Run length and the predictability of stock price reversals

Juan Yao*, Graham Partington*, Max Stevenson*

Abstract

In this paper, we develop a model for estimating the probability of stock price-reversals in the Australian stock market. We estimate time-varying probabilities of the transition from a run of positive (negative) price changes to a run of negative (positive) price changes. Models of the transition probabilities are estimated using daily and monthly data for the Australian All Ordinaries Price Index. Lagged price changes that are observed prior to the commencement of the run are found to lead to persistence in the run when they are of the same sign as the run. However, the probability of a reversal in the run increases when the lagged price changes are of the opposite sign. An increase in the number of runs observed in the previous twelve months for monthly data and the previous thirty days for daily data also increases the probability of price reversal. In predicting the length of individual price runs out-of-sample, forecasts from the estimated models were found to be less accurate than either those from the random walk model, or from those based on the proportion of runs of different lengths in the estimated sample.

JEL classification: G10; G14; E32; C14

Keywords: Survival analysis; Stock market predictability; Cox regression model.

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1. Introduction

In a recent paper, Partington and Stevenson (2001) developed models for estimating the time-varying probabilities of price reversals in the property market. Using a valuation index from the UK property market, they found their models offered predictive power. The probability profiles of the predicted lengths of runs before a reversal provided a perfect rank ordering when compared with the actual lengths of runs in a holdout sample. In their paper, they posed the question as to whether the predictive power attributed to a property index could be translated to prices of assets in financial markets.

The Efficient Market Hypothesis (EMH) states that financial asset prices (like security prices) fully reflect all information. This strong version of the hypothesis implies that trading costs are always zero. The more empirically testable, but weaker version states that prices well reflect information to the point where the marginal benefits from acting on information are less than the marginal costs (Jenson, 1978). In other words, for weak form efficiency to hold, it should not be possible to forecast price reversals from the history of a price series.

Although weak form efficiency of asset prices is a widely held view, this view has been subject to increasing challenges. While the earlier work of Fama (1965) and Fisher (1966) found evidence of predictability in daily, weekly and monthly returns from past returns, Fama (1970, 1991) concluded that the predictability found earlier suffered from a lack of statistical power. Further, the variance in returns explained by the variance in the expected returns was small enough to render the weak form hypothesis and, therefore constant expected returns, as a creditable model.
More recent studies have focussed on not just whether current returns are predictable from past returns, but whether other variables such as financial ratios (e.g. dividend yield) or macro-related variables enhance predictability. As well, the existence of well-known anomalies such as seasonals, earnings-to-price and price-to-book ratios, along with momentum and contrarian trading strategies for stock returns further empirically challenge the weak form of the EMH. On the other hand, if the EMH does hold then price changes are unpredictable and, are at best, random events.

The random nature of price changes has been discounted as a result of, and following the seminal empirical work of Lo and MacKinlay (1988). McQueen and Thorley (1991) showed that low (high) annual returns of NYSE stock portfolios tended to follow runs of high (low) returns in the post-war period. Furthermore, McQueen and Thorley (1994) argued that, for monthly real stock returns on the NYSE, the probability of observing an end to a run of high returns declined with the length of the run. Maheu and McCurdy (2000) used a Markov-switching model to sort the monthly returns of value-weighted NYSE stock portfolios from 1834 to 1995 into either a high-return stable state or a low-return volatile state and defined them as bull and bear markets, respectively. They showed that the probability that a run of price changes would end was dependent on the length of the run in both bull and bear markets.

The conflicting empirical evidence surrounding the validity of the weak form of the EMH, along with the reported success of predicting the probability and timing of price reversals in the property market forms the basis of the motivation for this study. By modelling state transition rates for reversing price runs, we determine whether predictability of price
reversals holds for a transaction index of financial assets like that for the property valuation index of the type used in the Partington and Stevenson (2001) study.

The paper is organized as follows. Section 2 discusses the design of the study and estimation techniques, while estimation technique and the approach to forecast evaluation are covered in Section 3. Section 4 provides detail on the data used in the study with the results presented and discussed in Section 5. Section 6 presents our conclusions.

2. Study design

The event of stock price reversals is of great interest to finance academics and practitioners alike. If reversals can be predicted using historical data, then the predictions can be used to establish specific rules for buying and selling securities with the objective of maximising profit and minimizing loss.

