t, N_{pt} denotes the number of shares held, P_t denotes the price of each share, and r_f denotes the quarterly risk-free rate.
We can see from Equation 7 that the wealth position each week is equal to the value of the shares held plus the cash holdings the week immediately before, adjusted for both interest and the cash flows associate with trading in shares.

The actual number of shares to be purchased by each investor is determined by their wealth relative to the total wealth of all investors (which at time t for the p^{th} investor is denoted as $n_{p,t}$) and the level of their demand as determined from their demand function (which is denoted as $z_{p,t}$) Based on the previous discussion, the excess demand of the risky asset $z_{e,t}$ at time t is then given by:

$$z_{e,t} \equiv \sum_{p=1}^{P} n_p z_{p,t} \quad (8)$$

where $z_{p,t}$ denotes the demand functions of the different traders as defined in (3)-(6).

Market Maker and Market Clearing Price

In addition to the seven types of investors, we also have a market maker whose role is to clear the market each period of any excess demand. Hence the market maker will take a long position when $z_{e,t} < 0$ and a short position when $z_{e,t} > 0$. At the end of period t after the market maker has transacted, he adjusts the price for the next period in accordance with the experienced excess demand. Using μ to denote the corresponding speed of price adjustment of the market maker in the face this excess demand, and η to denote a random noise, then the market-clearing price at time $t+1$ is given by:

$$P_{t+1} = P_t + \mu z_{e,t} + \eta_t \quad (9)$$

The market maker behaviour in this model is highly stylised. For instance, we do not consider the inventory level of the market maker built up as a result of the accumulation of various

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[15] For simplicity, we do not consider the case of a positive or a negative bias in the noise traders' demand, even though it is possible to analyse the impact of their moods by multiplying their demand by a constant (see Alfarano *et al*, 2005, De Long *et al,* 1990).
[16] See also Levy, M., Levy, H., and Solomon, S., 1995.

long and short clearing positions. This could affect his behaviour, e.g. the market maker price-setting role in (10) could also be a function of the inventory level.

Section 4: Findings

We outlined in Section 2 that our objective is to investigate the price formation processes that evolve in markets composed of investors pursuing different styles and also to consider the impact of these different combinations on the risks and returns realised by, and the trading behaviour of, investors pursuing each of these styles. In Section 3, we developed a model composed of five different investment styles to allow us to simulate pricing behaviour within a market composed of seven implementations of these five investment styles. The focus in this section is to vary the composition of markets by changing the proportions that each style of investor represents in the market in order to provide insights into the resulting price behaviour and also the resulting returns, risk and trading activity for each style of investing The various combinations of investors within the test cases that we examine in the first part of our analysis are set out in Table 1. For each test case we ran 300 Monte Carlo simulations of the market behaviour for both random and serially-correlated earnings growth over a period of 25 years (1,300 weeks). Moreover for purposes of comparability, we use the same Monte Carlo earnings path for all the different market structures. This means that all the results we document are generated from the same series of random or serially correlated earnings growth.

We calibrated the model as developed in Section 3 with the objective that an equivalent signal will translate into a similar level of trading for each of the rational active investors: fundamental, momentum and contrarian. For all simulations, the selected parameters are as follows:

$$\lambda = 0.8,\ \ \mu = 0.5,\ \ \alpha_s = 1,\ \ \alpha_m = 5,\ \ \alpha_c = 2\mathrm{e}+03,\ \ \beta_p = \sigma_p^2 = 1,$$
$$\overline{\alpha}_s = \overline{\alpha}_c = \overline{\alpha}_m = 0.03/13,\ W_{p,0} = 5e+05$$

Efficient Pricing

The evidence most relevant to our major findings is to be found in Tables 2 and 3 and most of the discussion in this section will be based on these Tables supplemented where appropriate. Table 2 provides us with information about the risk and return characteristics for both the market and each individual investor style under each of our 27 test where quarterly earnings growth is generated randomly while Table 3 repeats this information where serial correlation and mean reversion is built into the growth of quarterly earnings One important piece of information, not reported in the tables, is the mean of the difference between the actual and the fundamental prices established each week[17]. The fact that this mean is effectively zero for all test cases under both random and serially–correlated earnings growth informs us that the price is on average correct over the 25 years covered by our simulations. This is a necessary but not a sufficient condition for market efficiency which would require that the price be correct throughout the 25 years rather than to be correct on average over these years. With this in mind the measure reported in Tables 2 and 3 that best captures the potential for market inefficiency is the standard deviation of the difference between the actual and the fundamental prices which we report in the *mispricing* column. In a market with no potential for inefficiencies this mispricing measure would have a value of zero so we can use its magnitude to provide us with insights into extent of any mispricing opportunities. We have defined an inefficient market as one where investors cannot use available information to formulate an

[17] The mean of the difference between the weekly price and the fundamental price is calculated for each simulation and then the average of these means is calculated.

investment strategy that consistently generates excess returns. We discuss below this mispricing measure first in the case of random earnings growth and then where we have serial correlation in earnings growth. Subsequently we examine the performance of the investors utilising the different investment styles in order to determine the extent to which the opportunities indicated by the mispricing measures are exploited by the various types of investors.

Mispricing under Random Markets

Under test case 1 where the market is entirely composed of investors who effectively know the fundamental price, the mispricing measure is 0.42 (units of currency) which is indicative that prices very quickly adjust to the release of new information and suggests that the market in this case is highly efficient[18]. A review of the information contained in the mispricing column of Table 2 reveals several test cases where the level of mispricing is much higher than it is in test case 1[19]. The greatest departures, both in excess of seven dollars, are be found in test cases 4 and 9, which represent a combination of the fundamental or the growth investor with the longer-term momentum investor. In order to obtain a greater insight into the nature of the pricing process associated with these two test cases, we report in Figure 1 a typical test path and the average serial correlation for each test case. These charts clearly indicate that it takes several weeks for the price to adjust to new information but then prices overshoot their fundamental value which is a finding that is consistent with the under and over-reaction identified in many previous studies[20].

