SOUTH AFRICAN ACTUARIAL JOURNAL
SAAJ **19** (2019) 27–52
http://dx.doi.org/10.4314/saaj.v19i1.2

Regime-based tactical allocation for equity factors and balanced portfolios

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Submission date 17 August 2018
Acceptance date 3 October 2019

ABSTRACT
It is now an accepted fact that the majority of financial markets worldwide are neither normal nor constant, and South Africa is no exception. One idea that can be used to understand such markets and has been gaining popularity recently is that of regimes and regime-switching models. In this research, we consider whether regimes can add value to the asset allocation process. Four methods for regime identification—economic cycle variables, fundamental valuation metrics, technical market indicators and statistical regime-switching models—are discussed and tested on two asset universes—long-only South African equity factor returns and representative balanced portfolio asset class returns. We find several promising regime indicators and use these to create two regime-based tactical allocation frameworks. Out-of-sample testing on both the equity factor and balanced asset class data shows very promising results, with both regime-based tactical strategies outperforming their respective static benchmarks on an absolute return and risk-adjusted return basis. We also turn our attention to a potentially major recent development in the local fund management space; namely, the introduction of Capped Shareholder-Weighted indices as new benchmarks. We provide comparative analysis between the capped and uncapped Shareholder-Weighted indices in terms of sector weights, stock concentration, currency exposure and factor risk contributions.

KEYWORDS
Tactical asset allocation; equity factors; balanced portfolios; market regimes; regime-switching models; turbulence index; technical indicators

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1. INTRODUCTION

1.1 It is now an accepted fact that the majority of financial markets worldwide are neither normal nor constant, and South Africa is no exception. Flint et al. (2012; 2014) examined the statistical properties of South African equity index returns and highlighted the following key points:

— Daily index returns display volatility clustering and a strong negative correlation to volatility.
— Market returns are negatively skewed and fat-tailed for return horizons up to one year. Asset class returns and fund returns are asymmetric in both volatility and correlation across various market states.
— Return distributions and particularly average return estimates change significantly depending on the specified historical period.
— Extreme outlier returns—both positive and negative—occur more frequently than one might expect and can have a significant impact on long-term portfolio returns.

1.2 Researchers have found similar behaviour in a wide variety of markets worldwide, to the point where many of these return characteristics are now termed 'stylised facts' (Cont, 2001). As a result, practitioners and academics alike have turned to new frameworks and models that are consistent with these observations. In the derivative space, this manifests in the form of curved implied volatility surfaces and stochastic or local volatility models for the valuation of exotic options (Seymour, 2011). In the portfolio management space, this results in extensions of the Modern Portfolio Theory (MPT) framework for time-dependent asset dynamics like GARCH volatility and dynamic conditional correlation, or tail risk measures such as value-at-risk and expected shortfall (Seymour et al., 2015). One framework that has been gaining popularity recently in both of these areas is that of regimes and regime-switching.

1.3 Ang & Timmermann (2012) identify three reasons for the popularity of the regime-based framework. Firstly, regimes are intuitive and can naturally fit the *ex-post* narratives that investors use to explain market moves. Estimated regimes are often found to tie up with low- and high-volatility periods, up- and down-trending return periods and/or changes in underlying macroeconomic policy. Secondly, regime models are capable of accurately capturing the nonlinear and non-normal stylised facts outlined above. Figure 1 depicts this by showcasing a mixture of two normal distributions. Notice the significant negative skew and excess kurtosis of the mixed distribution. Thirdly, because regime models are generally constructed as a linear combination of (log)normal distributions, they are simple to understand and implement. A regime-based framework thus allows one to capture the intricacies of the market while still affording analytical tractability and familiarity.

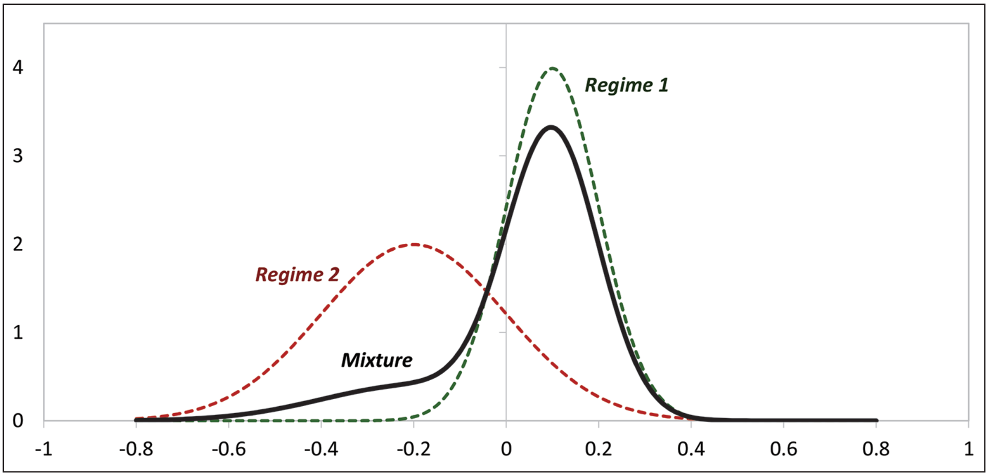


FIGURE 1. Mixture of two normal distributions

1.4 Although South African research on the subject is limited, there have been some studies that incorporate regimes into the investment process. For example, Flint et al. (2014) examine the use of regimes for systematically timing option hedging decisions in equity portfolios and Seymour et al. (2016) consider the use of regimes in multi-asset portfolio optimisation problems, both finding promising results. In this research, we extend this work by considering the use of a regime-based framework to enhance the asset allocation process. If one assumes that markets oscillate between divergent regimes, then it stands to reason that an asset allocation process that tactically changes portfolio exposure to account for these regime changes should add value relative to a static portfolio mix. The goal of this work is thus to examine whether such a regime-based asset allocation process can indeed add value in the South African context.

1.5 Throughout this research, we make use of two specific asset universes. The first universe consists of seven South African long-only fundamental equity factors; namely, size, value, profitability, investment, momentum, low volatility and low beta. These factors are constructed according to international industry standards but using South African stock data. Please see Flint et al. (2017) for a complete outline of the factor construction process. Factor return data for the period January 2003 to March 2017 was downloaded from the open-source Legae Peresec factor data library.[1] We select the long-only return database constructed from a constrained FTSE/JSE All Share Index (ALSI) stock universe as a representation of a tradable set of equity factors.

1.6 The second universe represents the set of asset classes most commonly found in a South African balanced portfolio; namely, local equity (ALSI), local bonds (FTSE/JSE All

1 The Legae Peresec factor data library can be accessed at https://legaeperesec.co.za/.

Bond Index), local property (FTSE/JSE SA Property Index), global equity (FTSE World Index), global bonds (JP Morgan Government Bond Index), global commodities (RJ CRB Commodity Index) and the USDZAR exchange rate.

1.7 The rest of this paper is organised as follows. Section 2 motivates the use of regimes in finance and discusses and implements four of the most popular regime identification methods and variables. Section 3 discusses a major recent development in the South African portfolio management space; namely, the introduction of capped Shareholder-Weighted equity indices as new fund benchmarks. We compare how the capped indices differ from their uncapped originals based on sector weights, stock concentration, currency exposure and factor risk contributions. Section 4 builds on the previous regime classification work and tests the out-of-sample performance of two regime-based asset allocation frameworks. The first framework is based on technical indicators and is implemented on the equity factor universe, and the second is based on a regime-switching model of financial turbulence and is implemented on the balanced portfolio universe. Section 5 concludes and outlines some ideas for further research.

2. IDENTIFYING MARKET REGIMES

Below, we outline some of the most popular methods and variables currently used for defining and estimating economic environments and market regimes. Note that some of the methods described here are not strictly regime-switching models in a statistical sense. However, they still have the goal of categorising the market into different underlying states and are commonly used in practice.

2.1 Macroeconomic Environments: Yield Spread, Inflation and CLI

2.1.1 The idea of the economic or business cycle dates back to the early 1800s and was formalised in 1860 by the French economist, Clement Juglar. Juglar argued that economic prosperity oscillated in some systematic fashion around a long-term trend and that a full cycle was likely to be between 7 to 11 years. Nowadays, the standard definition of such a business cycle is taken from the seminal work of Burns & Mitchell (1946). In particular, the cycle is defined as a combination of four periods: economic expansion, deceleration, recession/contraction and finally, recovery/acceleration. These cycles are certainly recurrent—with the prevailing recovery phase blending into the following expansionary period—but probably aperiodic, meaning that the exact length of each period will likely differ within each complete cycle. Figure 2 is a reproduction from the work of Van Vliet & Blitz (2011) illustrating the standard four-period economic or business cycle.