In this study we develop two models for estimating the time-varying probability of a price reversal of a specific sign. When an upward price movement turns down, we denote such a state transition as switching from an up-state to a down-state. The state transition from a down-state to an up-state captures a switch from a downward price movement to an upward one. Understanding the probability of a price reversal after an upward or downward run of prices is of fundamental interest in a decision to go long or short on an investment in a traded asset. The models developed in this study can be generally described as conditional duration models. They model state transition probabilities using a popular model from the family of models used for survival analysis. This model is the proportional hazard model as proposed by Cox (1972). It is the same model as that used in the Partington and Stevenson (2001) study.
Cox’s proportional hazard model has been extensively used in biometrics, criminology and other scientific fields in order to analyse survival times, as well as for duration studies in economics (see, Kiefer, 1988; Kalbfleisch and Prentice, 1980; Han and Hausman, 1990 and Tunali and Pritchett, 1997). Examples from the finance literature include the study of Crapp and Stevenson (1987) who used the proportional hazards model to identify the significant variables that contributed to the failure of Australian credit unions, while Partington et al. (2001) adopted it to predict return outcomes to shareholders of companies entering Chapter 11 bankruptcy. Lunde et al. (1998) also used the proportional hazards model to estimate the conditional probability of closure for mutual funds. In another study by Santarelli (2000), Cox’s regression model was utilized to analyse the duration of new firms in banking.

An advantage of using Cox’s proportional hazard model is that it utilizes a semi-parametric regression approach to estimate the time-varying probability that an irregularly spaced event (a price reversal) will occur. It is parametric whereby it specifies a regression model with a specific functional form, while non parametric in that it does not specify the exact form of, or place restrictions on the distribution of event times. This is in contrast to the Engle and Russel (1998) Autoregressive Conditional Duration (ACD) model which also measures the durations of transaction events that are assumed to be irregularly spaced. In representing the relationship between present and past durations, Engle and Russel (1998) define a duration process that is a multiplicative function of expected duration at time, t, and the standardized returns (residuals) from the model. These residuals are assumed to be independent and identically distributed. This parametric assumption many well be acceptable for the usual microstructure applications.
that employ the ACD model to explain price changes and the duration between them caused by price volatility resulting from varying levels of information flows. However, it is unlikely to be the case for modelling the lower frequency data used in this study. A further reason for Cox’s proportional hazard model being the preferred method for modelling price reversals is that it can be easily adapted to modelling price reversals in both directions. While this may be possible using the ACD model, applications only concentrate on duration changes in one direction. Model extensions to incorporate specific changes in either direction are not well documented nor are they obvious.

3. Estimation technique and forecast evaluation

3.1 Estimation technique

The behaviour of runs is modelled through their transition rates. A price state is classified as unchanged if successive price changes remain in either an up-state or a down state. However, when a run of upward price movements (up-state) turns down or when downward price changes (down-state) turns up, then we classify price as having undergone a state transition. It is the probability of such a state transition that forms the kernel of our model.

The price is define to be in an up-state when

\[ P_t - P_{t-1} > 0, \]

or the down-state when

\[ P_t - P_{t-1} < 0. \]

If a price change is equal to zero, the price state is defined as a continuation of the previous state.
The state transition probability, $P_{ij}(t, t+\delta t)$, defines the probability that a price in state $i$ at time $t$ will shift to state $j$ by time $t+\delta t$. This state transition probability is expressed as a rate by first defining the state transition probability as a rate of change over an interval, $\delta t$, and then taking limits to realise the transition rate:

$$r(t) = \lim_{\delta t \to 0} \frac{P_{ij}(t, t + \delta t)}{\delta t}.$$  \hspace{1cm} (1)

We model the transition rate, $r(t)$, as a multiplicative interaction between two components. The first component is the underlying transition rate. This is defined as the transition rate over the length of time that the price has remained in the same state, $r(t-t^*)$, since the time of entry into the starting state, $t^*$.

The second component captures the effect of other covariates on the transition rate at a particular transition time, $i$. Cox (1972) proposed the functional form of this component to be an exponential function which ensures a positive transition rate. Thus, for a vector of explanatory variables corresponding to transition time, $i$, namely $Z_i$, and a corresponding vector of coefficients, $\beta_i$, the second components is defined as $exp(Z_i \beta_i)$.

