DEVELOPING MULTIVARIATE MODELS TO PREDICT ABNORMAL STOCK RETURNS

Using Cross-sectional Differences to Identify Stocks with Above Average Return Expectations

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Abstract: This paper describes the development of multivariate models used to identify stocks with above average return expectations. While most other research involving the development of stock return models involves time-series prediction of future returns, this paper focuses on the modelling of cross-sectional differences between stocks. The primary measure used in this paper to evaluate potential predictors of future stock returns is based on sorted category returns, an approach that was previously applied to NYSE listed stocks; in this paper the same approach is applied to stocks listed on the JSE. This measure is used to identify a number of fundamental and technical indicators that differentiates between high and low performing stock categories. Linear and non-linear multivariate models are subsequently developed, utilising these indicators to improve prediction performance. It is demonstrated that much of the useful stock return behaviour is present in the extremes of the population, that significant differences exist between different size categories, and that different aspects of stock behaviour is exposed using appropriate measures for portfolio returns. Portfolio performance results achieved using individual indicators as well as multivariate models are reported and compared with previously published results, and planned future work to improve on the results is discussed.

1 INTRODUCTION

The identification of stocks that provide above average return expectations has not only been the focal point of interest for market analysts but has also received much attention in academic literature (Fama and French, 2008; Alcock *et al*, 2005). Two broad schools of thought can be identified in this domain: while many market participants favour a technical approach to predict future stock behaviour, academic research in general gives preference to an approach based on fundamental analysis to identify stocks that are over- or undervalued (Fama and French, 2004).

Both technical and fundamental approaches to stock analysis usually identify a set of indicators that are believed to have predictive capabilities regarding future stock returns. The predictive ability of an indicator is typically based on some kind of hypothesis regarding the way in which the market is believed to behave within a specific set of circumstances. A useful indicator can be viewed as a behavioural trait that becomes apparent before the price of the associated stock will display some form of predictable behaviour (typically going up or down over a defined period of time).

Several obvious questions present themselves, resulting from the prior discussion: how can potential indicators of future returns be assessed and compared objectively, and in which way can several indicators with proven predictive ability be combined to generate an even more useful indicator?

The purpose of this paper is to investigate an approach to stock selection that falls somewhere between a passive buy-and-hold strategy and an active trading strategy involving either time series prediction or the daily monitoring of technical indicators as part of portfolio management. The objective is furthermore to determine whether a more basic approach to stock selection can produce returns that are comparable to returns claimed to result from time series prediction. The strategy that is considered will require the updating of the composition of a portfolio only once a month, based

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on a number of indicators of which the values tend to change relatively slowly over time.

An innovative approach to the statistical analysis of stock return behaviour is used, borrowing ideas from the work reported by Fama and French (Fama and French, 2008) in their analysis of abnormal stock returns. This work is further extended by the use of multivariate modelling to combine different indicators, some fundamental and some technical in nature, to create more representative indicators of the medium term return expectations for specific categories of stocks.

The data set used for this study involves all of the stocks listed in the Johannesburg Stock Exchange over the period March 1985 to February 2010, covering a period of 25 years. The number of stocks for which data were available over this time period range from about 60 during the early years up to more than 400 by the end of the period.

The outline of the paper is as follows: Section 2 provides and overview of relevant literature and a description of the main techniques used in the rest of the paper. Section 3 describes the definition of and motivation for the set of indicators used in this study, while section 4 explores the statistical behaviour displayed by the stocks included in this study, and explains why the selection of optimal portfolios is not a trivial task. The sorted returns technique to assess the predictive ability of indicators is described in section 5. In section 6 the multivariate techniques used to combine individual indicators into more comprehensive models are described, and the challenges to extract good models are discussed. Section 7 covers the results that were obtained using different stock selection approaches, and compares these against results reported elsewhere in literature. The paper is concluded with section 8 which provides a summary and overview of results, as well as references to future work.