2.1.2 Business cycle identification and the application thereof in economics and finance continues to be a widely researched area. While most research uses a four-period cycle—with some decreasing this to two or three periods—there is far less consistency in the economic variables chosen to identify these periods. This is to be expected given the structural differences in the national economies. We thus turn towards the relevant South African literature to facilitate economic variable selection.

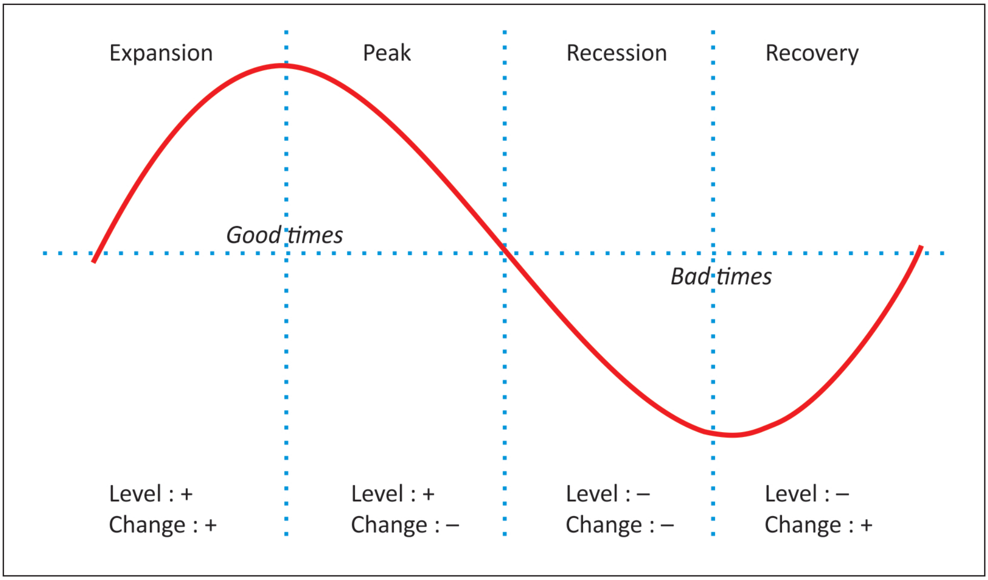


FIGURE 2. Economic cycle with four phases, reproduced from Van Vliet & Blitz (2011)

2.1.3 Moolman (2003) conducted one of the first studies of this kind using South African data, testing the ability of more than twenty economic indicators to predict turning points within the business cycle. Moolman found that short-term interest rates, the yield spread between 10-year and 3-month government bonds, and the composite index of leading indicators published by the South African Reserve Bank (SARB) were the best performing variables. Khomo & Aziakpono (2007) found similar results with regard to the predictive ability of the yield spread and showed that it had similar levels of predictive power to that of price momentum indicators (see Section 2.3 for more on this). A recent study by Mohapi & Botha (2013) also showed that the yield spread was able to accurately predict the 2008 sub-prime mortgage crisis in addition to all other major recessions dating back to 1980. It would thus appear that we have three prime candidates predicting the business cycle.

2.1.4 However, there is a problem here. The studies above all use some form of linear probit regression framework to consider whether lagged observations of the economic variables are significant predictors of an unobservable recession indicator variable. To answer this question, the studies all make use of the SARB's *ex-post* quarterly recession indicators. Unfortunately, this means that the economic cycle has already been defined and the variables are being tested after the fact, which is somewhat putting the horse before the cart in terms of any *ex-ante* regime-based applications.

2.1.5 Figure 3 compares the monthly drawdown series for South African equity against the regimes identified by a range of business cycle variables over the period January 1960 to April 2017. Motivated by our previous discussion, the economic variables include the 10-year to 3-month yield spread, 12-month changes in inflation and 12-month changes in the composite leading index (CLI). Periods are classified as recessions when the indicators take on negative values, displayed in the graphs as the respective blue shaded areas. We also include a final profile which defines recessions as those periods when the underlying equity index is below its 10-month moving average (MA). This technical price indicator is commonly used in current tactical asset allocation strategies and serves as a useful benchmark (Faber, 2013).

2.1.6 The regime profiles from the economic indicators are clearly quite different, both in terms of total frequency and average length. Although Mohapi & Botha (2013) showed that the yield spread accurately predicted all the SARB-indicated recessions back to 1980, if one extends the period back to 1965, being the start of available yield data (demarcated by the greyed area), then a very different conclusion is reached regarding its predictive ability. The South African equity market was under water for the majority of the 1970s and early 1980s and there are two very large and obvious market crashes over this period. However, neither of these is flagged by the yield spread variable.

2.1.7 In comparison to the yield spread, the inflation indicator, which has data available back to 1970, captures a portion of these early recessions prior to 1990 but still misses certain periods. We also observe that nearly half of the complete period is flagged as recession, which is clearly at odds with the yield spread regimes and also with underlying economic rationale.

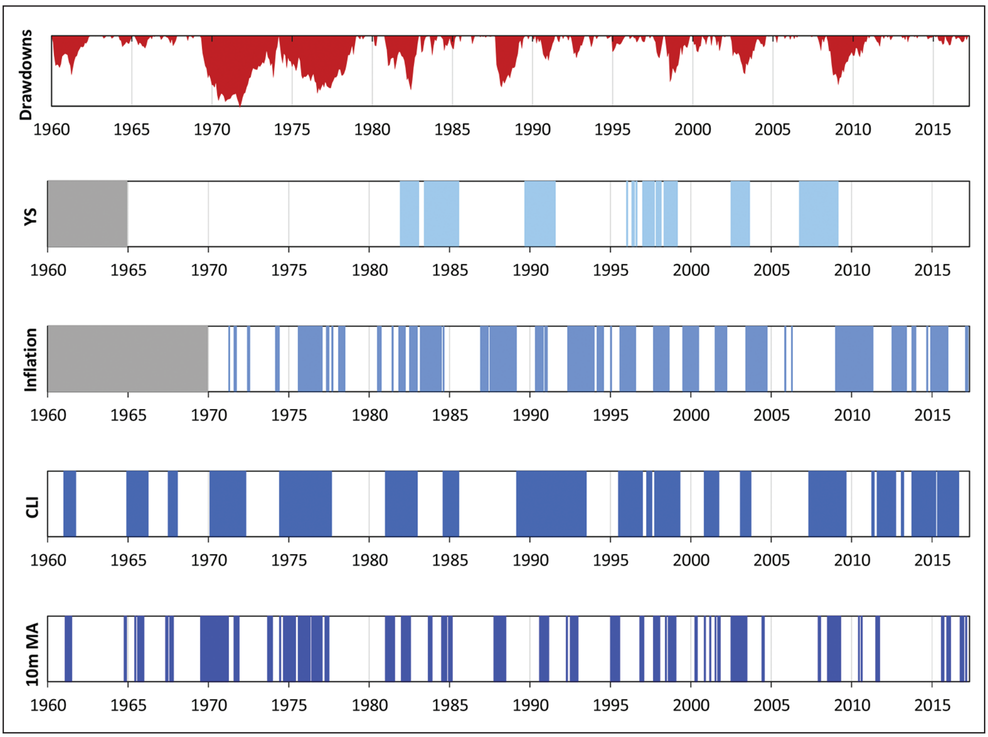


FIGURE 3. South African equity drawdowns versus business cycle recession profiles, Jan 1960 to Apr 2017

2.1.8 The CLI indicator also identifies a surprisingly high proportion of the full sample period as recession. Based on a graphical comparison with the equity drawdown curve, it would seem that the majority of the CLI-identified recessions occur close to the start of the actual market downturn but seem to continue quite far into the recovery phase. This is in contrast with the technical MA recessions, which line up with the CLI starting points but are considerably shorter and oscillate far more. A pertinent illustration of this divergence is the recessions—or lack thereof—identified from 1987 to 1994.