Assuming a multiplicative interaction between the underlying transition rate and the effect of covariates results in the following specification for the transition rate:

$$r(t) = r(t-t^*) e^{Z_i \beta_i}.$$  \hspace{1cm} (2)

The likelihood function defining the probability of transitions over times, $k$, when transitions occurred, is given by:

$$L(\beta) = \prod_{i=1}^{k} \frac{r(t-t^*) e^{Z_i \beta_i}}{\sum_{l \in R_i(t)} r(t-t^*) e^{Z_l \beta_i}} = \prod_{i=1}^{k} \frac{e^{Z_i \beta_i}}{\sum_{l \in R_i(t)} e^{Z_l \beta_i}}.$$  \hspace{1cm} (3)
It is notable that, due to the proportionality property of Cox’s (1972) model, the calculation of the $r(t-t^*)$ term in equation 2 results in a likelihood function without the underlying time-varying transition rate. This is the important semi-parametric feature of Cox’s (1972) method, as there is no need to assume a specific functional form specifying the relation between the transition probability and time.

The parameters of this model can be estimated by maximising the resultant log-likelihood function:

$$\log L(\beta) = \sum_{i=1}^{k} \sum_{j \in R_i(t)} \log \left[ \sum_{Z_i} e^{\beta Z_i} \right],$$

where $R_i(t)$ is defined to be the set of runs still to experience a transition at time, $t$, the time when a transition occurs. $k$ is the number of transition times observed.

It is necessary, however, to derive values of the underlying time-varying transition rate, $r(t-t^*)$, in order to forecast probability profiles of future transitions. Link (1984) derived a method for estimating the cumulative transition rates and, therefore $r(t-t^*)$, given estimates of $\beta$ and values for the covariates, $Z_i$.

The probability that a run will continue to a future time, $t$, is defined to be:

$$S(t) = P(T > t).$$

$T$ is a random variable that specifies the time to the next transition. It follows that $S(t)$ is the probability that the time to the next transition is greater than some future time, $t$. $S(t)$ can be calculated from the relation between it and the transition rate, $r(t)$, and is given by:

$$S(t) = \exp[- \int_0^t r(u)du].$$

1 The functional form of the underlying baseline hazard is not known, however, we can recover the point estimates at each event time.
Two models, one to capture price movements from an up-state to a down-state and the other from a down-state to an up-state, were estimated. Probability profiles that capture the time to the next transition were generated from these models.

There is little theory to guide the choice of the covariate variables. However, the rationale underlying duration modelling implies that the current state of price changes is correlated with the history of past price changes. Then, in the spirit of an autoregressive model, lagged price changes were chosen as covariates. Lagged price changes were used for up to 12 lags with monthly data, and up to 30 lags for daily data. A further covariate included in the models was the number of state transitions that occurred in the previous 12 months with monthly data, and thirty days with daily data. The motivation for including the number of state transition changes in the regression is to capture the volatility of the market, with an expectation that state transitions would be more likely in volatile periods. At least for the monthly data, these were the covariates used by Partington and Stevenson (2001) in their model specification. Further, we included dummy variables to indicate whether runs were observed in a bull or bear market. We could have extended the list of candidate variables, but we deliberately refrained from doing so. We purposely avoided the sort of search process that runs a high risk of capitalizing on chance.

The probability of state transitions may depend on market conditions. Therefore, in the analysis of monthly prices, a dummy covariate was included to distinguish bull and bear market regimes.\(^2\) Using an algorithm by Bry and Boschan (1971) from the business cycle literature, Pagan and Sossounov (2003) developed a set of rules to define a bull and bear market in asset prices. They considered that the market was in a bear state (bull state) if

\(^2\) The dummy covariate was not included when analysing the daily data.
prices declined (increased) for a substantial period since their previous local peak (trough). Following Pagan and Sossounov (2003), the framework for the dating algorithms was as follows:

(i) Potential peaks and troughs are located by tracking the high and low points over a window of eight months.

(ii) Durations between these points are measured and a set of censoring rules are adopted which set minimum lengths of bull and bear states. Pagan and Sossounov (2001) set this length of the states to be four months.

(iii) To fit with the identification of original peaks and troughs using a symmetric window of eight months, a minimum length of sixteen months was also specified for the complete cycle over the two states.

(iv) The minimum four months for a bull or bear state are disregarded if the stock price falls by 20% in a single month. This enables the accommodation of dramatic events such as October 1987.

3.2 Forecast evaluation

We can assess the predictive performance of the models at the aggregate level by taking the estimated probability of survival to time \( t \), \( S_i(t) \), for each run, \( i \), observed in a holdout sample and summing the probabilities at each time \( t \). The result is the number of runs expected to survive transition beyond time \( t \), which can then be compared to the actual number of runs surviving transition beyond \( t \). The expected number of runs to survive transition beyond time \( t \) is given by:

\[
E(m) = \sum_{j=1}^{a} \hat{S}_i(t)
\]  

(7)
for each $t$, where $q$ is the number of runs in the sample.