2 LITERATURE REVIEW

There has been much fundamental debate in literature about the predictability of financial time series, and more specifically of stock returns (Blasco *et al*, 1997; Kluppelberg *et al*, 2002). Initial views in favour of the efficient market hypothesis stated that stock prices already reflect all available knowledge about that stock, making the prediction of stock returns to earn abnormal returns on a portfolio impossible in principle. Much has however been published in recent years confounding those early views, and today it is widely accepted that the strong form of market efficiency does not hold up in practice (Fama and French, 2004).

Many studies have demonstrated the ability of both linear and non-linear time series prediction models to predict future stock behaviour, contrary to earlier beliefs that the market behaviour should be described as a random walk model (Lorek *et* al, 1983; Altay and Satman, 2005; Bekiros, 2007; Jasic and Wood, 2004; Huang *et al*, 2007). An obvious issue to be addressed is the most appropriate benchmark against which to measure the performance of such prediction models.

3 DEFINING THE PREDICTORS

The analyses in this paper are based on monthly data, and returns are calculated relative to the market index as calculated from the set of available stocks. Returns were calculated using the change in the baseline value of each stock, with the baseline value being the value referred to the initial date when the stock was first listed. The formula used to calculate relative returns was as follows:

$$RR_{i,j} = \frac{RelShBL_{i,j} - RelShBL_{i,j-1}}{RelShBL_{i,j-1}}$$

with $RR_{i,j}$ indicating the relative return of stock i over period j and $RelShBL_{i,j}$ the relative share baseline value of stock i for month j.

As will be explained in subsequent sections, this paper will use sorted stock returns per category as measure for the quality of a candidate predictor, a technique that was first reported by Fama and French (2008). For purpose of comparison the same set of stock return predictors as defined by Fama and French (mostly fundamental indicators) is used in this paper, complemented by a number of additional parameters that broadly fall in the class of 'technical indicators'. This paper therefore also serves the purpose of comparing the predictive ability of fundamental versus technical indicators, in the process making a contribution towards the long standing debate regarding the respective merits of these two approaches to stock analysis.

The following list of parameters was incorporated in the study as potential predictors of future stock returns:

- Market capitalization (MC), defined as the natural logarithm of the stock price multiplied by the current number of issued shares;
- Momentum, defined as the relative return of the stock over the period from 12 months to 1 months prior to the current date (relative return

Table 1: Correlation between candidate predictors and future stock returns: a comparison between time-based and cross-sectional correlations.

Predictor	Time-based correlation			Cross-sectional correlation		
	Ave	Std	Ave/Std	Ave	Std	Ave/Std
MC	-0.0912543	0.0836058	-1.0914829	-0.1575078	0.1149865	-1.3697937
BtoM	0.1074284	0.055503	1.935544	0.0790633	0.1667667	0.4740954
Momentum	0.0043152	0.0412991	0.1044854	0.0179527	0.1187149	0.1512252
NS	-0.0286184	0.0379534	-0.7540394	-0.0348528	0.0628141	-0.5548568
YtoB	0.0118392	0.0380539	0.3111155	0.0333755	0.1374055	0.2428976
deltaAssets	-0.0127946	0.0171016	-0.7481523	0.0034774	0.0810011	0.0429297
Accr	0.0021115	0.0212071	0.0995646	0.0064688	0.0707932	0.0913755
DO	0.0122353	0.0295008	0.4147464	0.0340647	0.1442936	0.2360794
DO_RR	0.0008196	0.0385019	0.021286	0.044983	0.0964287	0.46649

being the return on the stock compared to return on the market index);

- Book-to-market (BtoM), defined as the ratio of the book value of equity per share to the market value of a share;
- Net share issues (NS), defined as the logarithm of the ratio between the current number of shares issued by the company and the number of shares issued 12 months ago;
- Yield-to-book (YtoB), defined as the earnings yield per share divided by the book value per share;
- Accruals, defined as the proportional increase of operating assets over the past 12 months;
- Delta Assets (DAssets), defined as the proportional increase in total assets over the past 12 months;
- Detrended oscillator for relative share baseline (DO_RelShBL), defined as the difference between the short and long term moving average of the relative share price, divided by the maximum value of the share price over a defined historic time period (relative share price being the price of the stock relative to the market index, with price at the start of the period of evaluation serving as baseline):

$$DO_{RelShBL} = \frac{MA\_RelShBL_{Short} - MA\_RelShBL_{Long}}{Max\_RelShBL}$$

- Detrended oscillator for relative return (DO_RR), defined as the difference between short and long term moving average in relative stock returns (opposed to relative stock price used in the calculation of DO_RelShBL):

$$DO_{RR} = MA\_RelRet_{Short} - MA\_RelRet_{Long}$$

- Historic 12 month moving average of relative stock return over a period ending one or more years before the current time (e.g. RR12m60 for a 60 month delay);
- MAEY, defined as the 12 month moving average of earnings yield on the stock (earnings yield being the earnings per share divided by stock price).

