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Abstract

I construct a behavioral model of asset pricing in which agents choose whether to base their expectations on chartist or fundamental forecasts. I simulate the model in order to test its efficacy in explaining the moments and time series properties of the FTSE All-Share index, and find that the model cannot be rejected as the data generating process.

JEL classification: G12, D03

Key words: Behavioral finance; Asset pricing

1 Introduction

In a recent paper, Meenagh, Minford and Peel (2007) test an efficient markets model of the FTSE and conclude that,

> "the hypothesis of efficiency, if constructed to incorporate the possibility of extreme events, can mimic the behavior of the FTSE. It remains to be seen if the same is true of alternative hypotheses, such as behavioral finance"

In this paper, I respond to that challenge by showing that a simple behavioral model can account for all of the time series properties of the FTSE All-Share Index.

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There is, in fact, widespread evidence that financial market practitioners make use of a variety of forecasting techniques, both technical analysis and fundamental analysis, in forming their investment decisions. Furthermore, in contradiction to the efficient markets hypothesis (EMH), evidence suggests that technical analysis is often profitable (see Park and Irwin (2007) for a review of the literature).

Behavioral finance theory accounts for this phenomenon through the presence of an additional source of risk in the market, often known as noise trader risk (see De Long et al (1990) for the seminal account). This inefficiency is caused by traders using simple, heuristical forecasting rules in preference to basing their expectations on an analysis of the fundamentals. Such forecasting rules may be self-reinforcing because the inefficiency they create may make their use more profitable than fundamental analysis.

Behavioral finance models have been shown to be effective in accounting for many of the famous puzzles in the finance literature. For example, Benartzi and Thaler (1995) show how loss aversion can explain the equity premium puzzle. However, to date, there has never been an attempt to test whether behavioral models can explain all of the features of an asset price series.

2   A Behavioral Asset Pricing Model

The model that I test is a development of the behavioral model used by De Grauwe and Grimaldi (2006) (henceforth, DGG) to model the exchange rate. I have chosen this model for two reasons. Firstly, it models noise trader risk explicitly, using a simple and general forecasting rule. Secondly, DGG use the model to explain the entire time series properties of an asset market rather than particular anomalies (though they consider the exchange rate market, and only make general comparisons to the dynamics of real world markets, rather than providing a full test).

In this model, heterogeneous agents make a portfolio choice in order to maximize their utility. However, the expectations on which they base their choice are not rational in the conventional sense, but based on one of two simple heuristical rules. Agents choose to base their expectations either on a fundamental model of the asset price, or on a technical (or chartist) analysis of past asset price movements. Their choice of which rule to apply depends upon the past profitability of the rules. In this way the model can be viewed as being evolutionarily rational.

2.1 Details and Characteristics of the Model

Heterogenous agents choose the portfolio of risky and riskless assets that maximizes their utility. Utility is a mean-variance function of wealth, based on the forecasting rule, i, that the agent employs:

$$U\left(W_{i,t+1}\right) = E_{i,t}\left(W_{i,t+1}\right) - \frac{1}{2}\mu V_{i,t}\left(W_{i,t+1}\right) \tag{1}$$

Agents face the wealth constraint:

$$W_{i,t+1} = P_{t+1}d_{i,t} + (1+r)(W_{i,t} - P_t d_{i,t}) \tag{2}$$

where μ is the coefficient of risk aversion, $d_{i,t}$ is the quantity of the risky asset held from period t until $t+1$, and $(W_{i,t} - P_t d_{i,t})$ is therefore the holdings of the risk free asset.

It is straightforward to derive that the optimal holding of the risky asset is equal to its risk adjusted expected excess return. By aggregating across all agent types I get the market demand function. Setting this equal to the supply of the asset, which is normalized to zero, gives rise to the market clearing price in period t:

$$P_t = \frac{\displaystyle\sum_{i=f,c} \frac{w_{i,t} E_{i,t}(P_{t+1})}{\mu V_{i,t}(P_{t+1})}}{(1+r)\displaystyle\sum_{i=f,c} \frac{w_{i,t}}{\mu V_{i,t}(P_{t+1})}} + \eta_t \qquad\qquad \eta_t \sim iid(0,\sigma_\eta) \tag{3}$$

where $w_{i,t}$ is the proportion of people who use forecasting rule i in time period t. η_t is a white noise pricing error.

The essence of the model is the forecasting rules that individuals use. They choose between two possible rules. The fundamentalist rule forecasts that the market price will move towards its fundamental value, P^*, during the next period, unless it is already close to the fundamental, defined by the bounds $\pm C$:

$$\begin{aligned} E_{f,t}\left(P_{t+1}\right) &= P_{t-1} - \psi(P_{t-1} - P_{t-1}^*) \qquad where(P_{t-1} - P_{t-1}^*) > C \tag{4}\\ &= P_{t-1} \qquad\qquad\qquad\qquad where(P_{t-1} - P_{t-1}^*) \leqslant C \tag{5} \end{aligned}$$

We can think of C as a band of uncertainty around the fundamental price. It is only when the gap between the actual asset price and its fundamental value is large enough (greater than C) that fundamentalists take an active trading position.