Evaluating the forecast performance of our model for individual runs is more difficult. The model produces a set of probability forecasts but we cannot observe probabilities. All we can observe is whether the state changed and when. Probabilistic predictions were evaluated against the actual observed frequency of outcomes. Johnstone (1998, 2002) showed by simulation that probability scoring rules outperform categorical rules. One popular probability scoring rule is the Brier score. It was proposed by Brier (1950) to address the problem of assessing probabilistic forecasts. The Brier score is extensively used in the assessment of the accuracy of meteorological forecasts. It has also been adopted in financial applications for the evaluation of probabilistic forecasting (see, for example, Samuelson and Rosenthal, 1986).

It is defined as

$$B = \frac{1}{N} \sum_{n=1}^{N} (p_n - a_n)^2,$$

where $N$ is the number of forecasts, $p_n$ is the predicted probability that an event will happen, and $a_n$ is the actual outcome. When the event happens then $a_n = 1$, and when it does not happen, $a_n = 0$. As a Brier score of 0 indicates perfect prediction and a score of 1 indicates the worst possible prediction, a lower Brier Score implies better forecasting ability.

4. Data

Daily and monthly data are analysed in this study. The daily and monthly data have different signal-to-noise ratios which may have an impact on predictability. The daily data also provides a larger sample of price transactions than does the monthly data. The
monthly data was collected from DATASTREAM and covers the All Ordinaries Price Index from February, 1971, to December, 2001. For the monthly dataset, the sample period from January, 1995, until December, 2001, was retained as a holdout sample. The daily data was obtained from SIRCA and covers the All Ordinaries Price Index from 31st December, 1979, to 30th January, 2002. For the daily dataset, the last two years make up the holdout sample. In dealing with the daily data, a few cases arise when the price change was zero. There were 11 days on which the price index did not move either up or down. These cases were treated as a continuation of the pre-existing price state. Graphs of the monthly All Ordinaries Price Index and its differences are depicted in Figures 1 and 2 below, while the corresponding plots of the daily data are given in Figures 3 and 4. [Figure 1, Figure 2, Figure 3 and Figure 4 about here]

Descriptive statistics for the monthly estimation sample of price changes are given in Table 1. There were a larger number of positive changes (211) than negative changes (159) with the mean of the absolute value of positive changes greater than the absolute value of the negative changes. This mean difference existed despite the inclusion of the substantial negative difference corresponding to the 1987 stock market crash. These differences in the averages (and indeed the medians) are confirmed by the distinct upward drift of the monthly series over time that can be observed in Figure 1. This upward drift in the monthly series could not occur without an upward drift in the series of daily price changes. This is evident from the graph of the series of daily price changes depicted in Figure 3. [Table 1 about here]
Statistics for run lengths in the estimation samples for both the monthly and daily data are given in Table 2. For the daily data in Panel A, we observe that there were 1092 positive price runs which vary from a minimum of 1 day to a maximum of 14 days. There were 1093 negative price runs which vary from a minimum of 1 day to maximum of 13 days.  

[Table 2 about here]

A summary of run length statistics for the estimation sample of monthly data (February, 1971, to December, 1994) is given in Panel B of Table 2. There were 65 positive price runs, which vary from a minimum of 1 month to a maximum of 10 months. There were 65 negative price runs which vary from a minimum of 1 month to a maximum of 7 months.  

The bull and bear market periods, as identified by the Pagan and Sossounov (2003) criterion, are given in Table 3.  

[Table 3 about here]

5. Results

5.1 Model Estimation

The monthly estimation sample covers 287 months from February, 1971, to December, 1994, while the daily estimation sample covers 5077 days from 31st December, 1979, to 28th January, 2000. In the interests of estimating a parsimonious predictive model, a forward stepwise estimation procedure was used. Variables significant at the five percent

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4 The longest positive run starts at August, 1986, and finishes at May, 1987 and the longest negative run starts at March, 1974, and is completed by September, 1974.

5 The stepwise procedure enables the order of entry and departure of the variables to be observed. However, the results from the estimation of the full model are essentially same.
level are allowed to enter the model and, once entered, are allowed to remain in the model as long as they remain significant at better than the ten percent level.