4 STATISTICAL BEHAVIOUR OF THE PREDICTORS

As a first step to unravel those relationships that can potentially form part of prediction models the linear correlations between the identified candidate predictors and 12 month future returns were calculated. Two types of correlation were calculated: firstly the correlation over time between a stock return and an explanatory variable was determined, repeating this calculation per stock. To obtain a summary measure representative of the entire population the average is taken of the time-based correlations for all stocks. This calculation is repeated after each period once new data has been added to the training set. While this correlation parameter measures the ability of an explanatory variable to predict the future return per stock, it does not directly measure the degree to which differences in the indicator value between stocks is correlated with differences in future returns for those stocks.

The alternative correlation measure, which is generally called the cross-sectional correlation, is calculated by correlating, for each time period, the stock return differences between different stocks with the differences in values of the explanatory variable over the same set of stocks. This calculation is also repeated after each period and the average of all cross-sectional correlations is taken over the entire period for which training data is available. As this correlation parameter directly measures the ability to predict differential future returns of the stocks, it could be expected that it would be a superior indicator based on which to select stocks that will on average outperform the market for the prediction period.

As is the case with most statistical modelling exercises, there is no guarantee that a relationship that exists over a specific period of time will persist during subsequent periods. For this reason the standard deviation of correlation coefficients over time is also calculated for both correlation measures, to indicate how stable these measures are to detect relationships that can be exploited over extended time periods.

The averages and standard deviations for both types of correlation are displayed in Table 1, for each of the predictors as defined in the previous section. To allow the comparative assessment of the stability of the correlations a column is added to display average correlation normalised with respect to standard deviation of correlation over time.

Firstly it can be seen that the relationships between the respective indicators and future returns vary substantially over time: for all of the indicators, with the exception of MC (for both correlation types) and BtoM (for time-based correlations), the normalised average correlations have absolute values smaller than one. This indicates that MC should be the most consistent indicator for above average returns, which is in line with prior research (Fama and French, 2008), while the other indicators could be expected to posses less predictive power.

For some predictors, e.g. MC, the two different correlation measures provide consistent indications of the relationship between the predictor and future returns. For others, e.g. DO_RR, the time-based correlation provides no indication of predictive capability, whereas the cross-sectional correlation, while not being very consistent, does indicate some predictive power for this indicator.

For most modelling exercises the order in which predictors are added to the model is potentially of importance. While the time-based correlations indicate BtoM as the most significant predictor, this role is awarded to MC when using cross-sectional correlations.

A further question is what minimum level of correlation, or normalised correlation, should be sufficient to indicate consistent predictive capability, either for the indicator in isolation or when considering the addition of that indicator to a existing model in combination with other indicators. This question was addressed by using the technique of sorted returns, which is the next topic of this paper.

5 EVALUATING PREDICTIVE VALUE OF INDICATORS

One of the key focal points of this paper is to compare the different correlation measures of the previous section with sorted returns as basis for selecting predictor variables to be incorporated into a prediction model. Using the same approach as described in Fama and French (2008), the ability of each of these parameters to explain cross-sectional differences in returns between different stocks is investigated as follows:

- For each of the above parameters in succession, all stocks are sorted based on the value of the respective parameter for each individual stock (e.g. the first sort is done based on MC; next a sort is done based on Momentum, etc.).
- Once a sort has been done, the stocks are divided into five categories, each containing the same number of stocks, from the lowest to the highest values for the respective sorting parameter.
- The aggregate return for all stocks within each sorted category is calculated, both weighted equally as well as weighted based on market capitalization, using the following formulas:

$$EqW\_Ret = \frac{1}{N}\sum_{n=1}^{N} RelRet(n)$$

$$ValW\_Ret = \frac{\sum_{n=1}^{N} RelRet(n) MarketCap(n)}{\sum_{n=1}^{N} MarketCap(n)}$$

where *RelRet(n)* is the relative return of the n-th stock, *MarketCap(n)* is the market capitilazation of the n-th stock, and *N* is the total number of stocks in the portfolio under consideration.