There are many less severe instances of market mispricings that can be observed from reviewing the other test cases and these provide us with further insights into the effect of the composition of investment styles within markets on efficiency of the price formation process:

- The level of mispricing is higher in those test cases where there is a growth investor rather than an accurate fundamental investor (c.f. the mispricing measure for test case 3 with that for test case 8, test case 13A with test case 16A, and so on). This comes as no surprise as the growth investor contributes to price departures by valuing stocks too highly at times of strong earnings growth and placing too low on them at times of weak earnings growth;
- The shorter-term momentum investor contributes less to mispricing than does the longer-term momentum investors (c.f. test case 3 with test case 4, test case 8 with test case 9 and so on). This reflects that the longer-term momentum investors take longer to adjust their "buying" behaviour in response to a change in the pattern of reported earnings growth and then hold on to their stocks longer once they have been "acquired";
- Index investors and noise traders neither enhance nor mitigate any mispricings in markets caused by investors following other investment styles (c.f. test case 13 with tests cases 14 and 15, test case 16 with test cases 17 and 18). This is because mispricings in markets do not encourage index investors to trade while noise traders effectively trade randomly independent of the existence of any mispricing in markets although they increase the level of volatility experienced in markets.
- The investment styles that do most to redress any mispricings in markets are the accurate fundamental investor and the contrarian investor (c.f. 16A with 16, 20 with 19) who both trade when they perceive that the actual price has diverged from its fundamental value.

[18] The average price over the 25 years is approximately $140 and so a standard deviation of 42 cents is 0.3% of the price. Although we might expect that the standard deviation would be zero in a market 100% composed of accurate fundamental investors , this small standard deviation reflects that there is a one week gap between the earnings announcement and the first opportunity to trade.

[19] There are five test cases where the mispricing measure represents more than 4% of the average price.

[20] One criticism that could be levied is that the mispricing identified largely reflects the "no trade" zone that we have imposed on investors to account for transactions cots and risk. When we repeated our analysis without this "no trade" zone, the mispricings only fell by between 10% and 15%.

Mispricing under Serially-Correlated Markets

Although the growth investors, in association with the momentum investors, contribute to mispricing in markets where earnings announcements are random, their impact on mispricing approximately doubles in markets where earnings growth is serially-correlated (see Table 3). There are numerous instances of test cases having a mispricing measure of around 15 or higher and the unique aspect of each of these test cases is that they include growth investors[21]. Further, these extremes in mispricing even occur in markets that include no momentum investors (i.e. test cases 11 and 12). Our findings highlight that the growth investor is the main contributor to mispricing in markets characterised by serially-correlated earnings growth (Soffer and Walther, 2000). An example of a typical pricing path under one of these test cases (test case 9) and the associated serial correlation chart is reported in Figure 2. These charts highlight that the growth investors by over-extrapolating earnings growth cause levels of overshooting in prices that we do not see in markets where earnings growth is random through time. The periodicity of the pricing cycle is longer (c.f. test case 9 in Figure 1 with that in Figure 2) reflecting that adjustment process is longer and the extent of overshooting is greater. Whereas previously with random earnings growth, it was the momentum investors who were the main contributors to a higher level of market mispricing with the growth investor playing a secondary role, these roles are basically reversed when we experience trends in earnings growth. The level of mispricing is basically left unchanged by the introduction of momentum investors, which leads us to suggest that the destabilising influence of the momentum investors is no greater in the serially-correlated markets than it is in the random markets. This proposition gains support from the fact that combinations of the accurate fundamental investors with momentum investors result in the same level of mispricing in both types of markets (c.f. tests cases 3 and 4 in Table 2 with the same test cases in Table 3). One aspect of the pricing process that is common to both random and serially-correlated markets is that combinations of growth and momentum investors do result in both under- and over-reactions to earnings announcements (see Figures 1 and 2), with the resulting distortions in pricing being more sustained in the case of serially-correlated earnings announcements.

Other insights that we gain from the findings reported in Table 3 are very similar to those previously commented on from our review of Table 2:

- The shorter-term momentum investor contributes less to mispricing than do the longer-term momentum investors (c.f. test case 3 with tests case 4, test case 8 with test case 9 and so on).
- Both index investors and noise traders neither enhance nor dampen any mispricings in markets introduced by investors following other investment styles (c.f. test case 13 with tests cases 14 and 15, test case 16 with test cases 17 and 18).
- The two investment styles that redress any market mispricings most are the accurate fundamental investors and the contrarian investors (c.f. 16A with 16, 20 with 19)

In summary, it is the growth investors and/or the momentum investors that are the major contributors to mispricing in markets and a source of the under- and over-reaction in prices to information releases and the sustained periods of mispricing that have been commonly found in many empirical studies. The accurate fundamental and contrarian investors are the greatest mitigating forces against such mispricings but even they cannot prevent mispricings persisting over long time periods. Neither the index investors, by effectively withdrawing funds from the market and the random investment behaviour of the noise traders make a significant

[21] There are nine test cases in which the mispricing measure represents 10% or more of the average price

contribution to mispricings in markets nor do they play a role in correcting any mispricings. However, it is interesting to observe the four-fold drop-off in mispricing from test case 19 (75% momentum and growth investors) to test cases 21 and 22 (both 60% momentum and growth investors), which leads one to observe that extent of any mispricing is quite sensitive to the proportion of the market represented by growth and momentum investors.

