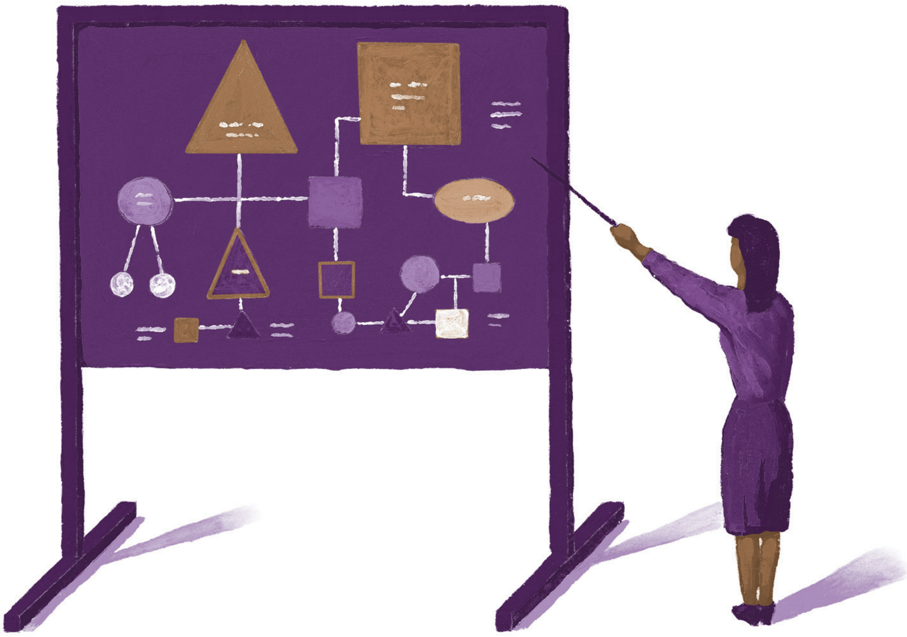


Do market-timing strategies work?

A South African study shows it is possible to outperform the JSE All Share Index by using predictive models that prompt switching between cash and shares ahead of looming up- and downturns.

by Johan Keuler and Niel Krige

The predictability of stock market returns is an issue that always captures the interest of investors. Over the past decades, researchers have devoted much attention to mathematical models on which to base investment strategies. The prediction capabilities of such models are used to drive strategies that will change asset holdings on a continuous basis with a view to achieving the highest returns. Some models shift funds between share classes, for example between small-cap and large-cap shares, while others switch between asset classes: shares on the one hand, and cash or bonds on the other.

The strength of these models lies in their ability to beat stock market indices over extended periods of 15 years and longer. Many studies, predominantly from the United States and the United Kingdom, have shown that timing strategies can outperform the underlying stock market indices. Moreover, researchers have found that asset-class allocation models perform better than share-class allocation models.

International findings such as these prompted similar research at the University of Stellenbosch Business School (USB) in which advanced analysis and modelling techniques were applied to two South African asset classes, namely the JSE All Share Index (ALSI) and cash. The objective was to determine whether, in a South African context, a predictive model could facilitate an investment strategy – which alternates between the ALSI and cash – that outperforms the ALSI.

Timing strategies *can* pay off

The results of this study confirmed the findings of international research: it is possible to find mathematical models that can predict where to place your funds at any given point in time in order to outperform the stock market. What is more, the best models tested in the USB study performed in line with the best models tested internationally. The best model recorded returns of 9% above the ALSI over a period of 15 years. All returns were inclusive of dividends where applicable.

With strategies that imply a regular reallocation of funds, however, the impact of *transaction costs* has to be taken into account. But even after transaction costs, the return was still 5% better than the ALSI over the 15-year period.