- This process is repeated after each month, in every case only using information that was already available before the start of the month.
- The average return of the sorted categories is calculated over a period of time, and the difference between returns of the lowest and highest sorted categories is determined:

$$AvRelRet(i_{cat}) = \frac{1}{M_i}\sum_{m_i=1}^{M_i} RelRet(m_i)$$

Table 2: Sorted returns and t-statistics for candidate cross-sectional stock return predictors.

	MC	RR_Momentum	BtoM	DO_RR	DO_RelShBL	NS
Average Corr Coeff with Predicted Return	-0.150	0.016	0.075	0.054	0.055	-0.028
Std of Average Corr Coeff	0.115	0.119	0.165	0.091	0.135	0.053
EqW High-low Returns						
All	-0.043	0.019	0.014	0.023	0.013	-0.016
Micro	-0.050	0.014	0.003	0.027	0.017	-0.039
Small	-0.003	-0.116	0.018	0.009	0.017	-0.006
Big	-0.002	-0.004	0.018	0.011	0.019	-0.005
EqW High-low t-statistics						
All	-8.931	4.845	2.838	4.485	2.444	-3.298
Micro	-9.143	-0.660	0.521	4.753	2.869	-7.246
Small	-0.584	3.006	3.984	2.014	3.400	-1.429
Big	-0.525	-0.660	4.604	2.741	4.314	-1.135
ValW High-low Returns						
All	-0.023	0.023	0.028	0.012	0.024	-0.003
Micro	-0.016	0.020	0.007	0.020	0.031	-0.003
Small	-0.002	0.017	0.018	0.005	0.017	-0.003
Big	-0.005	0.019	0.019	0.007	0.021	-0.008
ValW High-low t-statistics						
All	-5.426	5.380	6.763	2.676	5.279	-0.736
Micro	-3.344	4.192	1.505	3.961	6.062	-0.675
Small	-0.423	3.912	4.085	1.212	3.613	-0.574
Big	-1.108	4.517	4.493	1.565	4.417	-1.848

where M_i is the number of months over which the average return is calculated, i_{cat} is the i-th sorted category for which the return is calculated, and $RelRet(m_i)$ is either the equal or the value weighted average return of all stocks falling into that category.

$$AvRelRet_{High-Low} = AvRelRet(i_{max}) - AvRelRet(i_{min})$$

- t-statistics of these high-min-low sorted returns are calculated to determine if the returns of the sorted stock categories differ significantly from the return of the overall population of stocks.
- Parameters of which the t-statistics of high-min-low sorted returns falls outside of the range ±1 are considered for inclusion as predictors in the subsequent modelling exercise.

Table 2 below displays the values of sorted returns for the above set of candidate predictors, as well as the t-statistics for high-min-low returns. The predictors justifying inclusion into a stock selection model, based on the above results, include MC, Momentum, BtoM, NS, DO and DO_RR; three of these can be regarded as fundamental indicators (MC, BtoM and NS) while the other three fall into the category of technical indicators.

The indication of predictive ability of the respective indicators based on sorted returns differs significantly compared to the outcome of the analysis based on correlation coefficients. While Momentum displayed relatively insignificant correlation with future returns, this indicator proves to be significant when assessed based on sorted returns. The same is true for DO_RR, demonstrating that there can be useful return behaviour associated with the extreme behaviour of an indicator, even though that indicator may not in general be well correlated with future returns. It can furthermore be seen that DO performs better than DO_RR for value weighted portfolios, but that the opposite is true for equally weighted portfolios. This indicates that DO may be more strongly present amongst Big stocks, with DO_RR more prominent amongst Micro stocks. MC is clearly the most significant sorted returns based indicator, confirming that cross-sectional correlation is a more reliable measure compared to time-based correlation.