Returns from Alternative Styles

We now turn our attention to first the returns, and then the risks, experienced by the different investor styles under the various test cases. We have reported in Tables 2 and 3 the absolute and relative returns and risks realised by each type of investor for each of the 27 test cases where the earnings growth is both random and serially correlated[22]. We choose to first comment on the returns as they have implications for (i) the exploitable opportunities flowing from the identified mispricings discussed in the previous sub-section and (ii) the longer-term sustainability of investors following each of the various investment styles. One obvious winner is the accurate fundamental investor who consistently outperforms under all market conditions but realises their greatest outperformance in markets where they are in competition with growth and/or momentum investors. The other outperformer in the majority of the test cases is the contrarian investor who realises handsome gains at the expense of the same growth and/or momentum investors. Indeed in markets driven by randomly generated earnings growth, the added value realised by the contrarian investor is very similar to that realised by the accurate fundamental investors. However there are instances in markets driven by serially-correlated earnings growth where the performance of the contrarian investor is much inferior to that realised by accurate fundamental investors. This is particularly true when the contrarian investor is in single competition with the accurate fundamental investor and/or when the two types of momentum investors are also present in the market. The contrarian investors actually underperform in those markets driven by serially-correlated earnings growth where they are in competition with fundamental investors (see test cases 4, 13A and 23 from Table 3) whereas they have the greatest upside in these same markets when fundamental investors are absent (see test cases 10, 16A and 24 in Table 3). This reflects that although the accurate fundamental and the contrarian investors both seem to have the ability of identifying when a stock is cheap, it is the fundamental investor who is able to do so with greater accuracy and superior timing.

The index investors and the noise traders effectively realise the market return under all market compositions irrespective of whether earnings growth is random or serially-correlated. This should come as no surprise in the case of index investors whose main objective is to replicate the market returns but is more interesting in the case of noise traders and implies that contrary to what Friedman suggested, the truly random investor might survive under most market compositions.

This leaves us with the two most interesting types of investors; the growth and the momentum investors. The growth investors perform relatively well in random markets typically eking out small profits, although their returns are always inferior to those of the fundamental investors and/or the contrarian investors. The outcome changes in markets impacted by serially-correlated earnings growth, where the growth investor experiences significant under-performance in markets populated by fundamental and/or contrarian investors in combination with momentum investors. The strong trends in such markets cause the growth investor to significantly misprice stocks in both up and down markets with the resulting mispricing opportunities being exploited by the accurate fundamental and/or contrarian investors.

[22] The returns that we report are the average of the 25-year returns over the 300 simulations and the risks are the standard deviation of these returns.

The long-term momentum investors are the consistent losers largely as a consequence of markets not trending over sufficiently long periods to accommodate their implementation of the momentum style. Indeed, these investors underperform in all of the test cases examined, but more so in the random markets that obviously do not suit an investor whose style is dependent upon trending markets. In contrast the short-term momentum investors do outperform in all test cases as a result of their implementation being more in tune with pricing behaviour, with the exception of where they are in sole competition with fundamental and growth investors. The best performance of short-term momentum investors is realised in random markets populated by fundamental and longer-term momentum investors.

As well as providing insights into performance of different styles in different markets settings, the above discussion also has implications for (i) the extent to which the mispricing opportunities that we have previously highlighted are exploitable and (ii) the likelihood of survival of investors pursuing different investment styles. We will consider (ii) at a later point in this paper but at this stage will make some observations regarding (i). The consistent winners across all market settings are the accurate fundamental investors while the contrarian investors also outperform in the vast majority of instances. Both of these types of investors follow a rational information-driven approach and achieve their greatest value added in those markets settings in which our mispricing measure are greatest. This leads us to conclude that our findings provide evidence to support the proposition that the interplay between investors pursuing different market styles can be the source of inefficiencies in markets. A conclusion that is strengthened by the fact that the price behaviour generated in many of our test cases is consistent with the stylised facts drawn from the market anomalies literature.

Risks associated with Alternative Styles

We will now turn our attention to considering the risks experienced by each style of investor and, in particular, the risks that they impose on those pursuing other styles. Before commencing the review we should point out that we have presented two measures of risk: an absolute risk measure being the standard deviation of the weekly returns generated for each investment style and a relative measure being the tracking error as measured by the standard deviation of the difference between the weekly returns of a particular style and that of the market. The low absolute risk and tracking error experienced by all types of investors involved in test cases 1, 5 and 6 as presented in Table 2 and Table 3 would lead us to dismiss fundamental, contrarian and index investors as being the source of any significant level of risk either to themselves or to those following other investment styles. Therefore, in the following discussion we can concentrate our attention on the risk faced by the growth, momentum and noise traders and the impact that these three types of investors have on the risk faced by the other types of investors.

Risks under Random Markets

An examination of the risks under test cases 2, 10 and 11 in Table 2 confirm that the growth investors are also not a major source of risk either to themselves through their impact on markets or to the fundamental, contrarian and index investors in markets where earnings grow randomly through time. We observe in such markets that the absolute risk of all investors increases significantly once one or more momentum investors and/or noise traders are introduced into the composition. However it is tracking error rather than absolute risk that have come to be accepted as the main measure of risk of an individual investor and our findings become more complex once we consider tracking error as the risk measure for investors in a random market setting (see the right-hand panel of part B). It shows that the tracking errors experienced by the momentum investors and noise traders are typically much less than that experienced by the investors pursuing other investment styles. Good examples of this can be found in test cases 23 and 24 where in both instances momentum investors and noise traders experience relatively low tracking error while the growth and contrarian investors, and to a lesser extent the fundamental investors, experience much higher levels of tracking error. With the exception of the index investors, the short-tem momentum investors experience the lowest risk, followed by the noise traders and the long-term momentum traders.

