Timing the Market with Valuation and Trend

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Abstract

A market timing strategy, based on a non-linear forecasting model, is shown to deliver economically significant returns over a buy and hold strategy. The model is developed on the S&P 500 index using macro economic variables. The distribution of returns has a conditional mean that can be determined ex-ante. Using the regime given by the classification model, a market timing strategy is implemented on out-of-sample data from July 1990-August 2004. The results indicate that investors can and should condition their investment strategy on the basis of their information set. However, in order to adopt such a strategy, it may be necessary to use a nonlinear forecasting technology.

Introduction

The advice often given to market participants is not to attempt to time the markets when investing. Yet we have seen investors attempt to do so especially as the cost of moving in and out of the market became cheaper with the proliferation of on-line trading. Day trading, a short horizon form of market timing, became popular during the boom years of the late 90's but these attempts along with other forms of market timing proved disastrous as investors often entered the market when it was overvalued. Staying fully invested (i.e. buy and hold) then became the mantra for successful investing. This paper argues that given the right tools, a strategy of successful market timing is possible. It develops a market timing model which considers market valuations as well as trends in key variables such as interest rates and inflation in determining when to enter or leave the market.

This model employs a classification tree. Unlike past models, it accommodates nonlinearities in the data. The model demonstrates that exploiting conditioning information can lead to an economically significant improvement in risk adjusted performance compared to a buy and hold strategy because the model is not confined to assumptions of normality or independence in the distribution of excess returns. Simply put, it distinguishes scenarios which could lead to high stock returns from those which could lead to low stock returns. For example, a scenario of high valuations along with rising interest rates and inflation rates could be expected to lead to low stock returns. In this regime, investors will not be invested in stocks.

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Background

Conditioning expected returns on investors' information is not new. Ferson and Harvey (1991) and Fama and French (1989) conclude that expected stock market returns vary in a predictable way based on the business cycle. Lagged economic variables ("instruments") explain some of the return variance. Subsequently, Goyal and Welch (2004), Bossaerts and Hillion (1999), and Pesaren and Timmermann (1995) show that linear models, including those used in prior research, have almost no out-of-sample forecasting power. This means that the forecasting parameters determined in one sample (the in-sample) cannot successfully predict outcomes in another sample. The reasons cited for this lack of forecasting power are non-stationery financial time series, non-linear relationships between instruments and returns and over-fitting of the in-sample data. These out-of-sample tests raise doubt as to whether linear models are capable of capturing predictability and whether market returns are predictable at all. Also, it is possible that these linear models were misspecified

Ang and Bekaert (2004) use a Markov Regime Switching model to demonstrate that stock market returns have two distinct regimes, that these regimes are very persistent, and that the regimes are correlated with the business cycle. These findings are consistent with the hypothesis posited by Ferson and Harvey (1991) and Fama and French (1989). If returns have a conditional mean and the business cycle is responsible for this environment, then market timing may be possible with a correctly specified model which may not necessarily employ linear technology.

We extend the literature on conditional asset pricing and market timing pioneered by Hussman(1998). Hussman uses a rule based model known as a Classification Tree [2] (or decision tree). He identifies four regimes for the stock market which can be determined ex-ante. Hussman finds the conditional moments of the return distributions are sufficiently different under the different regimes to suggest that market timing could prove to be a superior strategy to buy and hold. The first advantage of a classification tree is that it allows for non-linear relationships between conditioning variables and expected returns. The second advantage to this type of model is that only the direction of the stock market is forecast rather than a point estimate. This feature is significant because Leung(2000), Satchell and Timmermann(1995) and Leitch and Tanner(1991) have shown that the correct return sign is the predominant determinant of the actual benefits to be derived from a timing model.

The timing model developed in this study demonstrates evidence of market timing ability for the out-of-sample period 1990-2004. These forecasting results are consistent with the results of Ang and Bekaert (2004). The model delivers improved risk adjusted performance over buy and hold by reducing exposure to market risk during low return regimes. These findings suggest that investors can and should adjust their portfolio exposure to stock market risk based on the current market regime, increasing exposure when expected returns are high and reducing exposure when expected returns are low.