Table 4, Panel A, shows the results of the model for a transition from the up-state to the down-state, estimated from the monthly data. The covariates that measure the number of previous changes from an up-state to a down-state (CHANGES), and the price change at lag 2 (LAG2), are both significant. An increase in the number of previous changes increases the probability of a transition to the down-state, while the larger the positive (negative) price change at lag two the less (greater) the probability of a down-state. It is noteworthy that the dummy variables for bull and bear market were not significant predictors of the state transition. At first sight it may be surprising that the price change at lag two is a better predictor than the price change at lag one, but the price change at lag one is always constrained to be the opposite sign to the current run.

[Table 4 about here]

Table 4 Panel B shows the results of the model (using monthly data) for a transition from a down state to an up-state. In this case the prior changes variable was not selected as a significant predictor. Only the price changes at lags two and three are significant. The relationship between the state transition rate and lagged price changes is positive. The larger the positive (negative) price changes at lag two or lag three, the greater (smaller) the probability of a reversal from the down to the up-state.

The exponential of the coefficients in Table 4 can be interpreted as the ratio of state transition rates. This indicates the relative risk of a state change when the predictor variable changes by one unit. Therefore, for the up-to-down model, one more previous
state change will result in a 73%\(^6\) increase in the risk of the next price transition. In contrast, a one point increase in the price index at the second lag will reduce the risk of a transition by only 0.2 percent. In the down-to-up model, a one unit increase in the price index at lag2 and lag3 also has quite a small effect, increasing the risk of a transition to the up-state by 0.9 percent and 0.7 percent, respectively.

Table 5 below presents the Cox regression results for models estimated on daily data. We note that the bull bear state variable was not included in the analysis of daily data. The results are consistent with the models for monthly data in that CHANGES and LAG2 are among the first variables to enter both monthly and daily models for the risk of a transition from an up-state to a down-state, and these variables have the same sign in both models. Similarly, LAG2 and LAG3 are the first variables to enter both the monthly and daily models for the risk of a transition from a down-state to an up-state, and these variables also have the same sign in both models. The results differ in that price changes at other lags are significant predictors in the models for daily data, while CHANGES also becomes a significant predictor in the model of transition from a down-state to an up-state. For the models estimated using daily data, a one unit change in the number of previous state transitions has a much bigger impact on the risk of subsequent transitions than does a one point change in lagged values of the price index. This is consistent with the monthly model for a transition from an up-state to a down-state.

In summary, for both monthly and daily data, recent changes in the index lead to persistence in the run if they are of the same sign as the run, and the effect is greater the larger the lagged change. Conversely, lagged price changes increase the probability of a reversal if they are of the opposite sign to the run. For example, positive lagged changes

\[^6\] Calculated as \(1.732 - 1 = .732\) or 73 percent.
in the index reduce the probability of a transition from a positive to negative run, while negative lagged changes increase the probability of such a transition. However, the impact of a one point change in the index is relatively small, typically changing the transition risk by less than one percent. A much stronger effect comes from a one unit change in the incidence of transitions over the preceding twelve months. The greater the number of prior transitions, the higher the probability of a subsequent transition. This result is hardly surprising given the literature on volatility clustering (see, for example, Grossman et al. 1997).

[Table 5 about here]

5.2 Out-of-sample Forecast

From the in-sample analysis we find that lagged price changes and the number of previous transitions have a significant impact on the probability of a price run continuing. However, an out-of-sample analysis is needed to determine whether the significant variables from the in-sample analysis can be used to make effective predictions. The monthly out-of-sample test data runs from January, 1995 to March, 2000. The first negative run starts in January, 1995. There are 21 completed negative price runs and 21 complete positive runs. The out-of-sample daily data covers 31st January, 2000 to 30th January, 2002. For the daily data there are 121 negative price runs and 121 positive price runs.

The out-of-sample survival functions are estimated according to:

\[ \hat{S}_i(t) = [\hat{S}_0(t)]^p, \]  

(9)

where \( p = e^{(X;\hat{\beta})} \). The baseline survival function, \( \hat{S}_0(t) \), and the coefficients of \( \hat{\beta} \) are estimated from the in-sample analysis.
We first address the question of whether predictive ability exists at the aggregate level. For this purpose we utilize the daily dataset as it contains more observations in the hold-out sample. The aggregate number of runs expected to survive beyond each time \( t \) are computed from the sum of the individual probability forecasts for each run at each time \( t \). Figure 5 and Figure 6 compare plots of the number of runs which have actually survived beyond time \( t \) with the number of runs expected to survive beyond time \( t \). Two benchmarks are also included in the plots. One benchmark is a naïve forecast which is formed by setting the survival probability for time \( t \) equal to the proportion of runs which survived beyond time \( t \) in the estimation sample. The other benchmark assumes that prices follow a random walk. The random walk forecast is formed on the basis that the probability of each independent state change is 0.5. Therefore the survival probability at any time \( t \) is given by \((0.5)^t\).