Risks under Trending Markets

In the majority of our test cases the absolute risk of the market increases by less than 10% where the market is driven by serially-correlated earnings growth as compared to markets where it is driven by randomly generated earnings. However, there are isolated instances in markets heavily populated by fundamental investors of increases in market risk in the range of 50% to 100%. The switch from random markets to trending markets results in hardly any increase in absolute risk for the momentum, index and noise investors. The investor style most impacted by the move to trending markets are the contrarian investors who experience in several test cases a more than a doubling of absolute risk but we also note that fundamental and growth investors also experience sizable increases in absolute risk under certain test cases. In contrast to the relatively small increase in absolute risk experienced by the various investment styles under trending as compared to random markets, many of the investment styles experience much larger increases in their tracking error (i.e. relative risk). This is not true for the momentum and index investors and noise traders, whose tracking error remains almost the same under the trending markets as it was under random markets. However the fundamental, growth and contrarian investors experience much greater tracking error under the trending markets and particularly in those markets that are also composed of growth, momentum and/or noise traders This can be seen from a review of the more complex market compositions (i.e. test cases 19 to 26 in Table 3), where we see levels of tracking errors for fundamental, growth and contrarian investors that are ten- to 20-times those experienced by momentum, noise, and index investors. The extreme risks faced by the three more value-based investors as demonstrated in these test cases is largely a consequence of them trading too early in markets that trend away from fundamental value for extended periods resulting in these investors experiencing extended periods of underperformance prior to them benefiting from the eventual mean reversion in pricing. Indeed, we can see in a market composed of a balanced representation of all of our investment styles (test case 25) that the short-term momentum trader realises an information ratio much higher than that of the accurate fundamental and contrarian investors, due to the much higher relative risk experienced by these two later styles of investing. Therefore it would not be surprising to find that in such market settings, investors (and asset managers) being drawn away from more value-based approaches of investing and towards momentum investing (although our findings highlight that not all implementations of momentum outperform). Of course, if this drift from value-based to momentum investing occurs then it will result in even more volatility and mispricing within markets.

Section 5: Summary and Concluding Comments

The composition of investment styles in markets has changed significantly over time. The empirical evidence highlights a reduction in the influence of the information-driven fundamental investors due to more funds flowing to investment styles which rely on signals other than those that are supposedly relevant to market prices. In this study we have used artificial heterogeneous agent model to study the behaviour of markets populated by investors following implementations of investment styles such as *fundamental*, *momentum*, *contrarian*, *index* and *noise*. Our primary objective was to investigate the extent to which the major market anomalies identified in the empirical literature can be explained to some extent by the interplay of investors pursuing strategies representative of those common styles adopted in real markets. Our interests also extended to the analysis of the performance of the various investors populating constituting the market fractions considered and, in particular, the implications of the presence of each investment style on the performance of the other styles. In this regard, we considered two types of markets: one in which intertemporal information signals (in our model represented by the growth of quarterly earnings) are random as assumed in an efficient market; the other where there is serial correlation built into the earnings growth, which is more in line with the empirical findings. In both instances we found that markets composed of various combinations of accurate fundamental, contrarian, index and noise traders are fairly efficient. Further, the first three of these investor styles can be regarded as "*market-friendly*" in that they not only introduce negligible incremental market risk and trading volumes, but they also have little implications for the risks faced by the other investors[23]. In contrast, and consistent with previous finding in the literature, the noise traders are the source of a large portion of market risk, and cause the markets to be more risky for those pursuing other investment styles.

In relation to the other two styles investigated - *fundamental extrapolators* (*growth*) and *momentum investors* - they both individually and together seem to be the source of considerable destabilisation in pricing, with this being particularly so when the information flows are serially-correlated. This is important as both types of momentum investors and the growth investors seem to extend the trends in prices created by the serially-correlation in earnings announcements and so contribute to actual prices diverging from the fundamental prices for extended periods of time. In the random markets it is the long-term implementation of momentum investors that is the major source of mispricing, with the shorter-term momentum investors and the growth investors also contributing but to a less extent. In the case of serially-correlated information flows, it is now the growth investor that performs the primary role in generating mispricings, with momentum investors, along with index investors and noise traders, playing what is best described as a supporting role. The major question that remains outstanding is whether the market structures that give rise to anomalous pricing are sustainable. In other words, the explanation that we put forward to explain mispricings in markets may only persist if the market compositions that give rise to them persist. With this in mind, we evaluated the performance of the various investors and established the long-term viability of the various investment styles and found that it is only the longer-term price momentum investors that are likely to prove non-viable under all market conditions with the growth investors also proving non-viable under trending markets. The fact that the two least viable investors are the same ones that make the major contributions to anomalous pricing raise the question as to whether they will sustain such mispricing into the future if they indeed give rise to it in the first place. However in forecasting their demise we should remember that investors over-extrapolate and pursue momentum investing (herding) for a variety of reasons, many of which *are not strictly performance related*. This does not deny that many investors using such styles will either retire from the market or drift to some other style of investing. However, it is likely that they will be replaced by novices who are attracted by these styles for the same reasons that have been attracting investors for many decades.

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[23] We do find that a significant proportion of index investors slows down the rate at which prices adjust to new information (Bird and Woolley, 2003)

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Figure 1. Price Path and Autocorrelations for Different Test Cases: Random EPS. The figure shows the price path relative to the fundamental price (left side) and the autocorrelation function over 40 lags of the log return (right side) for different test cases for the simulations where the earnings are assumed to follow a random walk. Panel A depicts the results for test case 4 where the market is initially 50% composed of the accurate fundamental investor (F_{12}) and 50% composed of the long-term momentum investor who is denoted throughout the paper as $^{26}M_{26}$. In Panel B, we provide the same information for test case 9 where the market is initially 50% composed of the growth investor (F_{40}), who overextrapolates recent earnings growth, and the momentum traders $^{26}M_{26}$.