[2] This is a popular technique in the general field of Statistical Pattern Recognition

Data

The total returns of the S&P 500 index, with a buy and hold strategy, serve as the benchmark against which the returns earned with the ValuTrend model are measured. The data used in this study extends from January, 1948 to August, 2004 (N=680). The data is divided into a training period and a testing period. It is split according to the common convention of using 75 percent for the training (in-sample) period and 25 percent testing (out-of-sample) period. The conditioning variables used are commonly found in the literature and believed to affect asset prices. They are the S&P 500 earnings yield premium, the T-bill and T-note yields and inflation, measured by the one month change in CRB raw industrial index. The S&P 500 price, earnings and dividends data is from the American Association of Individual Investors (AAII), interest rates are from the St Louis Federal Reserve and the CRB data is from Reuters-CRB. Summary statistics are shown in Table 1.

Insert Table 1 here

Methodology

The approach follows Hussman (1998). He shows that the S&P 500 has four different return distributions or "regimes". He does not use a linear methodology but uses a rule based approach for classifying data known as a Classification Tree. He advocates using conditioning information which indicates the valuation of the market and the "trend" of the economy. For example he uses dividend yield as a measure of valuation and the six month change in interest rates and dividend yields as his measures of trend.

This paper uses the earnings yield premium (E/P less T-bill return) of the S&P 500 as a valuation measure. Following the literature, earnings are lagged one additional month. Campbell and Shiller (2001) suggest that earnings move too much over the business cycle to be useful for forecasting. They suggest smoothing the earnings over ten years with a simple moving average. However, as Muller (1999) has shown, the simple rectangular moving average has a serious disadvantage in its dynamic behavior. Additional noise is created when old observations are abruptly dropped from the observation window. Also, 120 months may not be the optimal period to use in computing the moving average and weighting the data equally with a rectangular weighting function may not be appropriate. We will let the data speak for itself and let the smoothing level and form be determined by optimization. The lagged earnings will be smoothed with a two parameter iterated moving average, IMA,[3] a methodology suggested by Gencay, et al (2001). An additional advantage of smoothing the earnings

[3] Details of the iterated moving average ("IMA") are given in Appendix I

this way is that the optimal parameter set of the IMA will tell us something about the optimal observation period of earnings. We may find that a shorter "average" of earnings works better. Trend is measured by the movements in the treasury bill (T-bill) yields, the treasury note (T-note) yields, the S&P 500 price index and inflation (for which the one month change in the CRB raw index serves as proxy). Trends are classified as "Up" or "Down" depending on the level of the variable with respect to it's exponentially weighted moving average (XMA). The smoothing constants are determined through optimization.

The general idea of this "Valu-Trend" model is that an investor should have a long position in the market, that is, hold the S&P 500 index with reinvested dividends if :

1. The market is not overvalued; and if
2. Three of the following four trend conditions hold:
    a. The S&P 500 price index is above its XMA.
    b. The T-bill yield is below its XMA.
    c. The T-note yield is below its XMA.
    d. The inflation level is below its XMA.

The market is assumed to be overvalued if the earnings yield premium is below the benchmark level determined by optimization. If the market is overvalued or if the trend requirements which hold are less than three, then the model recommends that investors should close their long position in the S&P 500 index and invest in T-bills. Alternately, in order to invest in equities, market valuations must not be too high and at least three trend requirements must be met.

The data from January, 1948 to June, 1990 (N=510) is used to optimize the parameters. The out-of-sample test period is from July, 1990 to August, 2004 (N=170). This test period is used to evaluate the parameter stability and out-of-sample forecasting power of our classification model. A genetic algorithm (GA) is used to find the highest risk adjusted performance over the in-sample period. The goal is to maximize the objective function represented by the Sortino Ratio, a return to risk relative measure. The parameters to be optimized are: (a) three measures of the earnings yield premium which include two smoothing parameters and one level parameter; and (b) four trend parameters as each conditioning variable has a smoothing parameter.

