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ABSTRACT

The proposition that a relatively new technology such as a Differential Evolutionary Algorithm (DEA) can violate the weak form of the Efficient Market Hypothesis is tested using daily data from the Australian share market from 2000 until 2008. An option trading strategy based on forecasts from a DEA is shown to perform better than a buy and hold strategy over parts of the sample space and, on average, over all of it. Speculators may make supernormal profits from new methodologies however such profits are unlikely to be sustained.

Keywords: differential evolutionary algorithm, market efficiency, speculation and arbitrage

Classification System for Journal Abstracts: G14, G17

1. INTRODUCTION

The earliest published work on efficient markets was undertaken by Bachelier in 1900 who proposed that speculation should be a 'fair game' inasmuch as expected profits to the speculator should be zero. This proposition was developed by Fama (1969) who formalised such fair game theories generally as:

$$E(\tilde{p}_{j,t+1}|\varphi_t) = [1 + E(\tilde{r}_{j,t+1}|\varphi_t)]p_{jt} \qquad (1)$$

where the tildes denotes random variables at t, $\tilde{p}_{j,t+1}$ is price of j in $t+1$, $\tilde{r}_{j,t+1}$ is a one period per cent return similarly sub-scripted and φ_t is information at t. It follows φ_t is fully utilised (or fully reflected) in determining next period price. Fama extended theory beyond the fair game model and, pertinent to this study, formalised the sub-martingale version of (1):

$$E(\tilde{p}_{j,t+1}|\varphi_t) \geq p_{jt} \text{ (or } E(\tilde{r}_{j,t+1}|\varphi_t) \geq r_{jt}). \qquad (2)$$

This extension of theory has an important property, derived from the non-negativity property of changes in sub-martingales, that no trading rule based only on φ_t can produce greater profits than could be achieved with a simple "buy and hold" strategy in security *j*. In addition, Harry Roberts, a Chicago economist, introduced the concepts[1] of *weak form*, *semi-strong form* and *strong form* tests of market efficiency. *Weak form* is where φ_t is historical prices, *semi-strong form* includes all publically available information and *strong form* includes publically and privately held information.

Grossman and Stiglitz (1980) argue that markets can never be efficient because if they were there would be no incentives for traders to gather information hence prices would not reflect any pertinent information and markets would break down. In their words "... the price system makes publically available information obtained by informed individuals to the uninformed. In general, however, it does this imperfectly; this is perhaps lucky, for were it to do it perfectly, an equilibrium would not exist." Grossman and Stiglitz do not explain the types of speculative behaviour they have in mind however it is easy to conjecture. One possibility is that traders might systematically monitor fundamental factors effecting price and take positions in the physical market or futures market reflecting their new information. For example, information on Brazilian weather might result in increased orders for coffee or new short or long hedge positions. Alternatively, a hedge fund might undertake 'data mining' on such a scale there is a flow of 'nuggets' of new information sufficient to make the activity rewarding. Malkiel (2003) argued

[1] Fama attributes Harry Roberts with initially categorizing the types of market efficiency in a footnote in his 1969 paper. A possible reference (not viewed by the author) is H. V. Roberts, "Statistical versus clinical Prediction of the Stock Market" an unpublished paper presented at the Seminar on the Analysis of Security Prices, University of Chicago, May 1967.

predictable patterns in prices can exist however seem to disappear when they are published in the finance literature and, presumably, become widely arbitraged. He used the January effect as an example of one of these ‘nuggets’ which disappeared shortly after publication of Haugen and Lakonishok’s book *The Incredible January Effect* in 1988. A third possibility, examined in this study, is that advances in forecasting techniques might be exploited on a large scale using publically available price data as a sort of ‘low grade ore’ from which enough information about the future can be extracted to make it worthwhile. That is, new methodologies, products of research being undertaken elsewhere, may reveal market inefficiency, at least in the short term.

In this paper it is argued weak form inefficiency may be detected, at least temporarily, if a new methodology is developed suitable for forecasting prices and, further, that the Differential Evolutionary Algorithm (DEA) that emerged in the 1990s (Storn and Price, 1997) was such a development. In this study, a DEA is used to examine the efficiency of the index for the top 200 stocks in the Australian share market (ASX200) using daily closing prices between Jan 6 2000 and Feb 1 2008.