Figure 5 presents the comparison for positive runs while Figure 6 presents the comparison for negative runs. For runs of positive price changes, as shown in Figure 5, the model seems to slightly under-estimate the expected number of survivors at each run length while the other two forecasts are very similar. However, for runs of negative price changes, the plot for the expected number of runs, the naïve forecasted number of runs and the random forecasted number of runs are practically indistinguishable from the plot of the actual number of runs. The results indicate that at the aggregate level, the model forecasts as well as the actual, the naïve and the random forecasts.

Figures 7 through 10 provide a graphical comparison of the Brier scores for the estimated model against the two benchmarks. The graphs for the estimated model are constructed as
follows. At the start of each price run in the holdout sample, data available at that time is used to form the survival probabilities for each time \( t \) over the forecast horizon. The estimation technique constrains our maximum forecast horizon to the maximum run length observed in the estimation sample. The probability estimates across all runs and the known outcome from each run are then used to estimate the Brier score at each time, \( t \). The Brier scores for the estimated model at each time, \( t \), are then compared to the Brier scores for the benchmarks.

Figures 7 and 8 plot the Brier scores of the monthly probability forecasts for negative and positive runs, respectively. Figures 9 and 10 plot the corresponding Brier scores for the forecasts based on daily data. The figures consistently show that the Brier score for the estimated model are higher than the scores of the naïve forecast and the random walk forecast; although, as time \( t \) increases, there is convergence in the accuracy of the three forecasting methods. It is clear, however, that the estimated model performs worse that the benchmarks in forecasting individual run lengths.

According to the Brier score, the accuracy of the naïve forecast and the random walk forecasts are very similar. Indeed, in the plots for the daily forecasts, the Brier scores for the naïve forecasts and the random walk are virtually indistinguishable. Figure 11 and Figure 12 present the comparison of forecasted probabilities from these two benchmarks. For the negative runs, the forecasted naïve probabilities and random probabilities are practically indistinguishable, while for the positive runs the forecasted random probabilities are slightly smaller than the naïve forecasts.
6. Conclusions

In this paper, Cox’s (1972) proportional hazard model was utilised to determine whether historical price changes are useful in predicting future price reversals. Lagged price changes and the previous number of transitions in the price state were found to be statistically significant determinants of the time-varying probability of a price reversal. The lagged price changes tend to lead to persistence in a run if they are of the same sign as the run, but increase the probability of a reversal in the run if they are of the opposite sign. This implies that in an up-state, lagged positive (negative) price changes decrease (increase) the probability of price reversals. Alternatively, if in a down-state, lagged positive (negative) price changes increase (decrease) the probability of a state transition change.

The state of the market, bull or bear, was not found to be a significant predictor of run length when tested on monthly data. However, the effect of volatility (proxied by the incidence of state transitions in the previous twelve months for monthly data and thirty days for daily) appears to have the stronger impact on the probability of a run ending than does lagged price changes. This indicates that the previous volatility of the market increases the probability of price reversals.

The results from the holdout sample show that the model possesses some predictive power at the aggregate level. However, in terms of predicting individual run lengths out-of-sample, the estimated model was less accurate than either assuming a random walk in stock prices, or forecasting based on the proportion of runs of different lengths in the
estimation sample. Interestingly, these latter estimation methods had almost identical predictive accuracy.

The results from the estimation sample are inconsistent with market efficiency in that price reversals are found to be related to information in previous prices. Specifically, the signs and magnitude of lagged price changes, as well as the previous volatility of the market, have a significant impact on the probability of stock price reversals. On the other hand, the results from out-of-sample forecasting tests are consistent with market efficiency. The poor performance of the model’s forecasts out-of-sample seem to rule out profitable trading based on the estimated model.