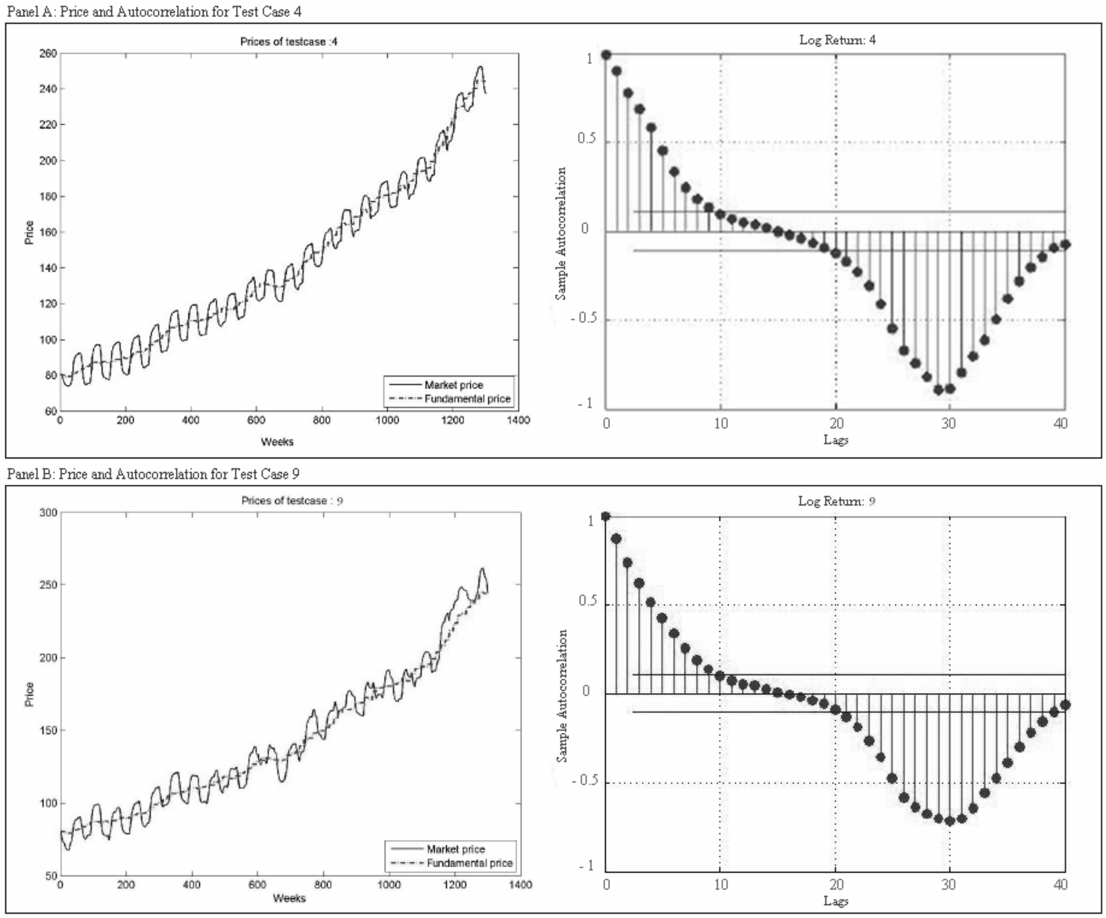

Figure 2. Price Path and Autocorrelations for Different Test Cases: Serially Correlated EPS. The figure shows the price path relative to the fundamental price (left side) and the autocorrelation function over 40 lags of the log return (right side) for different test cases for the simulations where the earnings are assumed to be serially correlated. We depict the results for test case 9 where the market is initially 50% composed of the growth investor (F_{40}), who overextrapolates recent earnings growth, and the momentum traders ${}^{26}M_{26}$.

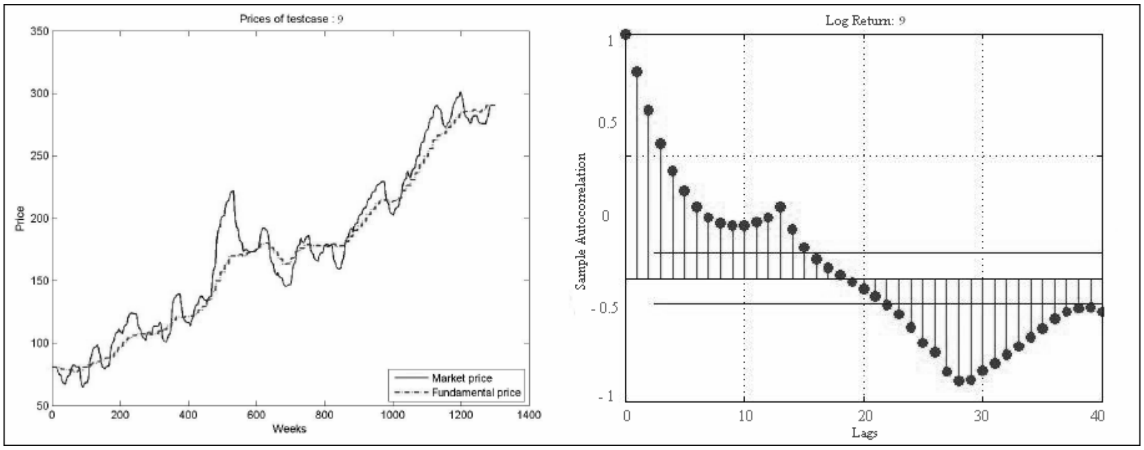

Table 1

The Initial Weights in the 27 Test Cases

In this table, we document the initial percentage of traders for each test case (or market structure). These percentages then vary according to the weekly proportion of the traders' wealth in relation to the total wealth in the market. There are two *fundamental* investors who trade on the difference between a stock's current price and its perceived fair value. F^{12} extrapolate recent earnings growth for 12 quarters while F^{40} over-extrapolate out recent earnings growth for 40 quarters. There are two *momentum* investors who trade on the basis of the price movement over some previous defined formation period and who hold the stocks for a fixed holding period. ${}^{13}M_6$ operates with a formation period of 13 weeks and a holding period of six weeks while ${}^{26}M_{26}$ operates with a formation period of 26 weeks and a holding period of 26 weeks. *Contrarian* traders based their signal on a market-based indicator that is represented by a stock's earnings-yield. The *Index* traders replicate the index whereas the *Noise* investors simply trade on a random signal.