Once the parameters are chosen in June 1990 they are not changed over the test period. The objective is to determine if the conditioning information embodied in the valuation level and the trends make any difference to subsequent returns. If returns are independently and identically distributed then conditioning information should not matter; this is the null hypothesis. There are two components to the alternate hypothesis. They are:

1) Superior risk-adjusted investment performance is possible by using our conditioning information, i.e. market timing can help investors in an economically significant way. This is possible because:

2) Returns have a conditional mean, i.e. investor information permits us to identify ex-ante two return distributions that are statistically different.

Since the latter condition has to exist in order to adopt a market timing strategy, the first test is a test of the differences in mean returns of the S&P 500 index in the "Up" state and the "Down" state. The states are given ex-ante by our ValuTrend model. The null hypothesis is that there is no difference in mean returns conditional on the regime suggested by the model. This test is popular because it is a demonstration of the principles of conditional asset pricing, i.e. returns have a conditional mean. However, as this test does not consider investor risk, another test, the Sortino Ratio will be used to measure risk adjusted performance. The Sortino Ratio uses the lower partial moments as its measure of risk so that only returns below a given threshold are used. The risk free rate is used as the threshold or minimum acceptable return. The Sortino Ratio has been shown to be a good measure of performance under asymmetric returns by Pedersen and Satchell, (2002). Therefore, it serves as the objective function which is to be optimized in our model. The general Sortino Ratio is given by:

$$\frac{\overline{R} - mar}{\sqrt{\frac{1}{T}\sum_{\substack{t=0 \\ R_t < mar}}^{T} (R_t - mar)^2}}$$

where: "mar" represents the minimum acceptable return or threshold return.

The Sortino Ratio can help measure asymmetric risk but it does not say anything about the series or clustering of losses. Most investors including absolute return managers consider "drawdowns" and "time underwater" to be important measures of risk. A drawdown measures the decline of the cumulative return line from it highest point. This is the total percentage loss an investor would have assuming he had invested at the time when cumulative returns were at their highest point. It is also the mark-to-market losses for investors since the high point. Similarly, time underwater refers to the length of time it takes to get back to a new high point in cumulative returns.

For example, consider a scenario in which two hedge funds have the same Sortino Ratio. Fund A has drawdowns of 10 % on average and it takes it 20 days to get back to a new high in equity returns. Fund B has drawdowns of 20% on average and it takes it 30 days to get back to new highs. Most people would prefer fund A, even though the Sortino Ratios are the same for both funds. Fund A has less "risk" because losses do not cluster as much and the client is "underwater" less often. The Ulcer Index (UI) was developed by Martin and McCann (1989) to capture this risk. It measures the depth and duration of percentage drawdowns in price from earlier highs. Technically, the Ulcer Index is the root mean square of the percentage drops in portfolio value. The greater a drawdown in value, and the longer it takes to recover to earlier highs, the higher the UI. The squaring effect penalizes large drawdowns proportionately more than small drawdowns. Thus, in effect, the UI measures the severity of drawdowns, as represented by the dark regions in the charts below:

Insert figure 1 here

The values of the Ulcer Index are lower for smaller and less frequent drawdowns with faster recovery times.

Martin (1989) also constructs a measure of risk adjusted performance called the Ulcer Ratio composed of the average (arithmetic) annual return less the risk free rate divided by the Ulcer Index of risk. Sampling distributions of the Sortino Ratio, the Ulcer Index and the Ulcer Ratio were generated by resampling with replacement (i.e. bootstrapping) the S&P 500 total return series. Prior to resampling, there was no evidence of serial correlation in the data[4]. Therefore the bootstrapping technique is an appropriate way of generating test statistics which enable one to draw inferences from the data.

Results and discussion

Evidence of market timing is demonstrated by the ValuTrend model. Test statistics are shown in Table 2.

Insert Table 2 here

Panel A suggests that the S&P 500 returns have a conditional mean. In the "Up" state, returns average 1.52 % per month with less volatility than in the "Down" state which has average returns of approximately zero. These results are net of transactions costs of 0.1 percent per trade[5]. The risk indices and performance measures in panel B indicate substantial mitigation of downside risk and improved risk-adjusted performance. A chart showing the growth of $100 ("equity line") for the entire sample is shown in figure 2 and the out-of-sample equity line is shown in figure 3.