The chartist rule, on the other hand, simply extrapolates the previous movements of the market rate:

$$E_{c,t}(P_{t+1}) = P_{t-1} + \beta \sum_{j=1}^{\infty} \rho^{j-1}(1-\rho)\Delta P_{t-j} \tag{6}$$

Neither of these expectations forming processes is rational in the conventional sense. The contention of behavioral economics is that the level of complexity in the real world makes it impossible for agents to fully comprehend the markets in which they trade. In such a world, the ex-ante use of simple rules such as those in this model may constitute a best response. However, even in a complex world, the ex-post assessment of trading rules is relatively cheap. Some limited rationality is therefore imposed in the form of an evolutionary switching procedure based on the ex-post profitability of the competing rules. Agents are assumed to assess the ex-post risk adjusted profitability, $\Pi_{i,t}'$, of each of the forecasting rules and then select the rule that they will use in the next period. Hence, the proportions of agents using each of the rules develops according to the following identities:

$$w_{f,t} = \frac{\exp(\gamma \Pi_{f,t}')}{\exp(\gamma \Pi_{f,t}') + \exp(\gamma \Pi_{c,t}')} \tag{7}$$

$$w_{c,t} = \frac{\exp(\gamma \Pi_{c,t}')}{\exp(\gamma \Pi_{f,t}') + \exp(\gamma \Pi_{c,t}')} \tag{8}$$

$$\Pi_{i,t}' = \Pi_{i,t} - \mu \sigma_{i,t}^2 \tag{9}$$

$$\Pi_{i,t} = [P_{t-1} - (1+r)P_{t-2}].\text{sign}\left[E_{i,t-1}(P_t) - (1+r)P_{t-1}\right] \tag{10}$$

$$\sigma_{i,t}^2 = \sum_{j=1}^{\infty} \rho^{j-1}(1-\rho)\left[E_{i,t-j-1}(P_{t-j}) - P_{t-j}\right]^2 \tag{11}$$

where $w_{f,t}$ is the proportion of agents at time t using the fundamentalist rule and $w_{c,t}$ is the proportion using the chartist rule. γ is a parameter measuring the intensity of revision of the forecasting rules. If $\gamma = 0$ then agents never change the forecasting rule that they use, and exactly half the population uses each rule. As γ approaches infinity all agents switch immediately to the rule that was most profitable in the preceding period. For all intermediate values agents switch between rules, but only sluggishly. This suggests some form of status quo bias, as suggested by Tversky and Kahneman (1974).

The tension between the simple heuristical rules produces the type of complex dynamics that are characteristic of many asset price series in the real world: fat tails, excess kurtosis and GARCH properties.

3 The Test Procedure and Data

We can think of the fundamental price on which fundamentalists base their expectations as being akin to a rational expectation of the asset price. In other words, it is a discounted sum of the future cashflows arising from ownership of the asset. In the case of equities, this is equivalent to the discounted sum of future profits.

I can, therefore, use the historical UK profits series as a basis for determining the fundamental value of the FTSE. Given this fundamental value, I can then test whether this model could have produced the historical FTSE time series. Figures 1 and 2 present the FTSE real quarterly returns and the first differences of the log of the UK profits series. They also report the estimated population moments for each series and the most parsimonious representation of the series, selected using the Hannan-Rissanen procedure with Schwartz selection criterion.

In order to test the model's ability to account for the empirical facts, I make use of the methodology adopted by Meenagh, Minford and Peel (2007). I begin by taking 50,000 bootstraps of the UK profits series and discount them to provide possible realizations of the fundamental value of the FTSE. I then stochastically simulate the model with each of these potential realizations of the fundamental. In this way, I derive 50,000 stochastic simulations of the FTSE series under the null hypothesis that the model is true.

I then use the distribution of the moments and time series properties from these simulations to construct 95% confidence intervals. If I find that the moments and time series properties of the actual FTSE series lie outside the confidence intervals then I can reject the null hypothesis that the model is true. Conversely, if the properties of the actual FTSE lie within the confidence bounds, then I cannot reject the model. I also employ a joint test of all the moments and GARCH parameters.

The model has a number of parameters. Of these, only the coefficient of risk aversion can be estimated independently of the model. I, therefore, use a search algorithm to find the best-fitting values for the behavioral parameters and the standard deviation of the pricing shock (subject to reasonable restrictions).

4 The Results

The search algorithm gives rise to the following parameterization:

ψ	β	ρ	γ	μ	C	σ_η
0.425	0.99	0.2	3.75	1.0	0.5	0.025

Table 1 summarizes the moments and time series properties of the FTSE simulations from the model and compares them to the actual data. As can be seen, in each case the actual data falls within the confidence bounds produced by the model simulations. I, therefore, cannot reject the behavioral model as the data generating process behind the FTSE.

I also use a Wald test of all the moments and properties. This test, proposed by Minford, Theodoridis and Meenagh (2007), is based on the Mahalanobis distance. Figure 3 shows the distribution of the test statistic for the simulated series, and the dashed line shows the value for the actual historical FTSE. Unsurprisingly, given that the model matches every individual moment, the model is also within the 95% bounds for the joint test. In fact the joint test yields a p-value of 0.46994, and a likelihood value of 6.66.