	Fundamental (correct)	Fundamental (Over-extrapolator)	Momentum (Short)	Momentum (Long)	Contrarian	Index	Noise
1	100						
2		100					
3	50		50				
4	50			50			
5	50				50		
6	50					50	
7	50						50
8		50	50				
9		50		50			
10		50			50		
11		50				50	
12		50					50
13	50		25	25			
13A	40		20	20	20		
14	40		20	20		20	
15	40		20	20			20
16		50	25	25			
16A		40	20	20	20		
17		40	20	20		20	
18		40	20	20			20
19	25	25	25	25			
20	20	20	20	20	20		
21	20	20	20	20		20	
22	20	20	20	20			20
23	20		16	16	16	16	16
24		20	16	16	16	16	16
25	15	15	14	14	14	14	14

Table 2

Mean and Standard Deviation of Absolute and Excess Returns: Random EPS

In the following table, we document the annualised mean and standard deviation of both the absolute returns and the excess returns relative to the benchmark (the all-equity index). These statistics are reported for each of the different traders in 27 test cases for the simulations where the earnings are assumed to follow a random walk. In addition we document the mean and standard deviation for the absolute benchmark returns and the standard deviation of the differences between the actual and the fundamental price which is termed mispricing. Each Case represents a particular market structure with the returns and standard deviations corresponding to the traders that populate the Case considered. We also report the mean and standard deviation of the fundamental price (fair value) over the 300 Monte Carlo draws.

Average absolute return for different market structures								
	Fund (correct)	Fund (growth)	Mom (Short)	Mom (Long)	Contrarian	Index	Noise	Benchmark
Case 1	4.07%							4.07%
Case 2		4.09%						4.08%
Case 3	4.33%		3.86%					4.08%
Case 4	4.70%			3.17%				4.05%
Case 5	4.09%				4.08%			4.08%
Case 6	4.07%					4.07%		4.07%
Case 7	4.09%						4.07%	4.07%
Case 8		4.31%	3.88%					4.08%
Case 9		4.69%		3.25%				4.08%
Case 10		4.04%			4.14%			4.09%
Case 11		4.09%				4.08%		4.08%
Case 12		4.11%					4.08%	4.08%
Case 13	4.25%		4.14%	3.17%				4.07%
Case 13-A	4.18%		4.13%	3.25%	4.24%			4.07%
Case 14	4.26%		4.18%	2.97%		4.07%		4.07%
Case 15	4.27%		4.17%	2.97%			4.07%	4.07%
Case 16		4.25%	4.08%	3.38%				4.08%
Case 16-A		4.14'%	4.06%	3.48%	4.48'%			4.09%
Case 17		4.26%	4.14%	3.24%		4.08%		4.08%
Case 18		4.26%	4.13%	3.23%			4.08%	4.08%
Case 19	4.50%	4.32%	4.10%	3.29%				4.08%
Case 20	4.33%	4.21%	4.09%	3.37%	4.34%			4.08%
Case 21	4.54%	4.32%	4.15%	3.12%		4.08%		4.08%
Case 22	4.55%	4.34%	4.14%	3.13%			4.08%	4.08%
Case 23	4.37%		4.19%	2.74%	4.32%	4.04%	4.04%	4.04%
Case 24		4.28%	4.20%	2.97%	4.55%	4.08%	4.08%	4.08%
Case 25	4.35%	4.18%	4.15%	3.19%	4.38%	4.08%	4.08%	4.08%

Standard deviation of absolute return for different market structures									
	Fund (correct)	Fund (growth)	Mom (Short)	Mom (Long)	Contrarian	Index	Noise	Benchmark	Mispricing ($)
Case 1	0.60%							0.62%	0.42
Case 2		1.64%						1.70%	3.87
Case 3	6.61%		6.60%					6.77%	4.38
Case 4	4.73%			5.45%				5.16%	7.08
Case 5	0.39%				0.41%			0.40%	1.14
Case 6	0.62%					0.57%		0.60%	0.70
Case 7	4.63%						4.37%	4.60%	1.38
Case 8		7.07%	7.04%					7.23%	5.61
Case 9		5.31%		6.10%				5.79%	7.85
Case 10		1.01%			0.99%			0.99%	1.65
Case 11		1.69%				1.57%		1.66%	3.75
Case 12		5.09%					4.79%	5.05%	3.96
Case 13	3.49%		3.33%	3.77%				3.54%	3.67
Case 13-A	2.21%		2.15%	2.42%	2.79%			2.28%	2.83
Case 14	3.06%		2.83%	3.30%		2.87%		3.02%	3.48
Case 15	3.58%		3.31%	3.86%			3.35%	3.54%	3.54
Case 16		4.45%	4.29%	4.74%				4.52%	5.09
Case 16-A		3.39%	3.26%	3.54%	3.98%			3.42%	3.43
Case 17		3.83%	3.55%	4.04%		3.58%		3.77%	4.88
Case 18		4.28%	3.97%	4.51%			3.99%	4.21%	4.92
Case 19	3.86%	4.41%	3.79%	4.24%				4.01%	3.96
Case 20	2.74%	3.38%	2.83%	3.12%	3.51%			2.98%	2.80
Case 21	3.37%	3.94%	3.15%	3.63%		3.18%		3.35%	3.73
Case 22	3.86%	4.49%	3.61%	4.14%			3.63%	3.83%	3.78
Case 23	2.33%		2.11%	2.54%	3.01%	2.15%	2.14%	2.27%	3.41
Case 24		3.38%	2.85%	3.35%	3.84%	2.89%	2.90%	3.04%	3.51
Case 25	2.52%	3.27%	2.42%	2.76%	3.46%	2.44%	2.43%	2.57%	2.51