Insert figure 2 and figure 3 here

The maximum drawdown shown in figure 3 is 47 percent for the buy and hold and 15 percent for the ValuTrend model. Overall, the results indicate that an investment strategy based on market timing can outperform a buy and hold strategy. The strong point of the ValuTrend model is its ability to mitigate market risk.

The optimal values for the IMA smoothing of earnings suggest that the optimal observation window to smooth earnings is considerably less that the 120 months recommended by Campbell and Shiller (2001)[6]. The optimal weighting function of earnings is shown in Figure 4.

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[4] The returns were tested out to 24 lags for serial correlation at individual lags and also with the Ljung-Box Q- Test.

[5] This is a typical transactions cost for trading futures, the preferred trading vehicle for this strategy.

[6] The range of the operator (see Appendix 1) is approximately 25 months. The range of an operator is the first moment of its weighting function and indicates a characteristic depth of the past covered by the weighting function.

Insert figure 4 here

The first 72 months account for approximately 90 percent of the cumulative weights. The results suggest that approximately six years of past earnings data may be sufficient to provide the necessary conditioning information that investors need to make better decisions about stock market valuations.

Conclusion

The results of this paper suggest that informed market timing can lead to better investment results than a buy and hold strategy. It also indicates that stock market returns are not independently and identically distributed. Consistent with Ang and Bekaert (2004) and Hussman (1998) we find evidence of conditional distributions in stock market returns. Extending the decision tree approach of Hussman, (1998) we develop the ValuTrend model. The inputs to this model include a valuation measure, the earnings yield premium, and the trends in interest rates, inflation and stock prices as inputs. In the out-of-sample period of 170 months, the risk adjusted returns of our ValuTrend model significantly outperform the returns delivered by a buy and hold strategy. Downside risk, as measured by the lower partial moments below the risk free rate and drawdowns, is minimized with this model. This simple model can be implemented via an excel spreadsheet making successful market timing accessible to all investors.

The strategy advocated in this paper is best implemented with S&P 500 futures or E-mini futures. Institutional and retail investors can easily adjust their exposure to market risk using this strategy enabling them to avoid large drawdowns as experienced during the recent market meltdowns of 2000-2002. Risk adverse investors will feel more comfortable putting a larger percentage of their wealth at risk when they believe that they will not suffer punishing losses thus providing them with additional opportunities to procure higher levels of terminal wealth.

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Table1: Summary Statistics (monthly percentages)

	Mean	Std	Max	Min
S&P500 total return	1.03	4.09	17.03	-21.64
3 month T-bill	4.87	2.95	16.3	.65
10Yr t-Note	6.15	2.68	14.14	2.19
CRB 1	.17	2.67	17.42	-11.66
EY Premium	1.31	3.25	9.64	-7.47

CRB 1 is the one month change in the CRB Raw Industrials Index. EY Premium is the smoothed earnings divided by price per share less the 3 month T-bill rate.

Table 2: Out-of-sample Test Statistics (one-sided) July 1990 -Aug 2004

A) Conditional Moments of SP500 (% monthly)

Regime	UP	DOWN	T-stat	p-value	Remarks
Mean	1.52	0.00	2.24	.012	the Regime is given ex-ante by ValuTrend
STD	3.86	4.60			

B) ValuTrend vs. B&H: Sortino Ratio and Ulcer Index/Ratio

	S&P500	ValuTrend	p-value	Remarks
Sortino Ratio	.44	.98	.03	Measure of risk adjusted *return* using the lower partial moments below r_f
Ulcer Index	15.12	3.23	< .01	Measure of *risk* using all drawdowns
Ulcer Ratio	.47 %	2.72 %	< .01	Measure of risk adjusted *return* using all drawdowns

The numerator in the Sortino Ratio and Ulcer Ratio is the average (arithmetic) annual return less 3 month T-bill rate.
The sampling distribution and subsequent p-values for the Sortino Ratio, Ulcer Index and Ulcer Ratio were derived by bootstrapping the data 5000 times. The time series of returns for the SP500 total return index were first tested for serial correlation at individual lags as well as the Ljung-Box Q-Test out to 24 lags. There was no evidence of serial correlation in the data.