To illustrate the effect of an excess return of 5% over a 15-year period, the table (**next page, top**) shows how an amount of R100 000 will grow over the period based on three different strategies. With the best modelled strategy, the R100 000 will

Capital amount invested: R100 000		
Asset class	**Compound return 15-yr period**	**Capital after 15 yrs**
Cash (at BA rate)	12.7%	600 978
ALSI	16.4%	975 651
Best model	21.4%	1 833 497

increase to more than R1.8 million. This is almost double the amount that will be returned by staying in shares (ALSI) over the whole period, and more than triple the amount that will be returned by investing in the cash market alone.

The other important factor to keep in mind is the *risk-adjusted return* of an investment. The effect of portfolio risk was examined by means of the Sharpe and Treynor ratios. Compared to the Sharpe ratio of 0.29 and the Treynor ratio of 6.11 of the ALSI, the corresponding values for a combined set of the best models (average values) after cost were 0.45 and 7.01 respectively. The significance of this finding is that the best modelled strategies not only outperformed the ALSI as far as the return is concerned, but also by providing their better returns at a lower risk.

The strength of these models lies in their ability to beat stock market indices over extended periods of 15 years and longer

Putting modelling strategies to the test

The research was conducted by constructing and testing a variety of modelling strategies, all based on a month-to-month asset allocation period. The same outcome function was used for all the models. The outcome function is shown in the next equation. y_t represents the difference at month t between the ALSI yield (plus dividends) and the BA yield.

$y_t = j_t + g_t - f_t$

Where: j_t = JSE overall monthly price change;

g_t = JSE overall monthly dividend yield;

f_t = BA rate (monthly yield)

Through logit scaling the predicted values in each case were transformed to a probability that shares will outperform cash in the next period – in mathematical terms: $p(y_{t+1})$.

At the end of each month the model would decide, based on this probability value, either to stay in the present asset class or to switch to the other for the next month. A slice of this process is shown in the diagram **below**.

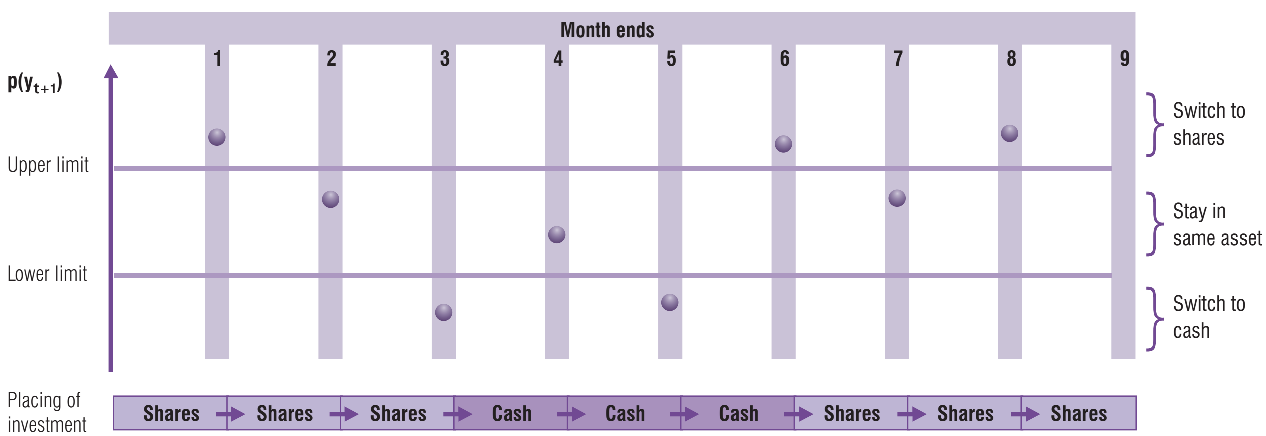
As can be seen in the diagram **below**, an upper and lower limit was set with a neutral zone in between. Switching would only take place above the upper limit, and below the lower limit. By choosing different values for and ranges between the upper and lower limits of the probability function $p(y_{t+1})$, it was possible to test many different strategies for switching between asset classes.