2.1.9 Table 1 gives SA equity return summary statistics for each of the four macroeconomic regime profiles identified in Figure 3, while similar SA bond return regime statistics are given in Table 2. Looking at the equity return statistics, the most important observation is that although the average returns in the recessionary periods are considerably lower than those seen in expansions, only the MA recession average is actually negative as one would expect. The difference in volatilities across the respective economic regimes is also not as extreme as that shown for the MA indicator. For the inflation and CLI regimes this is explained by once again considering the total number of observations identified within each regime. Around 44% and 48% respectively of all months are identified as recessions by these economic indicators. Assuming that there is in fact a dominant economic regime, it follows that the differences in these regime statistics are thus downwardly biased, albeit still directionally correct.

TABLE 1. In-sample recession and expansion statistics for South African equity returns

	Recession				Expansion			
	Yield spread	Inflation	CLI	MA	Yield spread	Inflation	CLI	MA
Average return	9.5%	15.8%	11.8%	–22.1%	20.5%	21.5%	24.2%	34.3%
Volatility	23.8%	22.7%	21.3%	24.5%	20.1%	19.8%	19.5%	16.4%
Sharpe ratio	0.40	0.70	0.55	–0.90	1.02	1.08	1.24	2.09
Skew	–0.50	–0.66	–0.50	–0.15	–0.39	–0.15	–0.37	0.11
Excess kurtosis	2.07	2.22	1.64	1.26	1.14	0.44	1.63	0.52
% No. Obs.	21.2%	44.3%	48.4%	28.4%	78.8%	55.7%	51.6%	71.6%

TABLE 2. In-sample recession and expansion statistics for South African bond returns

	Recession				Expansion			
	Yield spread	Inflation	CLI	MA	Yield spread	Inflation	CLI	MA
Average return	15.7%	9.6%	11.6%	9.3%	9.4%	13.0%	9.3%	10.8%
Volatility	9.6%	7.6%	7.5%	7.5%	6.0%	7.1%	6.0%	6.4%
Sharpe ratio	1.63	1.26	1.55	1.25	1.57	1.83	1.54	1.68
Skew	–0.26	–0.71	–0.02	–0.37	–0.27	0.35	–0.29	0.12
Excess kurtosis	2.40	3.30	3.80	6.25	2.96	2.74	3.48	2.17
% No. Obs.	21.2%	44.3%	48.4%	28.4%	78.8%	55.7%	51.6%	71.6%

2.1.10 In comparison, the yield spread regime statistics are somewhat similar in value to those of the other two economic indicators, but only 21% of observations are now being classified as recessionary. Looking at Figure 3, we see that although the majority of these recession periods match up with the largest equity drawdowns, the inclusion of an incorrect recession from 1983 to 1986 and exclusion of the short but significant downturn in 1987 provides the downward bias.

2.1.11 Considering the bond returns in Table 2, it would appear that only the yield spread indicator accurately captures their regime-specific behaviour. This is to be expected given that the yield spread is intrinsically linked to bond performance and, furthermore, that negative yield spreads imply increasing bond prices. The inflation and MA indicators provide counter-intuitive results in that we see lower returns during recessions and higher returns during expansions, which is opposite to what economic theory suggests. This result is understandable in the case of the MA indicator though as this indicator is purely focused on up- and down-trends in the underlying equity index. Finally, the CLI regimes provide economically reasonable results but only show minor differentiation when compared to the yield spread results.

2.1.12 From this analysis, it would appear that macroeconomic indicators provide limited ability to partition equity markets relative to technical price indicators and that only the yield spread indicator is able to accurately capture statistically different regimes in the bond market.

2.2 Fundamental Equity Valuations

2.2.1 The second method for identifying market regimes is based on the underlying principle of value investing. Fundamental equity data is used to identify whether markets are currently undervalued or overvalued relative to historical norms. Undervalued markets should unlock value over time as they revert to their correct long-term equilibrium valuation, while overvalued markets are similarly likely to fall down to this level. An example of such an indicator is the cyclically adjusted price-to-earnings ratio (CAPE) introduced by Campbell & Shiller (1988). The CAPE ratio is commonly referenced in day-to-day market commentary as a measure of equity market health and extreme highs are taken as being indicative of imminent market crashes. Apart from the CAPE ratio, one can also use the full suite of value metrics—for example, price-to-book, dividend yield and price-to-cash flow—in a similar fashion and create regime identification rules based on the value spreads relative to some historical average.

2.2.2 As a simple test, we consider the equity regimes identified by a PE ratio and dividend yield combination on the ALSI back to September 1986. The market is categorised into four states as given in Figure 4, based on whether the current PE ratio and dividend yield are above or below their respective historical running averages.

2.2.3 Based on the regime-specific statistics given in Table 3, there is a clear difference in realised volatilities across the high and low PE regimes and a similarly clear difference in average returns over the high and low yield regimes. The combination of the two metrics thus seems to provide a complete method for classifying over- and under-valued

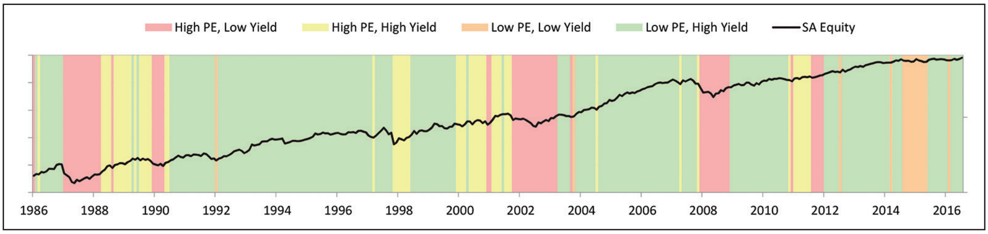


FIGURE 4. SA equity performance across fundamental valuations-based regimes, Sep 1986 to Apr 2017

markets. It is worth bearing in mind though that only 4% of the total sample period falls within the Low PE, Low Yield category, meaning that these estimated statistics are likely to be quite noisy.

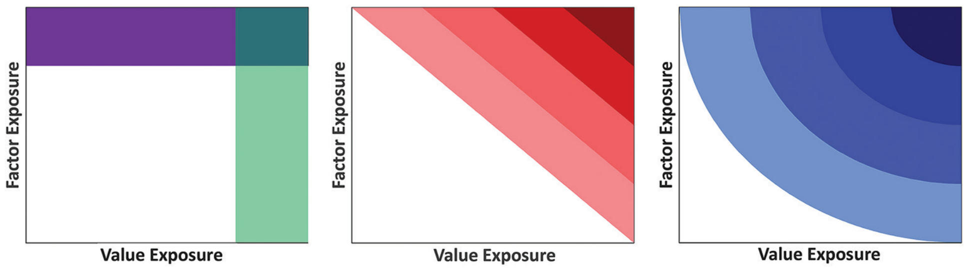
TABLE 3. In-sample valuations-based regime statistics for South African equity returns, Sep 1986 to Apr 2017

	High PE, low yield	High PE, high yield	Low PE, low yield	Low PE, high yield
Average return	–11.72%	14.36%	–12.00%	22.11%
Volatility	24.46%	23.45%	11.68%	15.90%
% No. Obs.	17%	16%	4%	64%

2.2.4 Recently, the idea of relative valuation and the use of value spreads has received considerable attention in the equity factor space. This is largely due to many investors looking for ways in which to time factor exposures. Rob Arnott and his co-authors at Research Affiliates—one of the major investment firms in the Smart Beta space—produced a series of online white papers in 2016 on this issue, claiming that factor timing using relative valuation really does work. In response, Cliff Asness and the team from AQR Capital—another large Smart Beta firm—have written several pieces in which they categorically disagree with Arnott et al.'s (2016) findings and rather advocate holding a static diversified factor portfolio.

2.2.5 Our views on the use of value spreads to time factors are aligned more with Asness et al. (2017), for two reasons. Firstly, there is likely to be some degree of dependence between the returns of a value-timed factor and the value factor itself. Investors may thus unknowingly increase their value exposure. Secondly and more importantly, using historical value spreads to time factors that are value-agnostic by construction equates to creating unintentional multi-factor portfolios. Such portfolios are likely to be sub-optimal relative to explicit multi-factor portfolios.