A motivation for this study was due to the Partington and Stevenson (2001) analysis of a property valuation index where they successfully estimated and forecasted state transitions of prices. The result reported here, where the same technique was applied to an index of asset prices, differed in terms of forecasting ability. This is not necessarily unexpected. A valuation index requires the surveying of market participants who, in turn, will most likely rely on historical perceptions as part of their responses. This is in direct contradiction to the mandate of weak form market efficiency. On the other hand, asset prices reflect information in existence within the market place at the time of trading, and this information may well contain information from the past history of prices. The important conclusion to be drawn from this study relates to the mandatory need for out-of-sample predictive tests to evaluate the strength of evidence against market efficiency.
References


Table 1: Descriptive Statistics for Price Changes for the In-Sample Monthly Series

<table>
<thead>
<tr>
<th>Sample</th>
<th>Count</th>
<th>Mean</th>
<th>Median</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
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<tbody>
<tr>
<td>All Observations</td>
<td>370</td>
<td>7.96</td>
<td>5.4</td>
<td>81.83</td>
<td>-954.7</td>
<td>264.9</td>
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<td>Positive Changes</td>
<td>211</td>
<td>48.60</td>
<td>35.1</td>
<td>46.99</td>
<td>0</td>
<td>264.9</td>
</tr>
<tr>
<td>Negative Changes</td>
<td>159</td>
<td>-45.68</td>
<td>-24.95</td>
<td>86.82</td>
<td>-954.7</td>
<td>-0.2</td>
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Table 2. Summary Statistics for Run Lengths.

<table>
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<tr>
<th>Run Type</th>
<th>Count</th>
<th>Min Length</th>
<th>Max Length</th>
<th>Mean</th>
<th>Std. Deviation</th>
<th>Skewness</th>
<th>Kurtosis</th>
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</thead>
<tbody>
<tr>
<td><strong>Panel A: Daily Price Changes</strong></td>
<td></td>
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<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Positive</td>
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<td>(0.148)</td>
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<td><strong>Panel B: Monthly Price Changes</strong></td>
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<td>(0.586)</td>
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Notes: The numbers in brackets are standard errors.
Table 3. Bull and Bear Market Periods.

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<th>Peak</th>
<th>Bear Cycle(months)</th>
<th>Bull Cycle(months)</th>
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<tr>
<td>03/1982</td>
<td>09/1987</td>
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<td>66</td>
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<tr>
<td>02/1988</td>
<td>08/1989</td>
<td>5*</td>
<td>18</td>
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<tr>
<td>10/1992</td>
<td>01/1994</td>
<td>12</td>
<td>15</td>
</tr>
<tr>
<td>01/1995</td>
<td>09/1997</td>
<td>12</td>
<td>32</td>
</tr>
<tr>
<td>08/1998</td>
<td>06/2001**</td>
<td>11</td>
<td>34</td>
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<tr>
<td><strong>Average Length</strong></td>
<td><strong>15.4</strong></td>
<td><strong>32.9</strong></td>
<td></td>
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</table>

Notes:  
* During October 1987, the price index dropped over 40%.  
** June of 2001 is the last identified peak in the sample.
Table 4. State transition models estimated from monthly data.

<table>
<thead>
<tr>
<th>Step number</th>
<th>Variable entered</th>
<th>Coefficient</th>
<th>Standard error</th>
<th>Wald statistic#</th>
<th>Df</th>
<th>Sig.</th>
<th>Exponential Of coefficient*</th>
<th>-2Log Likelihood</th>
<th>Chi-square</th>
<th>Sig.</th>
</tr>
</thead>
</table>

**Panel A: Transition from up to down-state**

| Step 1  | CHANGES | .542 | .171 | 10.044 | 1 | .002 | 1.720 | 420.023 | 10.287 | .001 |
|         | LAG2     | -.002 | .001 | 4.217 | 1 | .040 | .998 |

<table>
<thead>
<tr>
<th>Panel B: Transition from down to up-state</th>
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</thead>
<tbody>
<tr>
<td>Step 1</td>
</tr>
<tr>
<td>Step 2</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

Note: Two Cox regression models are estimated. One is for the transition from up to down-state and the other one is for the transition from down to up-state. The estimation method is the forward stepwise regression.

# The Wald statistic tests whether an estimated coefficient is different from zero in the population. It is distributed as chi-square variate. The column headed Df is the degrees of freedom for the Wald statistic.

* The confidence interval of the exponential of the coefficient is given by \( e^{\hat{\beta} \pm Z_{1-\alpha/2} \sqrt{\text{Var}(\hat{\beta})}} \).
Table 5. State transition models estimated from daily data.