A little known methodology and distant market are selected to maximise the chances the uptake of the new methodology by speculators would occur over a long enough period to be observed. The DEA has virtually no profile in the finance and broader economics literature and the Australian market is a long way from global financial hubs such as New York and London in terms of kilometres, currency, time zone and, possibly, culture.

Risk-adjusted returns from a daily trading strategy based on forecasts from a DEA are compared with those from a buy and hold strategy over the same period. Evidence is found that the Australian Stock market was weak form inefficient at times in the sample period and, on average, weak form inefficient for the whole period.

In the next section, the DEA and forecasting procedure are briefly described and, in Section 3, the performance of the DEA as a simple forecasting tool, ignoring transaction costs, is reported. In Section 4, the financial results from a trading strategy that uses the DEA with non-zero transaction costs are compared with returns from a buy and hold strategy in the ASX200. Discussion and conclusions are provided in Section 5.

2. USING A DIFFERENTIAL EVOLUTIONARY ALGORITHM (DEA) TO OBTAIN FORECASTS

A DEA is used to obtain values for the coefficients, $\tilde{\alpha}_i$*(i=1,2)* in the forecasting equation:

$$xjo_{t+1}^{F} = \tilde{\alpha}_1 xjo_t + \tilde{\alpha}_2 xsp_t \qquad (3)$$

where F denotes the forecast in the next period, the tildes indicate the variable character of the coefficients over time, xjo is per cent changes in daily closing values of the ASX200 and xsp is per cent changes in daily closing values of the Standard & Poors 500 index from the New York market. Ignoring daylight saving, New York closes four hours before Sydney opens and the time subscript, t, refers to closing bell in Sydney on say, Wednesday, and simultaneously, the closing bell on Tuesday in New York; the forecast is for t+1, closing bell on Thursday in Sydney.

Weekends are assumed not to exist and values for weekday public holidays, which are different between Sydney and New York, are the average of adjacent trading days.

The DEA obtains coefficient values for each period by solving:

$$\min_{\alpha} J = MOTAD(xjo_{t+1} - \tilde{\alpha}_1 xjo_t - \tilde{\alpha}_2 xsp_t) \quad (4)$$

where MOTAD refers to mean of total absolute deviation. Price data from day one, *t*=1, are applied to Eq. 3 to obtain 25 forecasts for *t*=2 using 25 initial values each for α_1 and α_2 chosen randomly from a uniform distribution such that $-1 < \alpha_i < 1$, for *i* = 1 or 2. These forecasts are then used to get 25 new values of α_1 and α_2 that are used in the next period forecasts. These new coefficient values are based on values of α that worked well in the preceding generation and on ranking and crossover procedures from the DEA. New values of α_1 and α_2 are then applied to *t*=2 data to obtain the forecast for *t*=3 and so on until *t*=1,999, resulting in 1,998 forecasts in all. Twenty five values of α_1 and α_2 are used in each 'generation' resulting in 25 forecasts for each period from *t*=1 to *t*=1,999. The 25 forecasts are averaged for each value of *t* and the whole experiment is repeated 500 times to remove noise by averaging the forecasts from each 'run'. A description of the DEA is provided in the Appendix.

Five differencing schemes for the price data are considered. The logic is that forecasting power might be located in particular parts of the frequency spectrum of the price series and these parts might be enhanced through different types of differencing. The following differencing is undertaken: no differences, conventional first differences, first percentile differences, first differences followed by additional percentage differencing and conventional second differences. First percentile differences perform best, conventional differencing is next best, no differencing next best and any form of double differencing performs badly. The results reported are all based on first percentile differences.

Finally, the algorithm starts its run on 6th January 2000 but does not record any forecasts until 2nd June 2000 to allow possible 'learning' in the early part of the run. The run stops at 1st February 2008.