2.2.6 Timing factors based on their relative valuations is analogous to creating a multi-factor portfolio via the portfolio mixing method, depicted graphically in Figure 5a. However, rather than holding both factors in some fixed proportion as would be standard in portfolio mixing, the replicating multi-factor strategy for relative value timing would be to



(a) Portfolio mixing (b) Signal Averaging (c) Signal Blending

FIGURE 5. Multi-factor portfolio construction methods

only hold those stocks within the overlapping exposure area in the top right corner of the panel. Periods when there are no stocks in this area then equate to 'sell' or 'under-weight' signals from the relative value indicator.

2.2.7 Rather than unintentionally following this very specific and likely concentrated approach to multi-factor construction, investors should instead explicitly define their multi-factor construction method. Furthermore, they should consider the use of the more robust integrated scoring approaches depicted in Figures 5b and 5c. The portfolio mixing method, while transparent, does not account for interactive factor effects nor does it allow for variable factor signal decay speeds. Integrated scoring approaches do account for these issues, with the additive signal averaging and multiplicative signal blending approaches given here being examples of simple but robust multi-factor construction methods.

2.2.8 In summary, the classification of the underlying equity market into over- and under-valued regimes shows promise. However, using a similar relative valuation framework to time factors does not seem particularly beneficial given that one ultimately creates sub-optimal multi-factor portfolios. Investors should rather consider explicit multi-factor construction methods such as signal averaging and signal blending.

2.3 Technical Indicators: Momentum and Implied Volatility

2.3.1 Apart from considering the macroeconomic or fundamental classifications given above, one can also partition markets based on a range of technical or quantitative indicators. Such indicators are commonly used in systematic trading strategies to tactically scale risk exposure across a range of sectors or asset classes. Successful indicators have strong theoretical and/or behavioural motivations; their predictive power stems from taking advantage of a particular characteristic or stylised fact of the underlying return distribution.

2.3.2 Flint et al. (2014) tested the ability of a range of such indicators to accurately predict South African equity index regimes under the assumption of a two-state regime model, comprising a down-trending, volatile market and an up-trending, stable market. It was found that a number of these timing indicators accurately identified the major equity drawdowns since the mid-1990s and produced compelling results when utilised in a systematic timed hedging strategy. In particular, indicators based on probabilistic momentum and implied volatility were found to have the highest predictive and practical value.

2.3.3 Probabilistic momentum, introduced by Varadi (2014), translates monthly excess market returns over a specified historical period into a probability of outperforming cash (or another specified asset). If the probability of outperformance is lower than a given threshold k, then the market is said to be down-trending. If the outperformance probability is greater than $1-k$ then the market is said to be up-trending. Assuming that $k<50\%$ there is therefore a $1-2k$ buffer that needs to be crossed before a regime change is signalled. This buffer range ensures that weak or incorrect momentum signals are ignored.

2.3.4 Mathematically, the probability of outperformance, PM_t, is calculated by transforming excess monthly market returns in a given period into a t-score and using the student's t distribution, Φ, with $n-1$ degrees of freedom to convert this score into a probability,

$$PM_t = \Phi\left(\frac{E\left(R_m - r_f\right)}{\sqrt{Var\left(R_m - r_f\right)/n}}, n-1\right). \tag{1}$$

2.3.5 The similarities to the Sharpe Ratio are clear and thus probabilistic momentum can be thought of as a risk-adjusted momentum indicator. In the classifications below, we use rolling 8-month periods and a threshold value of $k=30\%$. This means that if $PM_t < 30\%$, it will have to move above 70% before a regime change is recognised, and vice versa for $PM_t > 70\%$.

2.3.6 The implied volatility indicator is considerably simpler and is based on the stylised facts of volatility clustering and the inverse relationship between returns and volatility. These characteristics ensure that down-trending markets will coincide with high volatility and that this period should be somewhat persistent. The indicator is thus defined by whether 3-month at-the-money implied volatility is above or below a given historical percentile. Based on the work of Flint et al. (2014), we set this threshold to be the rolling historical 70th percentile.

2.3.7 Figure 6 displays the combined four-state market classification as well as the time series of the individual indicators over the period February 1996 to April 2017. Despite significant overlap, the periods in which the indicators denote contradictory regime signals are quite noticeable. For example, the absence of a high volatility regime during the 2002/2003 period, when markets were strongly down-trending, is an important reminder that the manner in which a downturn occurs can have a strong effect on the predictive capacity of the underlying technical indicators.

2.3.8 Another observation from Figure 6 is that implied volatility moves considerably faster than probabilistic momentum, meaning that although momentum regimes will be more stable—and thus generate less turnover—this will come at the cost of missing the initial phases of any crash or recovery.

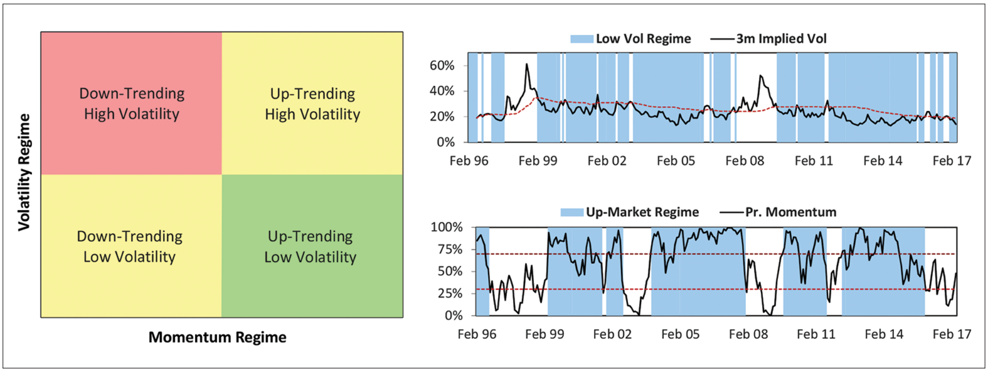


FIGURE 6. Technical indicator classification system and historical South African indicator profiles, Feb 1996 to Apr 2017

2.3.9 Table 4 gives the in-sample regime-specific statistics for the equity factor universe, and Table 5 gives similar regime statistics for the balanced asset class universe. The percentage in brackets next to each regime heading represents the proportion of months classified in that regime relative to the full sample. In line with Russo (2015), we report the p-values of a paired t-test of the return differences between each factor and the average returns of the remaining factors. For each regime, we show the annualised average return and volatility of the factor returns along with the Sharpe ratio, return skewness and excess kurtosis, and finally the minimum and maximum monthly returns.

2.3.10 Let us first discuss the factor statistics in Table 4. It is not surprising to see that the up-trending, low-volatility regime shows high average factor returns and generally low realised factor volatilities across the entire universe, or that one sees negative average factor returns and elevated realised factor volatilities in the down-trending, high-volatility regime. What is surprising though is that during up-trending, high-volatility regimes, we see even stronger negative returns but at very low-realised volatilities, while during down-trending, low-volatility regimes we see the highest recorded average returns but coupled with fairly high realised volatilities.

2.3.11 To understand these results, let us contextualise the timing of the four technical-based regimes in terms of the stylised business cycle given in Figure 2. Probabilistic momentum will lag markets by construction, while implied volatility is arguably one of the best forward-looking estimates of market risk. Putting these two facts together, one is likely to see a positive momentum and high implied volatility combination during markets that have already peaked and are beginning to decelerate. While uncertainty would be high during such a time, realised volatility may still be low as markets start to account for the possibility of a future recession. In such a situation one would also expect negative skewness to dominate the distribution, which is exactly what is given in the table.