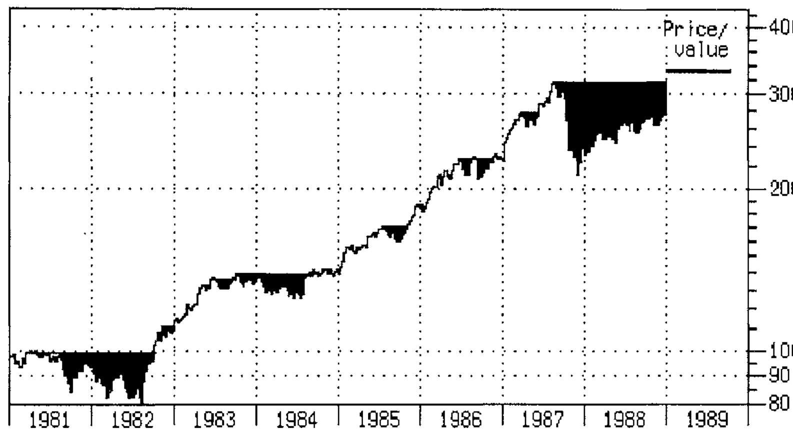

Figure 1: Drawdowns.
The shaded areas represent drawdowns of the Equity Line of the S&P500.
Courtesy Peter Martin, http://www.tangotools.com/ui/ui.htm.

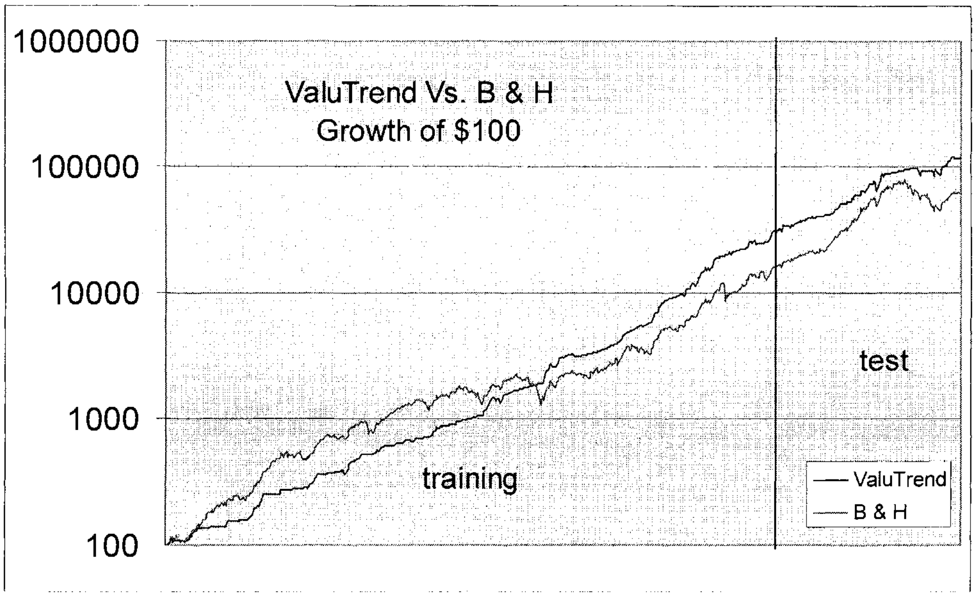

Figure 2: Equity Line for full sample Jan 1948 – Aug 2004 (semi-log scale)
Parameters are optimized over the in-sample ("training") period using a genetic algorithm. This parameter set is then used for the out-of-sample ("test") period.