3. RESULTS OF FORECASTING

The first test undertaken uses Theil's Inequality Coefficient (Theil, 1966) where the coefficient is defined (Koutsiannis, 1981):

$$U = \sqrt{\frac{\sum(P_i - A_i)^2/n}{\sum A_i^2/n}} \quad (5)$$

where P and A refer to predicted and actual price *changes* respectively. U is bounded, $0 \leq U \leq \infty$, and, if $U = 0$, forecasts are perfect and if $U > 1$ the model predicts worse than a naive forecast. That is, worse than the rule $price_{t+1} = price_t$. The result for the forecasts from the DEA is $U = 2.4$ which is not a good start. However, Theil's U statistic can be decomposed to reveal sources of variation in errors. U_m measures bias proportion, $U_s$measures variance proportion and U_c measures covariance proportion where $U_m + U_s + U_c = 1$. The results for these measures follow:

$$U_m = \frac{(\bar{P}-\bar{A})^2}{\sum(P_i-A_i)^2/n} = 0.00 \tag{6.1}$$

$$U_s = \frac{(S_P-S_A)^2}{\sum(P_i-A_i)^2/n} = .76 \tag{6.2}$$

$$U_c = \frac{2(1-r_{PA})S_P S_A}{\sum(P_i-A_i)^2/n} = .24 \tag{6.3}$$

where S_P and S_A are the standard deviations of P and A respectively and r_{PA} is the correlation coefficient between predicted and actual changes. More than three quarters of variation in errors arises from variance errors, U_s. This is consistent with the DEA forecasting the direction of change reasonably well and not inconsistent with the market having weak form inefficiency providing the trading rules used to test the hypothesis exploit predicted directions of price changes rather than their magnitudes.

The DEA made 982 predictions of price rises and 1017 predictions of price falls where, over the sample, there are in fact 1085 rises and 914 falls. Of these, 54% of the predicted downward movements are correct and 51% of upwards movements. In total, 52% of the predictions of direction are correct. It is pertinent whether the DEA predicts bigger price movements better since these yield higher speculative returns. It turns out big price movements are predicted better than small ones. The first quartile of actual price movements by absolute size are predicted correctly 51% of the time while the fourth quartile, the biggest movements, are predicted correctly 58% of the time.

A strategy of using the predicted direction of price movements from the model to invest $1 in either short or long positions at close of business each day and holding the position for precisely 24 hours would yield an average return of 0.6 cents per day if the model forecast perfectly and transaction costs are ignored. Based on the actual forecasts from the DEA, the yield is 0.05 cents per day under the same assumptions.

4. COMPARING DEA RETURNS WITH TRANSACTION COSTS TO A BASELINE

Establishing a Baseline

The Sharpe Ratio, also called the Reward to Variability Ratio (RVAR), is:

$$RVAR_p = \frac{ar_p - ar_f}{\rho_p} \qquad (7)$$

where $ar_p$is the portfolio return, ar_f is the risk free rate and ρ_p is the standard deviation of the portfolio return (Sharpe, 1966). The annual return from buying and holding the ASX200 over the sample period is calculated for the RVAR measure by multiplying the average daily return, 0.0348%, by 252 and turns out to be 8.77% p.a. ignoring transaction costs, which would be minimal, and dividends. The risk free rate is the 90 day Bank Accepted Bill rate from the Reserve Bank of Australia website which averages 5.7% over the period. The annualised standard deviation, ρ_p, is found by dividing the standard deviation of the nominal daily return by $\sqrt{1/252}$. It is 13.9%. $RVAR_p$ is 0.24. Incorporating dividends, assumed for simplicity to be risk free, increases this ratio to 0.44.

DEA Trading Performance

Predicted directions of price movements from the DEA are used in an option trading strategy with either a call or put being purchased at close of business each day and closed out after 24 hours. Transaction costs such as brokerage and spreads were decided after discussions with individuals working in option brokering and market making firms. In this regard, a diversity of views emerged from which it was at least clear that whether hypothetical traders are members of the public, market makers or brokers is important. In the end, a conservative assumption, supposedly corresponding to an upper estimate of the costs that would be incurred by a professional private trader, is made. Costs are assumed to be 0.5% to open a position and the same amount to close it, or one per cent per day with our strategy. In fact, a rational trader would not be so mechanical. If the model predicted a number of consecutive daily price movements in the same direction then several days might pass with no transactions being undertaken since there would be no need to change positions. This halves the cost of transacting so average daily transaction costs are set at 0.5%.