2.3.12 In a similar vein, the combination of negative momentum and low implied volatility is likely to be evident at the start of any recovery period. This is when markets would be accelerating at their quickest rate—hence the strong positive returns in the table—but

TABLE 4. In-sample probabilistic momentum and implied volatility regime statistics for long-only SA equity factor returns, Jan 2003 to Apr 2017

Up, Low Vol (62%)	Size	Value	Profit-ability	Invest-ment	Momentum	Low volatility	Low beta
Average return	26.4%	23.3%	29.8%	25.9%	34.3%	29.3%	29.0%
p-value	0.06	0.00**	0.33	0.26	0.00**	0.66	0.64
Volatility	12.0%	14.1%	12.3%	13.7%	13.9%	10.5%	11.7%
Return-risk ratio	2.21	1.66	2.42	1.90	2.47	2.80	2.49
Skew	0.17	0.03	–0.09	0.10	0.22	0.04	0.30
Excess kurtosis	–0.40	–0.05	0.25	–0.16	0.10	–0.31	1.56
Minimum	–4.6%	–9.2%	–7.9%	–6.4%	–6.4%	–4.3%	–6.6%
Maximum	11.6%	11.8%	10.9%	12.4%	14.4%	10.1%	14.7%
Up, High Vol (6%)							
Average return	–21.8%	–17.6%	–30.2%	–23.2%	–16.5%	–28.8%	–36.4%
p-value	0.42	0.22	0.42	0.76	0.25	0.58	0.22
Volatility	8.7%	8.7%	12.2%	8.1%	9.1%	9.4%	10.6%
Return-risk ratio	–2.49	–2.01	–2.47	–2.86	–1.80	–3.06	–3.44
Skew	–0.55	–0.36	–0.97	–0.58	–0.45	0.11	–0.81
Excess kurtosis	–0.70	–0.42	1.00	–0.08	–1.26	–0.67	0.61
Minimum	–5.9%	–5.9%	–9.9%	–6.5%	–5.0%	–6.8%	–9.0%
Maximum	1.6%	2.2%	2.2%	1.0%	1.9%	1.9%	1.5%
Down, Low Vol (15%)							
Average return	41.8%	39.5%	35.9%	41.5%	41.3%	26.7%	28.2%
p-value	0.08	0.29	0.96	0.21	0.21	0.06	0.09
Volatility	15.6%	16.1%	14.6%	17.0%	13.9%	11.5%	13.0%
Return-risk ratio	2.68	2.45	2.46	2.44	2.96	2.31	2.17
Skew	0.27	–0.23	0.53	0.30	–0.07	0.05	–0.57
Excess kurtosis	0.34	–0.17	0.02	–0.47	–0.32	0.83	1.44
Minimum	–5.0%	–6.9%	–4.6%	–4.5%	–4.1%	–5.9%	–7.7%
Maximum	13.7%	11.4%	12.1%	13.9%	11.9%	9.3%	9.8%
Down, High Vol (17%)							
Average return	–13.5%	–13.8%	–12.2%	–15.2%	–23.5%	–14.8%	–10.4%
p-value	0.74	0.82	0.48	0.94	0.15	0.97	0.48
Volatility	19.8%	18.3%	19.2%	23.9%	20.4%	14.6%	16.6%
Return-risk ratio	–0.68	–0.75	–0.63	–0.64	–1.15	–1.01	–0.63
Skew	–0.06	–0.30	0.18	0.36	0.28	–0.90	–0.88
Excess kurtosis	–0.57	0.33	–0.41	0.38	0.08	1.48	1.12
Minimum	–13.5%	–13.6%	–10.9%	–14.4%	–14.1%	–13.8%	–14.8%
Maximum	9.5%	9.8%	11.2%	16.1%	12.4%	5.5%	7.2%

would also still experience a high degree of realised volatility as market participants phase out existing defensive holdings in favour of growth assets. Despite this, it is still remarkable to see just how strong the returns are during this initial part of the recovery phase.

2.3.13 In addition to these general trends highlighted above, there are also some factor-specific nuances within the various regimes. Such a classification makes it clearer to identify when each factor is rewarded or unrewarded. For instance, momentum shows the least negative return of –16.5% during the decelerating component of the economic cycle—i.e. up-trending, high volatility—but contrastingly displays the worst return of –23.5% during the true recessionary periods—i.e. down-trending and high volatility. In contrast, the low beta factor is the least affected during market crashes, showing a return of only –10.4%, but instead records the worst loss by a considerable margin of –36.4% during up-trending, high-volatility market. Note, however, that the number of observations within this regime is considerably lower than in any of the other regimes and so there is bound to be some noise in the individual statistics.

2.3.14 We now turn our attention to Table 5 and the balanced asset class regime statistics. Note that international asset class returns are calculated in dollar terms and that we include the exchange rate as a separate asset in order to isolate any regime-specific currency effects. The local currency comparative values can be approximated by simply adding the asset and currency values together

2.3.15 As with the factor statistics, we see clear and significant differences in values across the four regimes, most of which are in line with our economic expectations. The asset classes generally perform best during the two low-volatility regimes, and realised volatility only significantly increases for all asset classes in the down-trending, high-volatility regime. Local and international bonds provide the best relative performance during the two high-volatility regimes but otherwise underperform the riskier asset classes. The currency average return values tend to move in opposition to the rest of the asset classes across the regimes owing to the ratioed nature of the underlying exchange rate. Positive returns thus imply a weakening local currency.

2.3.16 We also note significant negative returns in the up-trending, high-volatility regime and similarly significant positive returns during the down-trending, low-volatility regime. Again, this is due to the relationship between these two regimes and the deceleration and recovery periods of the business cycle.

2.3.17 Perhaps most importantly, and in contrast to the results from the factors which are all equity-based portfolios, we see that at least two asset classes display significantly different average returns (p-value <0.05) within each of the respective regimes. This suggests two things: firstly, that a strategy which tilts between asset classes on a regime basis should have the potential to considerably outperform a static multi-asset portfolio, and secondly, that the selected technical indicators do indeed classify markets into materially different and economically useful regimes.

2.4 Statistical Regime Models and Financial Turbulence

2.4.1 The final approach that we consider is statistical regime-switching models and, in particular, the hidden Markov model (HMM) introduced by Hamilton (1989). We

TABLE 5. In-sample probabilistic momentum and implied volatility regime statistics for the balanced universe asset class returns, Jan 2003 to Apr 2017

Up, Low Vol (59%)	SA Equity	SA Bonds	SA Property	Global Equities	Global Bonds	Commodi-ties	USDZAR
Average return	26.6%	12.3%	31.1%	10.6%	3.7%	5.2%	6.0%
p–value	0.00***	0.58	0.01*	0.23	0.00***	0.06	0.09
Volatility	14.5%	6.9%	29.8%	11.7%	5.1%	12.8%	14.1%
Return-risk ratio	1.83	1.78	1.05	0.90	0.74	0.40	0.42
Skew	0.21	–0.11	3.30	–0.21	–0.17	–0.33	0.74
Kurtosis	–0.12	0.85	43.47	0.06	0.17	0.54	1.36
Minimum	–8.2%	–5.0%	–44.4%	–8.7%	–3.9%	–10.8%	–8.3%
Maximum	13.1%	6.8%	77.9%	9.5%	3.7%	10.4%	16.8%
Up, High Vol (6%)							
Average return	–32.2%	2.1%	–26.8%	–34.2%	5.0%	–13.2%	34.7%
p-value	0.06	0.11	0.19	0.01*	0.03*	0.44	0.00**
Volatility	14.8%	7.4%	14.5%	12.2%	4.5%	12.9%	13.2%
Return-risk ratio	–2.18	0.29	–1.84	–2.79	1.11	–1.02	2.62
Skew	–0.76	0.02	–1.66	–0.75	–0.63	–0.33	0.61
Kurtosis	1.26	0.34	3.62	–0.35	0.15	–0.01	0.43
Minimum	–13.1%	–3.6%	–13.9%	–10.1%	–2.4%	–8.2%	–3.4%
Maximum	3.4%	4.2%	3.2%	1.1%	2.2%	5.6%	11.5%
Down, Low Vol (16%)							
Average return	28.8%	18.1%	13.2%	25.4%	6.6%	9.3%	–8.8%
p-value	0.01**	0.19	0.99	0.06	0.22	0.80	0.01*
Volatility	15.0%	5.8%	14.1%	14.7%	5.6%	10.7%	15.7%
Return-risk ratio	1.93	3.11	0.93	1.73	1.17	0.87	–0.56
Skew	0.57	0.85	0.21	–0.73	0.28	0.23	0.55
Kurtosis	–0.08	2.42	1.69	1.40	1.27	0.14	1.26
Minimum	–5.0%	–1.8%	–9.5%	–11.2%	–3.4%	–6.0%	–9.9%
Maximum	14.1%	7.3%	12.9%	10.6%	4.9%	8.3%	12.6%
Down, High Vol (19%)							
Average return	–14.2%	9.4%	–7.1%	–11.8%	6.4%	–19.5%	16.0%
p-value	0.21	0.02*	0.68	0.26	0.05*	0.04*	0.14
Volatility	26.3%	12.3%	24.2%	21.7%	7.5%	20.5%	20.4%
Return-risk ratio	–0.54	0.77	–0.29	–0.54	0.86	–0.95	0.78
Skew	–0.69	–0.24	0.91	–0.60	0.20	–0.43	0.59
Kurtosis	2.64	1.66	2.01	0.61	0.30	2.95	1.18
Minimum	–29.3%	–10.5%	–14.5%	–19.6%	–3.8%	–22.3%	–11.9%
Maximum	14.0%	9.2%	22.8%	11.5%	6.6%	13.8%	18.5%