Table 2 -*Continue*

Average excess return for different market structures							
	Fund (correct)	Fund (growth)	Mom (Short)	Mom (Long)	Contrarian	Index	Noise
Case 1	0.00%						
Case 2		0.01%					
Case 3	0.25%		-0.20%				
Case 4	0.65%			-0.86%			
Case 5	0.01%				0.00%		
Case 6	0.00%					0.00%	
Case 7	0.02%						0.01%
Case 8		0.24%	-0.17%				
Case 9		0.63%		-0.81%			
Case 10		-0.04%			0.05%		
Case 11		0.01%				0.00%	
Case 12		0.03%					0.01%
Case 13	0.17%		0.08%	-0.88%			
Case 13-A	0.12%		0.07%	-0.79%	0.15%		
Case 14	0.19%		0.11%	-1.07%		0.01%	
Case 15	0.19%		0.10%	-1.07%			0.01%
Case 16		0.17%	0.01%	-0.69%			
Case 16-A		0.05%	-0.02%	-0.59%	0.37%		
Case 17		0.17%	0.07%	-0.82%		0.01%	
Case 18		0.17%	0.06%	-0.82%.			0.01%
Case 19	0.41%	0.22%	0.03%	-0.77%			
Case 20	0.25%	0.12%	0.01%	-0.68%	0.23%		
Case 21	0.45%	0.22%	0.08%	-0.92%		0.01%	
Case 22	0.46%	0.23%	0.07%	-0.92%			0.01%
Case 23	0.32%		0.16%	-1.26%	0.25%	0.01%	0.01%
Case 24		0.19%	0.12%	-1.07%	0.43%	0.01%	0.00%
Case 25	0.26%	0.09%	0.07%	-0.86%	0.27%	0.00%	0.00'%

Tracking errors for different market structures							
	Fund (correct)	Fund (growth)	Mom (Short)	Mom (Long)	Contrarian	Index	Noise
Case 1	0.02%						
Case 2		0.06%					
Case 3	0.26%		0.18%				
Case 4	0.46%			0.42%			
Case 5	0.04%				0.03%		
Case 6	0.03%					0.03%	
Case 7	0.22%						0.26%
Case 8		0.29%	0.20%				
Case 9		0.52%		0.46%			
Case 10		0.16%			0.15%		
Case 11		0.08%				0.08%	
Case 12		0.25%					0.28%
Case 13	0.14%		0.22%	0.38%			
Case 13-A	0.16%		0.14%	0.25%	0.59%		
Case 14	0.16%		0.20%	0.42%		0.15%	
Case 15	0.19%		0.24%	0.48%			0.27%
Case 16		0.19%	0.24%	0.42%			
Case 16-A		0.39%	0.17%	0.32%	1.24%		
Case 17		0.22%.	0.23%	0.45%		0.19'%	
Case 18		0.25%	0.26%	0.50%			0.34%
Case 19	0.57%	0.81%	0.23%	0.40%			
Case 20	0.32%	1.03%	0.16%	0.30%	0.85%		
Case 21	0.55%	0.92%	0.21%	0.43%		0.17%	
Case 22	0.63%	1.04%	0.24%	0.48%			0.29%
Case 23	0.38%		0.17%	0.38%	0.81%	0.11%	0.23%
Case 24		0.90%	0.21%	0.47%	1.25%	0.15%	0.27%
Case 25	0.27%	1.24%	0.17%	0.37%	1.18%	0.13%	0.25%

Table 3

Mean and Standard Deviation of Absolute and Excess Returns: Serially Correlated EPS

In the following table, we document the annualised mean and standard deviation of both the absolute returns and the excess returns relative to the benchmark (the all-equity index). These statistics are reported for each of the different traders in 27 test cases for the simulations where the earnings are assumed to be serially correlated. In addition we document the mean and standard deviation for the absolute benchmark returns and the standard deviation of the differences between the actual and the fundamental price which is termed mispricing. Each Case represents a particular market structure with the returns and standard deviations corresponding to the traders that populate the Case considered. We also report the mean and standard deviation of the fundamental price (fair value) over the 300 Monte Carlo draws.

	Average absolute return for different market structures							
	Fund (correct)	Fund (growth)	Mom (Short)	Mom (Long)	Contrarian	Index	Noise	Benchmark
Case 1	4.09%							4.06%
Case 2		4.24%						4.20%
Case 3	4.35%		3.85%					4.06%
Case 4	4.70%			3.24%				4.04%
Case 5	4.31%				3.84%			4.06%
Case 6	4.12%					4.08%		4.06%
Case 7	4.14%						4.08%	4.06%
Case 8		4.42%	4.11%					4.21%
Case 9		4.66%		3.73%				4.20%
Case 10		3.95%			4.65%			4.29%
Case 11		4.28%				4.22%		4.20%
Case 12		4.30%					4.22%	4.20%
Case 13	4.23%		4.17%	3.37%				4.06%
Case 13.A	4.26%		4.19%	3.70%	4.11%			4.13%
Case 14	4.23%		4.23%	3.25%		4.09%		4.06%
Case 15	4.24%		4.22%	3.24%			4.09%	4.06%
Case 16		4.23%	4.35%	4.06%				4.18%
Case 16.A		3.95%	4.41%	4.27%	5.54%			4.30-/.
Case 17		4.21%	4.44%	4.07%		4.21%		4.18%
Case 18		4.22%	4.43%	4.06%			4.21%	4.18%
Case 19	5.10%	2.95%	4.28%	3.79%				4.16%
Case 20	4.72%	3.29%	4.32%	4.03%	4.80%			4.25%
Case 21	5.20%	2.73%	4.35%	3.72%		4.19%		4.16%
Case 22	5.20%	2.77%	4.34%	3.70%			4.20%	4.16%
Case 23	4.55%		4.29%	3.27%	4.15%	4.13%	4.11%	4.13%
Case 24		3.81%	4.49%	3.88%	5.37%	4.29%	4.28%	4.29%
Case 25	4.87%	2.66%	4.43%	4.06%	4.89%	4.26%	4.26%	4.26%