Daily volatility is measured for two weeks prior to each trading day and interest rates set to 5.7%. Option contracts are assumed to have 60 days to maturity and strike prices are set one per cent below spot prices at the time the position is taken. This information is used to solve Black and Scholes' option valuation formula (Cox & Rubenstein, 1985) to obtain returns from the strategy. Black and Scholes's formula has been criticised as being biased however it is widely used and has its supporters (Backus et al., 1997) and we believe the forecasts it provides here are accurate enough for our purposes. An annualised net return of 126% with a standard deviation of 228% is achieved. The RVAR value is 0.53, higher than the buy and hold strategy result of 0.44 indicating weak form inefficiency over the sample period. The cumulative percentage return from the option strategy, net of transaction costs, is reported in Figure 1:

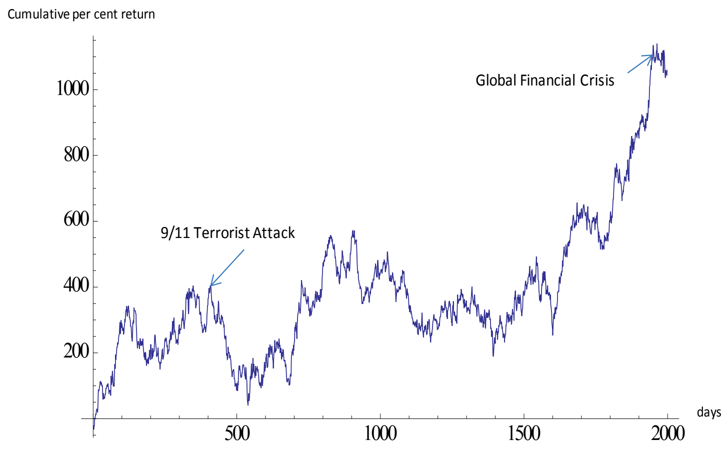

Figure 1: Option strategy cumulative financial per cent return net of transaction costs

The return is variable and rises relatively quickly over the first 300 observations (60 weeks), then performs poorly for a while then improves steadily as it enters the period of the global stock market boom until November 2007 when the Global Financial Crisis (GFC) started to impact on stock prices. Interestingly, the 9-11 Terrorist Attack, observation 441, and GFC (the last 30 observations) both reduce the forecasting power of the DEA dramatically. In Figure 2 cumulative net profits in points (or dollars) won are shown assuming the dollar value of the index is invested each day. Net profits, the 9-11 terrorist attack, GFC and ASX200 Index, showing general market movements, are shown together in this figure. The vertical axis is:

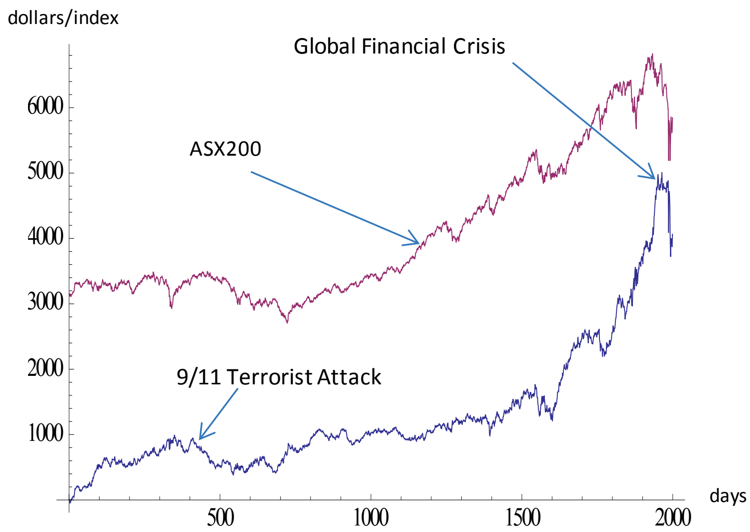

Figure 2: Cumulative Profits, the ASX200 index and the Global Financial Crisis and 911 Terrorist Attack in Market Points or Dollars

Extending the data series to the end of 2009 does not show any further gains from speculation. It appears the effectiveness of the DEA as a forecasting tool, at least in the Australian share market ends with the Global Financial Crisis.