consider a simple two-state regime-switching model of returns as an illustration. We can model the return r_t at time t in the following way:

$$r_t = \mu_{s_t} + \sigma_{s_t}\varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0,1), \tag{2}$$

where μ_s and σ_s are the mean and volatility of the process, $s_t \in \{0,1\}$ is a binary state indicator, and ε_t is an i.i.d. random noise term. In this model, we assume that the two regimes are represented by two normal distributions and are thus fully specified by the mean and volatility parameters. The (unconditional) probability of being in regime $s_t=0$ is given by π_0 and the probability of being in regime $s_t=1$ is thus given by $1-\pi_0$. Regime switches are governed by the transition probability matrix, $P_t = \{p_{ij,t}\}$, which represents the probability of transitioning from regime i at time $t-1$ to regime j at time t. These probabilities can be fixed or time-varying depending on the model.

2.4.2 The mixture of normal distributions displayed in Figure 1 was produced by this model. It is appealing because it allows one to match the most important statistical properties of empirical returns—negative skew, excess kurtosis and volatility clustering—in a fairly simple manner. The reason for this being called an HMM is because the actual regime variables are unobservable and need to be inferred from the available data. By fitting this model to empirical data, we thus attempt to estimate the underlying characteristics of each regime as well as the manner in which these regimes interact over the sample period.

2.4.3 Ang & Bekaert (2002) were one of the pioneers of regime-based asset allocation. Since then, there have been numerous studies making use of HMMs in portfolio and risk management applications—see Nystrup (2014) and Homescu (2015) for an overview. The majority of regime-switching models are applied directly to underlying asset or factor returns, but there are a few papers that apply the model to other variables such as statistical or economic indicators. In this work, we consider the latter approach and apply a regime-switching model to the financial turbulence index.

2.4.4 The financial turbulence index was proposed by Chow et al. (1999) and applied in portfolio optimisation and asset allocation by Kritzman et al. (2012). Chow et al. (1999) define a turbulent market as one in which assets behave in an 'unusual' fashion. Unusualness includes any period which shows either high volatility or different correlations, relative to the historical norm, or a combination of both features. In order to capture all facets of unusualness, Chow et al. (1999) proposed the squared Mahalanobis distance as a measure of financial turbulence. Letting μ be the mean return vector of the asset universe and Σ its covariance matrix, we can therefore define turbulence, d_t, at time t as

$$d_t = (r_t - \mu)\Sigma^{-1}(r_t - \mu)'. \tag{3}$$

2.4.5 Intuitively, turbulence can be thought of as the multivariate version of the univariate z-score. However, rather than dividing each asset's mean deviation by volatility alone, multivariate measures need to account for the correlations between the assets as well, hence the use of the covariance matrix as divisor.

2.4.6 One can then separate historical returns into quiet and turbulent regimes based on the turbulence index, either by using a fixed threshold level (Kritzman & Li, 2010) or through the use of a regime-switching model (Kritzman et al., 2012).

2.4.7 As a demonstration, Figure 7 displays the daily turbulence index for the factor universe over the period January 2003 to March 2017. A smoothed index using an exponentially-weighted moving average is overlaid and we also include as a threshold level the 75th percentile of a Chi-squared distribution with degrees of freedom equal to the number of factors. Quiet periods are defined as any periods when the smoothed index is below the threshold, while turbulent periods are those above the threshold.

2.4.8 Table 6 gives the average return, volatility and value-at-risk (VaR) factor statistics computed from the identified quiet and turbulent regimes. From this, it is clear that the indicator creates regimes with statistics that are exactly in line with the intuitive definition of a turbulent market but also, and perhaps more importantly, in line with our economic intuition. Statistical regime-switching models based on the turbulence index thus appear to be compelling candidates for estimating and predicting market regimes.

TABLE 6. In-sample turbulence index regime statistics for SA equity factor returns, Jan 2003 to Apr 2017

	Quiet statistics			Turbulent statistics		
Factor	Average return	Volatility	VaR	Average return	Volatility	VaR
Size	23.6%	10.0%	7.5%	–6.7%	24.4%	–37.4%
Value	21.8%	11.6%	2.8%	–8.8%	28.6%	–42.8%
Profitability	26.3%	12.0%	6.8%	–12.2%	28.6%	–44.7%
Investment	21.7%	12.2%	1.7%	–3.6%	30.9%	–41.9%
Momentum	29.5%	12.7%	9.0%	–13.9%	29.6%	–46.5%
Low volatility	25.7%	9.9%	9.9%	–21.4%	24.2%	–45.8%

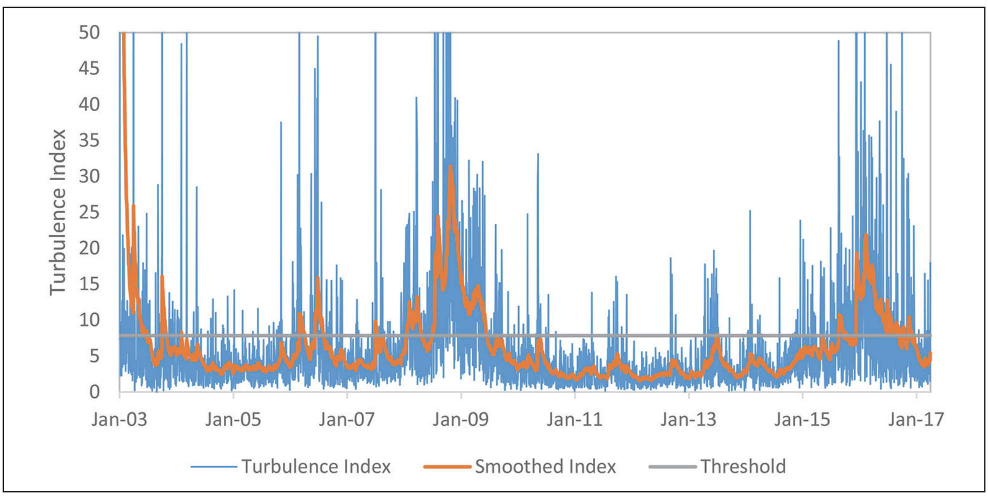


FIGURE 7. Factor universe turbulence index, Jan 2003 to Apr 2017

3. NEW SA EQUITY BENCHMARKS: CAPPED INDICES

3.1 Given that the theme of this work is to identify changes in market conditions, we feel that it is appropriate to highlight one of the major recent developments in the South African portfolio management space, namely, the introduction of capped versions of the FTSE/JSE Shareholder-Weighted Top40 (SWIX40) and FTSE/JSE Shareholder-Weighted All Share (SWIX) indices. The Capped SWIX indices are the same as their uncapped counterparts in terms of constituents, construction rules and the treatment of corporate actions. The only difference is that each constituent's weight is capped at 10% quarterly. Weights can go above 10% intra-quarter due to price movements, shares in issue or free float changes, but any breaches will be brought back to the limit at the beginning of the next quarter, with the excess being distributed amongst the uncapped constituents proportionally to their weights. For this research, we reconstruct the Capped SWIX indices historically in a manner that accounts for all corporate action events in order to create a market-consistent database of index weights and levels.

3.2 The addition of the 10% cap makes these indices very attractive to managers who have become concerned about the growing concentration in the underlying SWIX indices and, in particular, the large exposure to Naspers (NPN) which recently reached new highs of 25% and 20% on 5 May 2017 in the SWIX40 and SWIX indices respectively. In contrast, the NPN weight in both the Capped SWIX40 and Capped SWIX on the same date was around 12%.