<table>
<thead>
<tr>
<th>Step number</th>
<th>Variable entered</th>
<th>Coefficient</th>
<th>Standard error</th>
<th>Wald statistic</th>
<th>df</th>
<th>Sig.</th>
<th>Exponential Of coefficient*</th>
<th>-2Log Likelihood</th>
<th>Chi-square</th>
<th>Sig.</th>
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</tbody>
</table>

Note: Two Cox regression models are estimated. One is for the transition from up to down-state and the other one is for the transition from down to up-state. The estimation method is the forward stepwise regression.

# The Wald statistic tests whether an estimated coefficient is different from zero in the population. It is distributed as chi-square variate. The column headed Df is the degrees of freedom for the Wald statistic.

* The confidence interval of the exponential of the coefficient is given by $e^{[\hat{\beta} \pm Z_{1-\alpha/2}\sqrt{\text{Var}(\hat{\beta})}]}$. 
Figure 1. All Ordinaries Price Index (monthly), Feb., 1971, to Dec., 2001.

Figure 2. Returns on the All Ordinaries Price Index (monthly), Mar., 1971, to Dec., 2001.
Figure 3. All Ordinaries Price Index (daily), Dec., 1979, to Jan., 2002.

Figure 4. Returns of All Ordinaries Price Index (daily), Jan., 1980, to Jan., 2002.
Figure 5. A Comparison of the expected number of runs with the actual number as well as those generated naively and randomly (positive runs, daily data).

Note:
- “Actual” represents the actual number of runs that survived beyond $t$;
- “Expected” represents the expected number of runs that survived beyond $t$ and were generated from our state transition model;
- “Random” represents the number of runs that survived beyond $t$ that were generated randomly;
- “Naive” represents the number of runs that survived beyond $t$ according to the proportion of runs that actually survived beyond $t$ in the estimation sample.
Figure 6. A Comparison of the expected number of runs with the actual number as well as those generated naively and randomly (negative runs, daily data).

Note:
- “Actual” represents the actual number of runs that survived beyond $t$;
- “Expected” represents the expected number of runs that survived beyond $t$ and were generated from our state transition model;
- “Random” represents the number of runs that survived beyond $t$ that were generated randomly;
- “Naïve” represents the number of runs that survived beyond $t$ according to the proportion of runs that actually survived beyond $t$ in the estimation sample.
Figure 7. Brier Scores estimated from monthly data for negative runs.

![Graph showing Brier Scores for negative runs](image)

Note:
“Prediction” represents the Brier Score for the predictions from our state transition models; “Naïve” represents the Brier Score from the forecast by setting the survival probability beyond $t$ equal to the proportion of runs that survived over $t$ in the estimation sample; “Random” represents the Brier Score from the forecast by assuming prices follow a random walk.

Figure 8. Brier Scores estimated from monthly data for positive runs.

![Graph showing Brier Scores for positive runs](image)

Note:
“Prediction” represents the Brier Score for the predictions from our state transition models; “Naïve” represents the Brier Score from the forecast by setting the survival probability beyond $t$ equal to the proportion of runs that survived over $t$ in the estimation sample; “Random” represents the Brier Score from the forecast by assuming prices follow a random walk.
Figure 9. Brier Scores estimated from daily data for negative runs.

Note:
“Prediction” represents the Brier Score for the predictions from our state transition models; “Naïve” represents the Brier Score from the forecast by setting the survival probability beyond $t$ equal to the proportion of runs that survived over $t$ in the estimation sample; “Random” represents the Brier Score from the forecast by assuming prices follow a random walk.

Figure 10. Brier Scores estimated from daily data for positive runs.

Note:
“Prediction” represents the Brier Score for the predictions from our state transition models; “Naïve” represents the Brier Score from the forecast by setting the survival probability beyond $t$ equal to the proportion of runs that survived over $t$ in the estimation sample; “Random” represents the Brier Score from the forecast by assuming prices follow a random walk.
Figure 11. Naïve and random probability forecasts of run length (positive runs).

Note:
“Naïve” represents the forecasted probability by setting the survival probability for $t$ equal to the proportion of runs that survived beyond $t$ in the estimation sample; “Random” represents the forecasted probability by assuming prices follow a random walk.

Figure 12. Naïve and random probability forecasts of run length (negative runs).

Note:
“Naïve” represents the forecasted probability by setting the survival probability for $t$ equal to the proportion of runs that survived beyond $t$ in the estimation sample; “Random” represents the forecasted probability by assuming prices follow a random walk.