6 EVALUATING THE PREDICTORS USING A TRADING SIMULATOR

The analysis of sorted returns as described above does not take into account all of the practicalities related to composing and maintaining an actual stock portfolio. For this purpose a simulator was developed to model the behaviour of a stock portfolio over time, taking into account the following aspects that may impact upon the consistence and performance of such portfolios:

- The number of stocks to be incorporated into the portfolio (using a minimum number of 10);
- The size of the portfolio, against the background of limited trading volumes in some stocks, specifically micro cap stocks;
- Trading costs, setting this at 0.25%.

The simulator was used to simulate the expected returns on portfolios using each of the candidate predictors as criteria for stock selection. The results are displayed in table 4 below for different initial portfolio sizes and over different time periods when the stock market potentially displayed different types of behaviour.

It is clear that the simulated trading results confirm the findings of the sorted returns analysis, with MC providing the largest potential abnormal stock returns. The other indicators tend to perform differently over different time periods, each experiencing periods of strong predictive power, followed by periods where the relationship with future returns tends to weaken or sometimes even being reversed.

MC is the only predictor that retains its predictive capabilities over the entire period of evaluation. This performance is however only sustained for portfolios that are small in size. What is apparent from tables 1 and 2 is that abnormal returns explained by MC is mostly confined to micro caps: as soon as the portfolio size grows to a level where most investments must be made into stocks falling outside of the micro cap category, the predictive capabilities of MC tend to weaken substantially.

The above finding clearly indicates the need for models that can combine all of the predictors into a single measure that will be less dependent on portfolio size and that will perform more consistently over time. Both linear multivariate regression and neural networks were used for this purpose.

7 TRAINING MULTIVARIATE MODELS

The models used in this work were limited to single layer networks (to test the performance of linear models combining several variables) as well as two-layer network with one hidden layer (to determine if non-linear models could better capture the true cross-sectional relationships between predictors and abnormal stock returns). In all cases the networks were feed-forward, and used mean squared error with Levenberg-Marquardt optimization used for training 2 layer models. A general regression network based on radial basis functions was also trained to compare its performance with those of multilayer perceptron networks.

In order to investigate the consistency of the relationships between the predictor variables and future returns the respective models were trained on data sets covering different lengths of time. This will provide an indication of how long the memory of the market is and will indicate how often models should be retrained. In this study models were trained with training sets extending over periods varying from 24 months up to 120 months. Each trained model was then applied to the next 12 months of data, predicting returns over periods that were unseen during the training period. This model extraction and prediction process was repeated on a monthly basis covering the entire period.

In each case the historic data was divided into a training set (60% of samples), a validation set (20%) and test set (20%). The number of input parameters varied between 2 and 4, starting off with those parameters that were expected to contribute the most to predictive ability, based on the results of the sorted returns analysis, and testing the ability of additional variables to improve the modelled results.

The following criteria were used to assess the performance of the respective models:

- Average correlation coefficient between target and predicted variables over the unseen test periods;
- Using predicted returns as sorting variable, and then comparing the high-min-low sorted returns;
- Finally by comparing the portfolio returns obtained under different sets of circumstances, using simulated portfolio returns as measure for model performance.

8 RESULTS AND DISCUSSION

The results obtained with the different multivariate models that were trained are displayed in table 3, including the results for All Shares, Micro Shares, Small Shares and Big Shares. In each case the table displays average correlation coefficient between actual and predicted returns, the EqW and ValW High-min-Low sorted returns and the t-statistic for

Table 3: Sorted returns and t-statistics obtained with multivariate models.