3.3 Historically, the SWIX indices have not actually required much capping—particularly in comparison to the Top40 and ALSI—due to the fact that SWIX free floats exclude foreign holdings. This exclusion led to considerably lower Resource constituent index weights in the mid-2000s for Anglo American (AGL) and BHP Billiton (BIL) and, more recently, to lower index weights for multinational Industrial companies like Compagnie Financiere Richemont (CFR) and SABMiller (SAB). In fact, besides NPN, the only other constituent whose weight in the SWIX indices has gone above 10% historically has been MTN and the last time this happened was in 2015. Below, we provide a brief comparative analysis of the Capped SWIX indices versus their uncapped originals.

3.4 Table 7 gives the super-sector weight breakdown for the capped and uncapped SWIX indices as at the end of April 2017. The capped Industrial exposure decreases due to the effect of NPN being capped while the Financial and Resource sectors gain.

TABLE 7. Super-sector weights for capped and uncapped SWIX indices, 28 Apr 2017

Super-sector	SWIX40	Capped SWIX40	SWIX	Capped SWIX
Industrials	62.08%	55.31%	58.15%	53.92%
Financials	23.97%	28.25%	27.31%	30.07%
Resources	13.95%	16.44%	14.54%	16.01%

3.5 A similar but more granular picture emerges when we consider the historical capped versus uncapped sector weight differentials displayed in Figure 8. The Consumer Services sector is continuously down-weighted owing to the NPN cap, and this is proportionately distributed across the remaining factors. The effect of the quarterly rebalancing is also noticeable by the small but abrupt periodic weight shifts.

3.6 Taking this one level further, Figure 9 portrays the evolution of the five largest stock weights in the SWIX40 relative to the same in the Capped SWIX40. Over this period, NPN had the largest weight in the indices, peaking at 24.89% in the SWIX40 but only 11.55% in the Capped SWIX40. The reduction in index concentration can be seen graphically by the disappearance of the gap in the right-hand panel between the NPN weight and the remaining top five stocks.

3.7 The Herfindahl Index is a measure of weight concentration and is calculated as

$$H = \sum_{i=1}^{n} w_i^2, \tag{4}$$

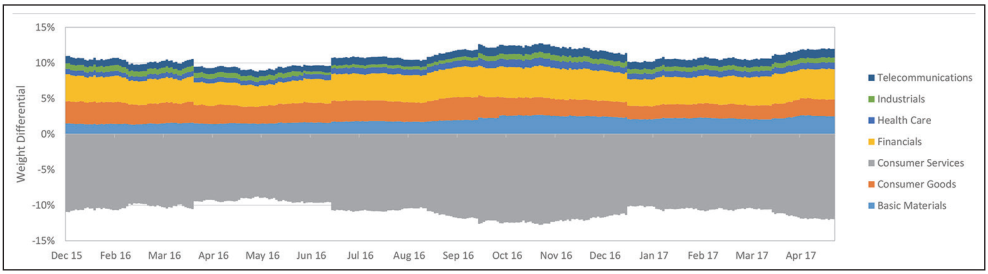


FIGURE 8. Sector weight differentials between Capped SWIX40 and SWIX40, Dec 2015 to Apr 2017

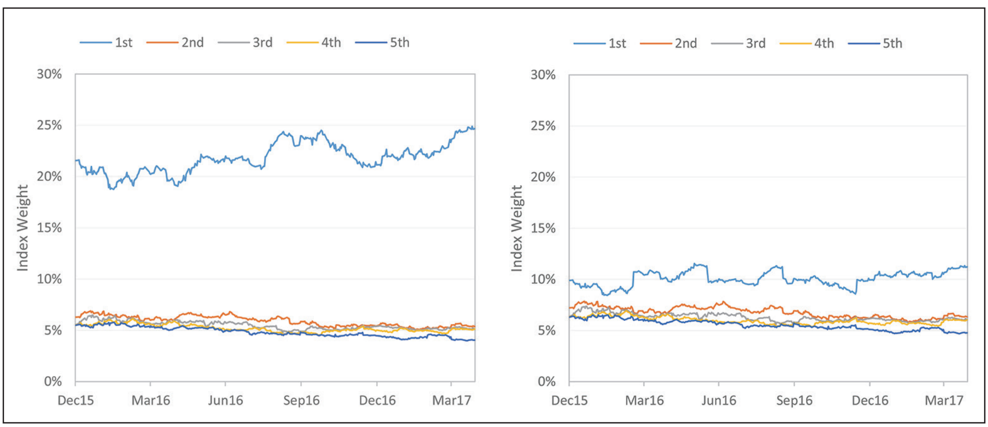


FIGURE 9. Evolution of five largest SWIX40 and Capped SWIX40 index weights, Dec 2015 to Apr 2017

where w_i is weight of the i^{th} constituent and n is the number of constituents. This measure allows one to quantify the additional diversification afforded by the capping procedure. The index ranges from $1/n$ to 1, with lower values indicating lower concentration (Herfindahl, 1950). Figure 10 graphs the Herfindahl index for the four capped and uncapped SWIX indices from December 2015 to April 2017. The relative improvement in capped index diversification is significant, ranging between 30% and 50% over the period in question.

3.8 Another aspect that has become increasingly important in recent times is the proportional currency exposure within each index. To compare this, we make use of the rand-hedge stock classification given in Holdsworth et al. (2007). This classification groups companies into four categories based on whether their earnings and costs are mostly in foreign or local currency. Rand-leverage companies are defined as those whose earnings are mostly in foreign currency but whose costs are mostly in rands (e.g. NPN). 'Rand-hedge' refers to companies whose earnings and expense are both given in foreign currency (e.g. CFR). Mixed companies have earnings and expenses that are exposed to both local and foreign currencies (e.g. MEI), while 'rand-play' refers to companies whose earnings and expenses are mostly given in rands (e.g. FSR).

3.9 The currency group weights given in Table 8 show that the capped indices are less exposed to currency fluctuations than their uncapped counterparts, with the combined rand-hedge and rand-leverage group weights decreasing by a total of 8.9% and 5.6% in the capped indices respectively. While this leads to a slight decrease in total index risk, it can also come at the cost of lowered returns if the local currency consistently weakens against global counterparts. This is the situation that has played out over the last few years, with the capped indices slightly underperforming their uncapped indices.

3.10 The final aspect we consider is the difference in underlying factor risk exposures between the indices. We conduct a factor risk analysis on the four indices using total return

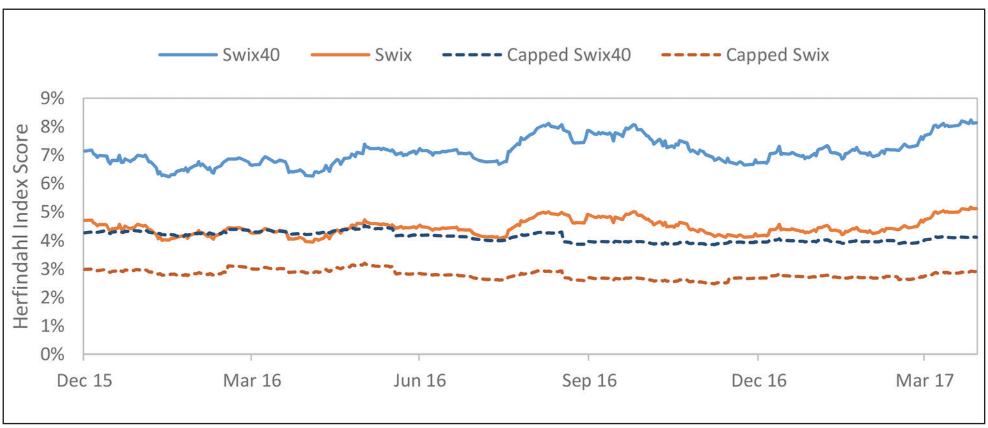


FIGURE 10. Herfindahl index for capped and uncapped SWIX indices, Dec 2015 to Apr 2017

data back to June 2011 and report the risk contribution weights in Table 9. The factor risk weights are fairly consistent across the indices due to their very high correlation, however we do note a down-weighting of the momentum weight for both Capped SWIX40 and Capped SWIX indices as well as a down-weighting of the size risk weight for the Capped SWIX40.