5   Conclusions

I have shown that a simple behavioral finance model can account for all of the dynamic properties of the FTSE. Profit-seeking switching between alternative heuristical forecasting rules produces complex, even chaotic, dynamics which are consistent with the FTSE series. The model involves a straightforward profits process but complex and inefficient market behavior.

On the other hand, Meenagh, Minford and Peel (2007) have shown that an efficient market coupled with a complex profits process can also account for the FTSE time series.
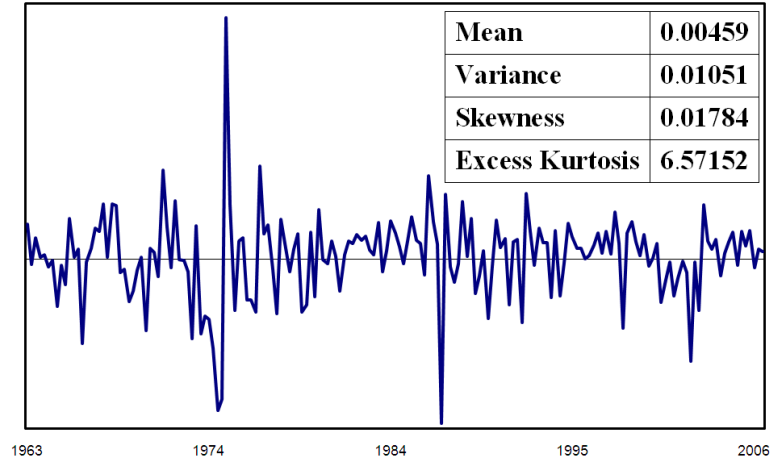
The implications of these two explanations are starkly different. If we accept the first then there is a source of inefficiency in equity markets, in the form of noise trader risk, and that might justify intervention in the market to mitigate that risk. If we accept the second then asset prices reflect the true riskiness of asset ownership.

Unfortunately, on the basis of the present test, we cannot reject either account as the basis for the FTSE.

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Fig. 1. FTSE real quarterly rates of return, estimated population moments, and parsimonious time series representation:

Mean	0.00459
Variance	0.01051
Skewness	0.01784
Excess Kurtosis	6.57152

$$\Delta(\ln[\text{real } FTSE_t]) = \underset{(0.0064)}{0.0080} + u_t$$
$$\underset{(std\ error)}{}$$

$$\sigma^2_{u_t} = \underset{(0.0011)}{0.0016} + \underset{(0.0795)}{0.1983}u^2_{t-1} + \underset{(0.1774)}{0.6343}\sigma^2_{u_{t-1}}$$

Fig. 2. Rate of change of real quarterly profits, estimated population moments, and parsimonious time series representation:

Mean	0.00759
Variance	0.00366

Skewness	0.17692
Excess Kurtosis	1.40859
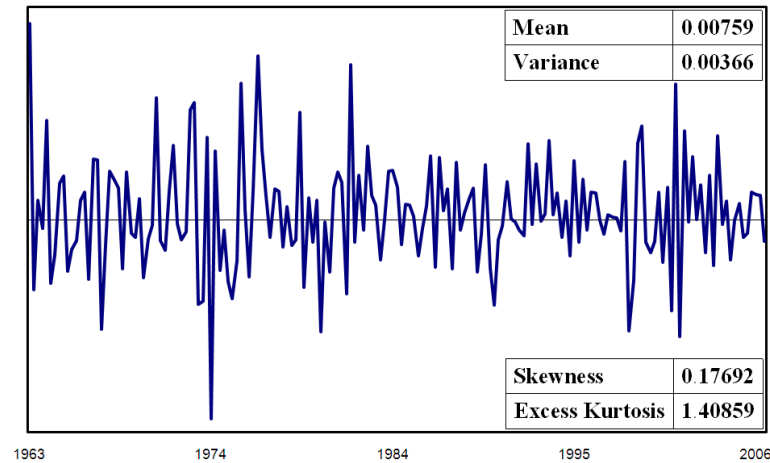
$$\Delta(\ln[\text{real } profit])_t = \underset{(0.004325)}{0.008435} - \underset{(0.070986)}{0.260975}\Delta(\ln[\text{real } profit])_{t-1} + u_t$$
$$\underset{(std\ error)}{}$$

Table 1

Moments and time series properties of the simulated and actual FTSE series

	ACTUAL	Behavioral Model	
	FTSE	Lower	Upper
		2.5% limit	2.5% limit
Mean	0.0046	-0.1403	0.1389
Variance	0.0105	0.0009	0.0155
Skewness	0.0178	-1.3116	2.2961
Kurtosis	9.5715	1.9121	14.1262
Trend	0.0080	-0.1517	0.1459
ARCH constant	0.0016	0.0000	0.0016
ARCH	0.1983	0.0000	0.9956
GARCH	0.6343	0.0000	0.9419

Fig. 3. Distribution of simulated normalized Mahalanobis distances