The data

A 20-year dataset plus an extra six months of data were obtained – spanning the period 31 January 1986 to 30 June 2006. The first five years of data were used only for the purposes of calculating the initial regression coefficients. This is referred to as the model training period. The modelling was done on the remaining 15 years of data. Because in certain models moving averages were used instead of the instant values of the predictor variables, an additional six months of data were required in the beginning (January to June 1986). Thus, modelling started from July 1991 and ran through to June 2006.

A rolling window training dataset was applied. »

EXPLANATION OF PORTFOLIO SWITCHING MODEL



Month-end prediction for next month: $p(y_{t+1})$
= Probability that shares will give a higher return than cash

The training period was kept constant at, say, 60 months. For each next prediction, the regression coefficients were determined by dropping the first month and adding the most recent month. The maximum regression training dataset was 60 months, but the effect of shorter training periods, down to 30 months, was studied as part of different modelling combinations.

Modelling variations

The modelling applied in this research was based on four different prediction approaches, or underlying models.

- The first three models made use of regression techniques. A variety of published indicator variables were used in the regression models. Besides the required JSE and capital market data, other variables included certain macroeconomic variables, the Rand gold price, the Rand Brent crude oil price, and selected United States bond and stock market indicators.
- The fourth model analysed the trend of the outcome function. Because of large fluctuations in the month-on-month changes in the outcome function, the monthly changes were not suitable for trend analysis. Therefore, the monthly values were summed over different preceding periods to obtain smoother functions for forward prediction.

In total, 29 different model variations were investigated. However, for each of these model variations a further 68 portfolio variations were constructed. The different models and portfolio combinations are explained in the diagram **below**.

How the four models performed

Model 1 performed the worst of the four models tested, despite the extended range of indicator variables used in the regression computations. Although the statistical properties of the in-sample predictions (during the training period) were very good, its forward predictions proved to be the least accurate.

Two reasons could be found for the inaccuracy of this model. The use of ratios in especially the calculation of moving averages based on inflation data caused the denominator to approach zero several times and resulted in large swings of these variables. Secondly, the large set of indicator variables introduced too much 'noise'. Although they provided a good fit during the training period, the underlying trend was often missed in the month-on-month predictions.

> **Model 4, which used a trend analysis of the outcome function instead of regression, proved to be the best model**

Model 2 was developed from Model 1 by reducing the indicator variables from 41 to ten. Many successive iterations were needed to move from Model 1 to Model 2. Because several of the original variables used in Model 1 were found to be good predictors only in some months, these and many others that added little value to the model could subsequently be removed from Model 2.

Overall, Model 2 performed very well. The best results were found with the 39-month training period for the regression coefficients. The average compound return for this variation (average of the 68 portfolios) was 19.3% per year, which was the second highest of all the model variations. With longer and shorter training periods, the model started to lose its accuracy.

Model 3 was a further simplification of Model 2, using only three predictor variables. Although Model 3 turned out to be a generally more correct predictor than Model 2 – it selected the winner between cash and shares more times – it failed to predict large upturns and downturns as accurately as Model 2 did. The compound growth rates given by Model 3 were therefore not as good as those of Model 2. Model 3 would tend to stay in the wrong asset class during sharp increases or decreases in the index.

Model 4, which used a trend analysis of the outcome function instead of regression, proved to be the best model. It was also the model that achieved the highest prediction accuracy. The best model »

DESCRIPTION OF MODELLING VARIATIONS

<table>
<tr><th colspan="3">Basic model and technique</th><th>Variables</th><th>Model variations</th><th>Portfolio construction</th></tr>
<tr><td rowspan="4">29 different modelling variations based on four approaches and further variations within each</td><td>1</td><td>Regression</td><td>41 predictor variables</td><td>1 variation
Training period of 60 months</td><td rowspan="4">68 portfolio strategies based on 5 different ranges between the upper and lower limits (from zero to 0.25) as well as varying the positioning of these ranges from low to high</td></tr>
<tr><td>2</td><td>Regression</td><td>Reduced to 10 predictor variables</td><td>7 variations
Training periods of 30, 36, 39, 42, 48, 54 and 60 months</td></tr>
<tr><td>3</td><td>Regression</td><td>Using the 3 most significant predictor variables from approach 2</td><td>6 variations
Training periods of 30, 36, 42, 48, 54 and 60 months</td></tr>
<tr><td>4</td><td>Trend analysis</td><td>Using the single outcome function</td><td>15 variations
3 categories of summed months (24, 36 and 48)
X
5 categories of training months (3, 6, 9, 12 and 15)</td></tr>
</table>