The experiment is repeated under less conservative assumptions about transaction costs by halving them. This corresponds to 0.25% of the option premium to open or close a position and might be achievable by a broker or market maker. The annualised net return is 193%, the standard deviation is 228% and the RVAR value increases to 0.81.

5. DISCUSSION AND CONCLUSIONS

The DEA produces supernormal profits over parts of the sample period and, on average, over all of it and the forecasting performance wavers, being sometimes strong and sometimes weak. In this regard, forecasting performance appears to improve during periods of rising prices suggesting the DEA might act as a momentum trader. However, this is not the case. The DEA takes as many short positions as long positions during these boom periods. The other aspect of performance is the DEA not only does not perform well following the disasters of the 911 terrorist attack and setbacks from the GFC, it actually goes into reverse and starts losing money (Figure 2). A speculator would do well using the DEA in the aftermath of these events doing the exact opposite of what it suggested.

DeBondt and Thaler (1985) argue investors are subject to periods of optimism and pessimism that cause systematic components in price series in the long run. The results from our study indicate this may also be true of the very short run. During optimistic periods, speculators are likely to overvalue information leading to exploitable opportunities from both momentum and related downward corrections in the very short run. Schiller (2000) refers to ‘psychological contagion leading to irrational exuberance’ or a bandwagon effect which justifies contrarian strategies. The DEA would rapidly detect such non-random patterns in prices and, given its variable coefficients, adapt to them. One might also conjecture of waves of pessimism, such as following the 911 terrorist attack, have exactly the opposite effect and result in information being undervalued and that the DEA, which has ‘learned’ to operate during more optimistic times, loses its power as a forecasting tool. However, it is not clear why it loses money in this situation.

The study began with Grossman and Stiglitz’ conclusion that all markets must be weak form inefficient and has provided evidence that forecasts from a new methodology such as a DEA might support their theory. It remains to be shown just how general these results are and whether the inefficiency detected by the DEA reflects the power of algorithm or simply reflects its application to a particularly bullish period of stock market history.

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Appendix: Description of Differential Evolutionary Algorithm

Readers are referred to Storn and Price (1997) for a detailed description of a DEA that is similar to the one used in this study and a discussion of how these algorithms perform in a range of difficult algebraic tasks including a stochastic one. A brief description of the DEA using some of the terminology from Storn and Price's study is provided below.

Step 1 Agents α_i, ($i = 1{,}2$) are initialised by creating two populations x_{ij} ($j = 1{,}2..25$) where x_{ij} are uniformly distributed random numbers representing the *candidates* for α such that the search space is $-1 \leq x_{ij} \leq 1$.

Step 2 Run loop:

> *Loop step 1 Three candidates a, b and c are randomly chosen from x and combined as* $y_i = a_i + F(b_i - c_i)$ *where, after experimentation, F was set to 0.2.*
>
> *Loop step 2 'Crossover' occurs based on a user specified crossover probability, around 0.8, so 20% of y are randomly selected to be replaced by members of x.*
>
> *Loop step 3 A pair-wise comparison of the fitness of candidates in corresponding positions in x and y was undertaken and the fitter (best fit) of each pair added to a new vector z.*
>
> *Loop step 4 The z candidates were ranked on the basis of fitness.*
>
> *Loop step 5 Candidates in z are used in Eq. 3 to obtain forecasts for later analysis.*

The loop is repeated 1,998 times with *z* becoming *x* in each successive iteration and the fitness function and forecasting equation being updated with new data values and new α values until the end of the data series is reached in February 2008[2].

In fact, a fair bit of experimenting occurred with specifications and constraints. Crossover and scaling (F) were set at unity and 0.2 respectively after a number of alternative values were tested. The population size, or number of candidates, was also tested. Populations greater than 25 performed either the same or worse while smaller populations tended to give noisier results. Several ideas were explored to impose bounds on the candidates. First, candidates violating bounds were replaced with the values of the boundaries violated. Second, various penalties were applied to the objective function to discourage bounds violations. Finally, after neither of these specifications made any difference, the simple expedient of imposing the search space at initialisation and ignoring bound violations in later generations was adopted.

[2] All computations were undertaken using Wolfram's *Mathematica* Version 7.