Predictors used		Lin Regr		Lin Regr		Lin Regr		FFNN Num_Std 0	FFNN Num_Std 2	RBF NN
		MC, BtoM, DO_RR		MC, BtoM		NS, BtoM, DO_RR		MC, BtoM	MC, BtoM	MC, BtoM, DO_RR
Num Months Train		120	24	120	24	120	24	120	120	120
Average Corr Coeff with Predicted Return		0.138	0.118	0.115	0.125	0.072	0.054	0.084	0.105	0.119
Std of Av Corr Coeff		0.134	0.140	0.148	0.137	0.117	0.147		0.110	0.085
EqW High-low Returns	All	0.050	0.032	0.042	0.033	0.023	0.013	0.025	0.041	0.039
	Micro	0.050	0.035	0.052	0.039	0.025	0.015	0.022	0.043	
	Small	0.010	-0.001	0.004	0.004	0.013	0.006	0.009	-0.005	
	Big	0.008	0.002	-0.003	0.003	0.012	-0.001	0.006	-0.001	
EqW High-low t-statistics	All	9.610	6.128	8.702	6.887	4.455	2.591	4.728	8.135	7.009
	Micro	8.431	5.938	9.560	7.202	4.179	2.515	3.672	7.593	
	Small	1.976	-0.143	0.874	0.806	2.733	1.334	1.917	-1.025	
	Big	1.958	0.476	-0.806	0.796	2.798	-0.248	1.421	-0.139	
ValW High-low Returns	All	0.030	0.017	0.019	0.022	0.018	0.003	0.023	0.025	0.030
	Micro	0.020	0.013	0.026	0.021	0.019	0.010	0.013	0.017	
	Small	0.009	0.000	0.003	0.004	0.009	0.007	0.007	-0.006	
	Big	0.011	0.006	-0.006	0.003	0.011	0.003	0.006	0.001	
ValW High-low t-statistics	All	6.444	3.690	4.592	5.277	3.877	0.551	4.957	5.787	6.008
	Micro	3.904	2.468	5.509	4.380	3.596	1.978	2.453	3.372	
	Small	1.941	0.082	0.583	0.893	1.908	1.582	1.568	-1.261	
	Big	2.271	1.247	-1.390	0.737	2.269	0.615	1.391	0.308	

that sorted return.

As could be expected, given the sorted returns of the individual predictors, the best results were obtained using sets of predictors that included MC. The highest EqW relative monthly high-min-low return is obtained with a linear model using MC, BtoM and DO_RR as inputs, and just exceeds 5% per month relative return, which implies an annual return in excess of 80% over market return (excluding trading costs). The relative return earned by this model for Micro shares only is almost the same, while much lower returns are generated with portfolios selected from the Small and Big share categories (0.96% and 0.84% per month respectively, equating to annual excess returns of 12.1% and 10.5% respectively). The very high relative returns generated by MC is therefore only possible for portfolios that are small enough in size to exploit the high returns of micro caps found in the extreme sorted categories.

It can however be noted that this model also provides a ValW relative monthly return of 2.95%, i.e. an annual excess return of 41.5%, for value weighted portfolios where Micro cap shares does not play such a dominating role. The returns produced by this model are also higher than the returns generated by any of the individual predictors, both for EqW and for ValW portfolios. It furthermore compares favourably with returns reported elsewhere based on time-series prediction techniques (Lorek *et* al, 1983; Altay and Satman, 2005; Bekiros, 2007; Jasic and Wood, 2004; Huang *et al*, 2007).

Table 3 also displays results for different lengths of the training set. It is clear that longer training periods tend to lead to more accurate models, as in all cases the best results are achieved when training the models over 120 months, with training over only 24 months resulting in the worst performance. It would therefore seem that the market has a relatively long ‘memory’, indicating that at least some elements of the relationships between predictors and future returns tend to persist over periods of at least up to 10 years. Conversely the conclusion can be made that a period of only 2 years is too short to train an accurate model, as this period of time does not display all types of behaviour that may occur

Table 4: Returns and fraction of good decisions produced by individual predictors and multivariate models.