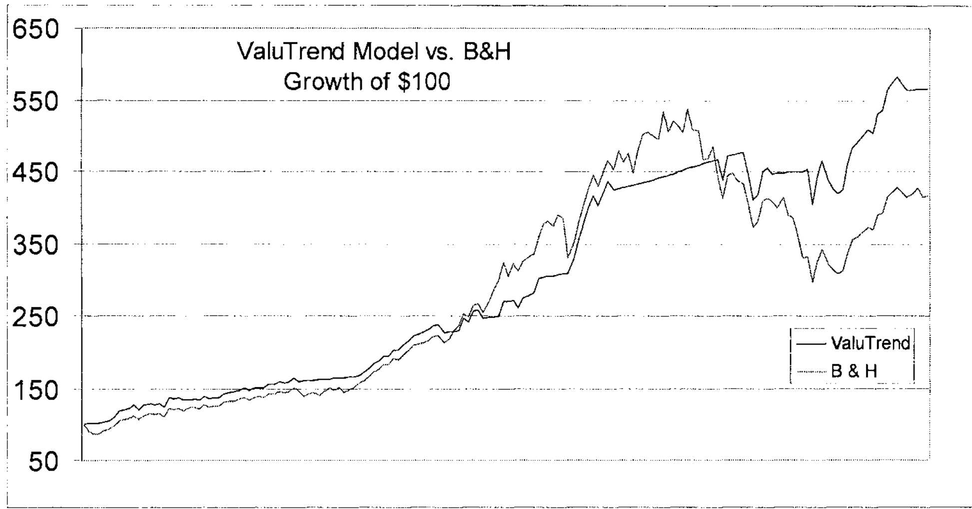

Figure 3: Equity Line over the Test period (July 1990 – August 2004)
Out-of-sample equity line for the ValuTrend model vs. buy and hold.

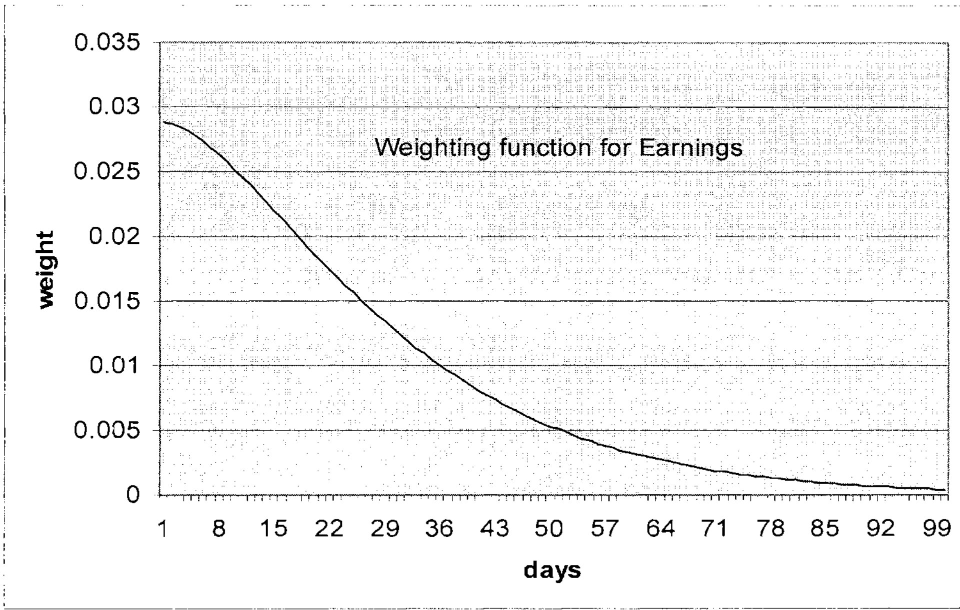

Figure 4: Weighting function of the IMA on Earnings
The first 72 months account for approximately 90 % of the cumulative weights.

Appendix 1

The iterated moving average has the following kernel (or weights) that are applied to each value of the data in order to smooth the data. (For further details about this approach refer to Gencay, et al(2001 and Muller(1999)).

$$ma[\tau,n](t) = \frac{n+1}{n}\frac{e^{-t/\tau'}}{2\tau}\sum_{k=0}^{n-1}\frac{1}{k!}\left(\frac{t}{\tau'}\right)^k$$

$$where \quad \tau' = \frac{2\tau}{n+1}$$

For example, the figure below shows some kernels for different values of τ and n denoted as "τ -n" in the legend box.