THE TOP INDIVIDUAL MODEL COMBINATIONS

Model 2

No	Model parameters: Training months	Portfolio parameters: Upper limit	Portfolio parameters: Lower limit	Before cost return	No of trans-actions	After cost return
1	30	0.55	0.30	23.7%	23	21.3%
2	30	0.55	0.55	25.4%	70	20.7%
3	30	0.55	0.35	23.1%	37	20.1%
4	30	0.60	0.35	22.8%	37	19.7%
5	39	0.65	0.45	23.8%	62	19.6%
6	39	0.65	0.50	23.8%	64	19.5%
7	39	0.60	0.40	23.1%	58	19.1%

Model 4

No	Model parameters: Summed months	Model parameters: Training months	Portfolio parameters: Upper limit	Portfolio parameters: Lower limit	Before cost return	No of trans-actions	After cost return
1	36	13	0.65	0.45	23.7%	19	21.6%
2	36	9	0.70	0.55	23.6%	19	21.5%
3	36	9	0.70	0.60	23.6%	19	21.5%
4	36	9	0.65	0.50	23.5%	19	21.4%
5	36	9	0.70	0.50	23.5%	19	21.4%
6	36	9	0.65	0.65	23.4%	23	21.0%
7	36	9	0.70	0.70	23.4%	23	21.0%

variation was the one with 36 summed months and nine training months, which was also the best of all the 29 variations tested. Its average compound return was 19.6% per year, compared to the 19.3% of the best Model 2 variation.

Comparing with the ALSI

The returns of the model variations could not be compared with the benchmark return, since they were merely averages of all 68 portfolio combinations of each variation. These averages were used to test the underlying characteristics of the model variation.

The best individual model combinations from Models 2 and 4, with their respective model and portfolio parameters, are shown in the table (**left**). The returns must be compared to the ALSI compound return of 16.4% per year.

The highest before-cost return of 25.4% was achieved by one of the Model 2 variations with a single cut-off probability of 0.55 (lower and upper limit) and a 30-month training period. This return is 9% higher than the ALSI. It was followed by quite a few variations of both Models 2 and 4 with returns in the high 23% bracket – more than 7% better than the ALSI.

However, transaction costs need to be taken into consideration, which changes the situation somewhat. It is clear from the table that Model 2 makes many more switching transactions than Model 4. As a result of the effect of transaction costs, Model 4 is the superior model as far as after-cost returns are concerned. Most of the best Model 4 variations still outscore the ALSI by 5% per year, whereas the performance of the best Model 2 variations drops more sharply.

Contextualised techniques

This research clearly shows that it is possible to build a model that can outperform the stock market benchmarks by switching to cash before downturns and getting back into shares before upswings. While international studies have for some time now demonstrated strategies for outperforming their respective stock markets, the USB study illustrates that similar techniques can work in the South African context. ■

Write to us: What other techniques have you used to beat the market?
lab@usb.ac.za

JN Keuler

JN Keuler and JD Krige published this research in a series of two articles: *Predictive models to determine market timing opportunities for the JSE* in the *Journal for Studies in Economy and Econometrics, 33(1), 2009,* and *Predictive models to determine market timing opportunities for the JSE (II)* in the *Journal for Studies in Economy and Econometrics*, 33(2), 2009. The articles were based on Dr Johan Keuler's MBA study project with the same title that was supervised by Prof Niel Krige and presented to the University of Stellenbosch Business School (USB) in December 2007.