Predictors used	Index	MC	Mom	BtoM	DO_RR	DO	NS	MC, BtoM, DO_RR	MC, NS, DO_RR
1985-2010									
Fraction Good Decisions		0.57	0.53	0.60	0.47	0.49	0.39	0.50	0.50
Annualised Returns (%)	22.5	44.98	49.60	33.17	31.64	34.21	22.34	42.89	40.24
NormStdRet	3.96	2.97	2.35	2.51	2.84	2.82	3.85	3.08	3.10
1985-1995									
Fraction Good Decisions		0.67	0.53	0.77	0.51	0.56	0.28	0.47	0.53
Annualised Returns (%)	27.75	95.31	59.46	69.40	51.07	46.84	13.17	57.34	71.59
1995-2005									
Fraction Good Decisions		0.60	0.54	0.53	0.44	0.47	0.38	0.61	0.51
Annualised Returns (%)	20.93	36.74	54.73	33.72	24.75	36.22	29.61	44.43	43.29
2005-2010									
Fraction Good Decisions		0.46	0.52	0.57	0.51	0.48	0.47	0.43	0.46
Annualised Returns (%)	21.83	28.65	33.13	9.29	31.29	21.45	16.13	26.96	9.73

over subsequent time periods when the model is used for return prediction.

When comparing the different measures for model quality, it is interesting to note that models or predictors with a higher correlation coefficient between actual and predicted share returns do not always produce better results in terms of portfolio returns. E.g. using MC as predictor produces a correlation coefficient of 15.0%, an EqW relative return of 4.3% and a ValW relative return of 2.3%. The linear model using MC, BtoM and DO_RR has a correlation coefficient of only 13.8% but produces EqW and ValW relative returns of 5.0% and 3.0%, respectively.

Another interesting aspect is the degree to which the same predictor or model retains predictive capabilities over all three stock categories (Micro, Small and Big). It is clear that models including MC as predictor do not perform well for the Big and Small categories, while models including BtoM and DO or DO_RR perform much better for these categories, indicating that these predictors capture a larger portion of cross-sectional share differences in the Big and Small categories.

Table 4 displays the results for simulated returns over the trading period 1985-2010, using either individual predictors or predicted returns generated by multivariate models to select portfolios. Results are shown for the entire period 1985-2010, as well as for the three periods 1985-1995, 1995-2005 and 2005-2010. In addition to the returns generated over the respective period, the table also displays the fraction of good decisions resulting from each stock selection criteria.

The highest returns over an specific time period is produced using MC as criteria, producing a return of 95.3% for the period 1985-1995. It must be noted that the size of the portfolio was still small during this period – as portfolio size grew over subsequent periods, the returns generated by MC reduced substantially.

The multivariate models based on several predictor variables tend to perform more consistently over the entire time period compared to the individual predictors contained in these models, and, except for small portfolios (where MC performs the best on its own) outperforms the performance of the individual predictors used to train these models.

9 SUMMARY AND CONCLUSIONS

The primary contribution of this paper is to show how robust statistical analysis can be used as basis for evaluating the ability of indicators, as well as of models based on such indicators, to identify stocks with above average return expectations. The simulated trading strategy demonstrates that employing these indicators as basis for stock selection can lead to risk-adjusted returns that far exceed returns associated with the market index.

The paper furthermore practically demonstrates that conventional statistical parameters like correlation coefficient are not necessarily the most appropriate to use for selecting stocks to produce abnormal returns. The approach introduced by Fama and French (2008) to compile sorted categories with associated sorted returns seem to be more suitable to select stocks that are associated with above average probabilities of outperforming the market.

The third important observation is that the relatively basic approach used in this work can produce results that compare favourably with strategies based on extracting time series prediction models for each individual stock. It is important to note that the indicators and models developed in this work are common to all stocks, whereas most other approaches require different models for individual stocks.

A fourth observation is that stocks from an exchange operating within a developing economy (the JSE representing the South African economy) behave in much the same way as stocks listed on the NYSE with respect to a number of fundamental and technical indicators. MC is confirmed to be the strongest individual indicator of abnormal returns (although this may be explained by the higher risk associated with smaller stocks), with BtoM providing the best indicator of abnormal returns for non-micro cap stocks. Between them these two parameters seem to be useful indicators to predict excess returns for growth and value stocks respectively.

The exercise to develop multivariate models using these predictors as inputs shows that, while the best performance of the multivariate models is not much better than the best results with individual predictors, the multivariate models tend to be more consistent over different time periods and for different size categories. These models seem to be able to use the abilities of the different indicators in such a way that the best predictive abilities of each is used when the others tend to loose some of their predictive capabilities (e.g. when moving from Micro to Big portfolios).

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