	Standard deviation of absolute return for different market structures								
	Fund (correct)	Fund (growth)	Mom (Short)	Mom (Long)	Contrarian	Index	Noise	Bench mark	Mispricing ($)
Case 1	1.02%							1.05%	0.66
Case 2		2.52%						2.58%	15.35
Case 3	6.45%		6.63%					6.81%	4.35
Case 4	4.59-/.			5.51%				5.15%	6.79
Case 5	0.88%				0.99%			0.87%	2.95
Case 6	1.08%					0.99%		1.05%	1.17
Case 7	5.03%						4.80%	5.11%	1.68
Case 8		7.38%	7.42%					7.71%	15.36
Case 9		5.53%		6.21%				5.99%	16.28
Case 10		1.98%			1.40%			1.53%	5.86
Case 11		2.68%						2.56%	14.94
Case 12		5.91%					0.62%	5.96%	15.02
Case 13	3.73%		3.60%	4.08%				3.87%	3.60
Case 13.A	2.48%		2.48%	2.70%	3.91%			2.64%	3.23
Case 14	3.20%		2.99%	3.49%				3.24%	3.43
Case 15	3.82%		3.59%	4.20%			0.67%	3.88%	3.48
Case 16		4.61%	4.35%	4.65%				4.67%	14.98
Case 16.A		3.62%	3.14%	3.29%	5.45%			3.33%	7.70
Case 17		4.10%	3.69%	4.01%				4.00%	1475
Case 18		4.64%	4.21%	4.58%			4.31%	4.57%	1477
Case 19	5.15%	6.99%	3.95%	4.33%				4.23%	26.85
Case 20	2.50%	5.44%	2.85%	3.04%	4.35%			3.02%	4.48
Case 21	4.82%	6.68%	3.28%	3.68%				3.54%	6.23
Case 22	5.60%	7.68%	3.83%	4.31%			0.90%	4.14%	6.27
Case 23	2.66%		2.47%	2.90%	4.27%		0.56%	2.67%	4.12
Case 24		4.65%	2.93%	3.29%	5.88%		3.01%	3.16%	6.48
Case 25	2.86%	6.51%	2.50%	2.72%	5.68%		2.55%	2.68%	4.45

Table 3 -*Continue*

Average excess return for different market structures							
	Fund (correct)	Fund (growth)	Mom (Short)	Mom (Long)	Contrarian	Index	Noise
Case 1	0.03%						
Case 2		0.05%					
Case 3	0.32%		-0.18%				
Case 4	0.67%			-0.79%			
Case 5	0.24%				-0.21%		
Case 6	0.06%					0.02%	
Case 7	0.08%						0.04%
Case 8		0.23%	-0.06%				
Case 9		0.48'%		-0.46%			
Case 10		-0.35%			0.36%		
Case 11		0.07%				0.02%	
Case 12		0.10%					0.04%
Case 13	0.17%		0.12%	-0.67%			
Case 13.A	0.13%		0.06%	-0.42%	-0.05%		
Case 14	0.17%		0.17%	-0.79%		0.04%	
Case 15	0.18%		0.16%	-0.80%			0.04%
Case 16		0.05%	0.18%	-0.11%			
Case 16.A		-0.34%	0.11%	-0.03%	1.20%		
Case 17		0.02%	0.26%	-0.11%		0.04%	
Case 18		0.03%	0.26%	-0.11%			0.04%
Case 19	0.95%	-1.21%	0.13%	-0.36%			
Case 20	0.49%	-0.96%	0.07%	-0.21%	0.51%		
Case 21	1.02%	-1.42%	0.19%	-0.43%		0.04%	
Case 22	1.03%	-1.39%	0.19%	-0.45%			0.05%
Case 23	0.41%		0.16%	-0.83%	-0.01%	0.01%	-0.01%
Case 24		-0.48%	0.20%	-0.40%	1.04%	0.00%	0.00%
Case 25	0.63%	-1.59%	0.17%	-0.18%	0.59%	0.00%	0.01%

Tracking errors for different market structures							
	Fund (correct)	Fund (growth)	Mom (Short)	Mom (Long)	Contrarian	Index	Noise
Case 1	0.06%						
Case 2		0.12%					
Case 3	0.62%		0.20%				
Case 4	0.71%			0.51%			
Case 5	0.26%				0.29%		
Case 6	0.09%					0.06%	
Case 7	0.37%						0.36%
Case 8		0.76%	0.31%				
Case 9		0.79%		0.45%			
Case 10		0.75.			0.76%		
Case 11		0.25%				0.13%	
Case 12		0.51%					0.39%
Case 13	0.28%		0.29%	0.40%			
Case 13.A	0.44%		0.17%	0.25%	1.66%		
Case 14	0.27%		0.26%.	0.42%		0.20%	
Case 15	0.33%		0.31%	0.52%			0.34%
Case 16		0.37%	0.35%	0.38%			
Case 16.A		1.11%	0.20%	0.29%	4.24%		
Case 17		0.43%	0.34%	0.40%		0.24%	
Case 18		0.48%	0.39%	0.47%			0.40%
Case 19	3.30%	4.33%	0.30%	0.36%			
Case 20	1.79%	3.61%	0.18%	0.26%	2.67%		
Case 21	3.33%	4.53"	0.28%	0.38%		0.21%	
Case 22	3.73%	5.21%	0.33%.	0.46%			0.36%
Case 23	1.02%		0.21%	0.40%	1.92%	0.15%	0.25%
Case 24		2.74%	0.24'%	0.39%	4.70%	0.17%	0.28%
Case 25	2.39%	4.96%	0.20%	0.33%	4.43%	0.14%	0.26%