TABLE 8. Currency group weights for capped and uncapped SWIX indices, 28 Apr 2017

Weights	SWIX40	Capped SWIX40	Spread	SWIX	Capped SWIX	Spread
Rand-hedge	12.55%	14.79%	2.24%	12.38%	13.63%	1.25%
Rand-leverage	37.74%	26.63%	–11.11%	31.96%	25.09%	–6.87%
Mixed	14.18%	16.71%	2.53%	15.04%	16.55%	1.52%
Rand-play	35.52%	41.86%	6.34%	40.63%	44.73%	4.10%

TABLE 9. Factor risk weights for capped and uncapped SWIX indices, Jun 2011 to Mar 2017

Factors	SWIX40	Capped SWIX40	Spread	SWIX	Capped SWIX	Spread
Size	–58.1%	–60.9%	–2.8%	–47.4%	–46.9%	0.6%
Value	29.7%	33.7%	4.1%	31.2%	33.3%	2.1%
Profitability	30.9%	33.6%	2.7%	31.4%	32.3%	0.9%
Investment	18.1%	21.4%	3.3%	17.1%	18.9%	1.9%
Momentum	46.3%	41.5%	–4.8%	40.1%	36.8%	–3.3%
Low volatility	8.5%	9.1%	0.6%	10.7%	10.4%	–0.3%
Residual	24.7%	21.6%	–3.1%	17.0%	15.2%	–1.9%
Adjusted R^2	75.3%	78.4%		83.0%	84.8%	

4. TACTICAL ALLOCATION FOR EQUITY FACTORS AND BALANCED PORTFOLIOS

4.1 Although Section 2 showcases a number of methods and variables for successfully identifying market regimes, these results are mostly in-sample and do not shed much light on whether one can successfully incorporate regimes into an out-of-sample asset allocation framework. To answer this question, we conduct two practical tests. The first uses the technical probabilistic momentum and implied volatility indicators to tactically tilt towards assets that are expected to outperform and tilt away from underperforming assets. For this test, we make use of the equity factor universe and compare the performance of a tactical strategy against an equal-weight factor benchmark, which is rebalanced annually. We apply the regime-specific factor weight tilts given in Table 10 based on the technical indicator rules given in Section 2.3, with the only difference now being that the regime signal is used as an identifier for the following month.

TABLE 10. Factor weight tilts across technical indicator regimes

Regime	Size	Value	Profit-ability	Invest-ment	Momentum	Low volatility	Low beta
Up, Low Vol		–10%			+10%		
Up Mkt, High Vol			+5%		+5%	–5%	–5%
Down Mkt, Low Vol	+5%				+5%	–5%	–5%
Down Mkt, High Vol	+5%			–5%	–5%		+5%

4.2 Table 11 displays the performance results for the tactical and equal-weight factor portfolios. The tactical portfolio returns are on average 0.9% higher than the benchmark per annum, which is both a material improvement and a statistically significant difference (p-value < 0.001). While this differential does not explicitly account for trade fees, based on the actual two-way portfolio turnover, we calculate that the total transaction costs required to zero this differential are 1.61% per rebalance, which is extremely high. In addition to the return improvements, there is also a slight reduction in volatility, leading to improved risk-adjusted performance relative to the benchmark. In light of the extremely high correlations between the long-only factor returns over this historical period, the overall improvements from the tactical factor allocation framework therefore appear to be quite meaningful.

4.3 For the second test, we calculate turbulence based on the return series from the balanced universe and fit a regime-switching model to a growing data window in order to predict the upcoming regime and thus tilt the balanced portfolio accordingly. This tactically tilting portfolio is compared to a strategic asset allocation of 40% local equity, 10% local property, 10% foreign equity, 35% local bonds and 5% foreign bonds, which is rebalanced annually.

TABLE 11. Equal-weight versus tactical allocation strategy performance with the factor universe, Jan 2003 to Mar 2017

	EW benchmark	Factor TAA
Average return	18.69%	19.59%
p-value	n.a.	0.001***
Volatility	14.01%	13.89%
Return-risk ratio	1.33	1.41
Skew	–0.19	–0.14
5% VaR (monthly)	–4.65%	–4.75%
Maximum drawdown	–31.74%	–29.76%
Average annual turnover (two-way)	5.2%	32.7%
Break-even costs per rebalance	n.a	1.61%

4.4 The regime-based weight tilts in Table 12 for the balanced universe are considerably larger than those for the factor universe because of the far larger differences in the performance of the various asset classes over the two regimes. Performance results for the strategic and tactical strategies are given in Table 13. Note that we conduct this test from the viewpoint of a local investor and thus convert the foreign assets into local currency.

TABLE 12. Asset class weight tilts across turbulence index regimes

Regime	SA Equity	SA Bonds	SA Property	Global Equity	Global Bonds
Quiet	+10%	–10%	+5%		–5%
Turbulent	–10%	+15%		–10%	+5%

TABLE 13. Strategic versus tactical allocation strategy performance with the balanced universe, Jun 1995 to Apr 2017

	Strategic benchmark	Balanced TAA
Average return	12.27%	14.62%
p-value	n.a.	0.000***
Volatility	11.89%	12.00%
Return-risk ratio	1.03	1.22
Skew	–0.88	–0.38
5% VaR (monthly)	–4.74%	–4.08%
Maximum drawdown	–30.41%	–26.20%
Average annual turnover (two-way)	10.4%	71.7%
Break-even costs per rebalance	n.a.	2.71%

4.5 We again see that the regime-based tactical allocation provides a significant improvement in average return of 2.4% relative to the strategic benchmark and that the estimated break-even transaction costs per rebalance are extremely high at 2.71%. While the improvement in return does come at the cost of a slight increase in volatility, we still find that the balanced tactical asset allocation (TAA) strategy meaningfully outperforms its benchmark on a risk-adjusted basis.

4.6 Based on the results of the tactical strategies presented above—which are only simple illustrations of the underlying thesis—we can thus conclude that a regime-based framework is definitely capable of adding value to an asset allocation process.

5. CONCLUSION

5.1 The use of regimes and regime-switching models is becoming increasingly popular in finance. The reasons for this are because regime-based frameworks align with the observed nonlinear and non-normal market dynamics, are intuitive in their underlying economic narrative, and provide significant modelling power in a simple and tractable manner.

5.2 In this paper, we considered four alternative methods for identifying market regimes, namely, macroeconomic variables, fundamental valuation metrics, technical market indicators and statistical regime-switching models. These methods were tested using a long-only equity factor universe and a representative balanced portfolio universe.

5.3 We found that the tested macroeconomic variables showed limited ability to partition equity markets but that the yield spread indicator was able to provide economically sensible bond return regimes. In contrast, we found that the valuation metrics that were tested were able to successfully partition the equity market into four different regimes. However, using relative valuations to similarly partition equity factors is analogous to creating some form of implicit multi-factor portfolio. Investors should rather consider explicit methods such as signal averaging or signal blending to create multi-factor portfolios if that is their goal.

5.4 Simple technical indicators based on probabilistic momentum and implied volatility were found to accurately partition both the factor and balanced data universes into up-trending, low-volatility states and down-trending, high-volatility states. We also showed that a simple two-regime switching model based on the turbulence index was able to accurately capture differing regimes in the underlying equity factor universe.

5.5 Based on these findings, we tested two out-of-sample regime-based asset allocation frameworks. The first test used technical indicator regimes to tactically tilt equity factor exposures, while the second used a regime-switching turbulence model to tactically tilt asset class exposures for a balanced portfolio. In both tests, we found that the regime-based tactical allocation strategies outperformed their static benchmarks on an absolute return and risk-adjusted return basis, suggesting that a regime-based framework can add value to the asset allocation process.

5.6 There exist several avenues for further research based on this research, of which we will highlight two. Firstly, it would be interesting to apply a regime-switching model directly to the underlying asset or factor returns and compare the performance of tactical strategies based on such an implementation versus the strategies given above. Secondly, the tactical strategies tested above are, by our own admission, fairly simple representations of what is possible when using a regime-based framework. One could therefore extend this work and consider the performance of a suite of more complex tactical and dynamic asset allocation strategies based on regime-switching models, particularly in a South African investment setting.

ACKNOWLEDGEMENTS

We are grateful for discussions with Edru Ochse and Anthony Seymour, and for the constructive feedback from the 2017 ASSA Convention attendees and *SAAJ* reviewers respectively. We are also grateful to the *SAAJ* editorial team for their help during the submission process.

AUTHOR DECLARATION

We declare no conflicts of interest in publishing this article and welcome any and all comments. The views expressed here are only our own and any errors are our responsibility.

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