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An Analysis of the Predictive Value of Business Cycle Indicators on South Africa's Stock Market Performance

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Abstract: The financial market's capital market stability and development are core drivers of progressive, sound and well-functioning economic operations relied upon in both the macro-and micro-economic spheres. The stock market, a key component of the capital market, generates substantial opportunities for businesses, traders, and investors. The stock market remains a daunting securities platform amid heightening uncertainty and market disruptions. In order to broaden the mechanisms for coherent understanding and interpretation of stock market performance, this study seeks to bridge the gap between the financial and the real economy through the utilization of business cycle indicator's (BCI) component series of the composite indicators, as potential leading signals of South Africa's stock market performance. In scrutinizing the concordance and usefulness of BCIs as key signals for stock market analysis, the study employed a cross-correlations test, Granger causality model, variance decomposition and charting techniques. Monthly observations from June 2003 to November 2017 were used. Findings revealed that most BCIs showcase significant leading, lagging and coinciding properties in explaining stock market behaviour. A myriad of indicators identified as leading stock market signals, where combined to form a single leading index, and successfully led the durational gap in South Africa's stock prices at consecutive periods. Based on the findings, inferences were made that BCIs are noteworthy signals for market analysis and interpretation.

Keywords: Business cycle indicators; stock market; capital market; South Africa

JEL Classification: H54

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1. Introduction

One of the most thought-provoking aspects of economic and market analysis is the link between real economic and financial dynamics. South Africa's financial economy, together with the global financial environment continue to be faced with proliferating market complexity and uncertainty amid dynamic forces of economic, social, and geopolitical factors (Ernest and Young, 2017). As such, the need for deepened knowledge of the stock or equity market performance is crucial, especially after the wake of the 2008-09 world financial crisis and its effects on international and domestic markets. This study has been conceptualized in the light of South Africa's relatively weak economic growth recovery post the 2008-09 financial crisis (OECD, 2013; Mminele, 2017). The paper has as its primary objective to analyse the explanatory capacity of the official sub-series of South Africa's composite business cycle indicators (BCIs) in forecasting the stock market's performance. In aiding the efforts aimed at curbing or preventing likely consequences of potential financial crises, the forecasting of adverse market fluctuations through a contingent of the market and economic agents is crucial.

Traditional and behavioural finance theories respectively make up the two-tiered centerpieces on the non-predictability and predictability of financial and econometric time-series. Traditional finance theory purports that market series possess stochastic processes equivalent to a mere random walk process underlined by the principle of market efficiency enforced by the efficiency market hypothesis (EMH) (Vinogradov, 2012). In such a setting, stock market series are characterized by fully available information and investors or traders react instantaneously to such information eliminating any opportunities for profit (Dupernex, 2007). Contrastingly, behavioural finance theory emphasises the inefficiency of markets and opine the predictability of market prices or returns to be made through input series exhibiting negative or positive autocorrelations (Glaser, 2004) which Abu-Mostafa and Atiya (1996) consider as the prime pieces of evidence against the EMH. Decisions of market participants are said to be bounded in rationality producing cognitive biases or errors leading to the market's irregularities and anomalies carrying with them predictable trends, seasonal cycles, turbulence, together with bubbles (Thomaidis, 2004). Henceforth, decision-makers' behaviour, under behavioural finance, is coined as systematic, and as a result, can thus be modelled (Illiashenko, 2017). Making markets efficient phenomena as exhibited by time-series autocorrelations and the contrasting conditional variances relative the event (Rachev, Stoyanov, Mittnik & Fabozzi, 2017).

Moreover, BCIs are a seminal tool in addressing the past, current and future performance of the general economy. It is on the grounds of their interrelatedness with the capital market that the understanding of the financial economy may be better delved into by relaying BCIs with the movements in the stock market other than merely utilising micro-finance variables. Enquiries into the causes of financial cycles, pertaining to the demand and supply of assets and credit, correspond with the simplistic principles of supply and demand which enforce fluctuations in the business cycle or real sector (Nason & Tallman, 2016). A wide array of scholars such as Braun and Larrain (2005), Claessens, Kose and Terrones (2012), have devoted their research towards the analysis and modelling of associations between the capital market and economic forces. Notwithstanding, most extensive research covering such scope of the study is derived predominantly from developed economies, highlighting the striking financial research infancy and underdevelopment in the African landscape (Allen, Otchere & Senbet, 2011). In South Africa's context, Jefferis and Okeahalam (2000), Van Rensburg (1995, 1998, 1999), Moolman and Jordaan (2005), have at least sought to analyse such interplays, whereas, most focus on the determinants of capital market movements has focused chiefly on micro-finance indicators or broad economic indicators through approaches of fundamental analysis and technical analysis (Rusu & Rusu, 2003).

Various scholars opine that variations in real economic activity are preceded by movements in the stock market, making the latter a key signal for economic forecasting (Carlstrom, Fuerst & Ioannidou, 2002). Thereby asserting that real economic activities are directly affected and led by stock market developments (Pearce, 1983). A crucial argument brought forth by Moolman and Jordaan (2005), is that despite the general regard of stock price movements as leading economic indicators, some BCIs seem to lead economic cycles over a much longer period and this potentially qualifies them as early stock price signals. Therefore, the capacity for BCIs in potentially leading stock price movements is worth investigating. For the longest time, BCIs have been used to identify the peaks and troughs or the reference turning points of the business cycle, which are aggregated to form single indexes, signaling either the leading, lagging, or coinciding business cycle features (Venter, 2005).

2. Review of Literature

The equity market, also known as the market for shares or stocks, constitutes different forms of listed and marketable corporational instruments within the financial market, as quoted and traded on the Johannesburg stock exchange (JSE) Ltd being South Africa's chief governing body of its marketable stocks (Van Zyl et al., 2009). Intangible assets of common stocks together with alternative stock-related instruments are traded to deliver prospective cash benefits (Lenee & Oki, 2017). Such a market fixates on the long-term trading of financial market instruments focused on the accruement of funds in servicing business operations. The investor, as the issuer of funds, attains access to the residual claim linked to the firm's income and becomes, thereof, the entity's shareholder and gains ownership to the productive assets of listed corporations (Darškuvienė, 2010). As of 1887, the JSE was established along with the discovery of the goldfields in the Witwatersrand. Its initial function was to galvanise capital and investment directed at the mining industry's operative extensions (Hassan, 2013). The JSE has since then been marked as South Africa's official market for listed stocks. Overseeing the primary market's creation of share capital provided by borrowers, and the secondary market trading of these securities by the lenders (or investors) (Van Zyl *et al*., 2009).

Most of Africa's stock market capitalization is largely regulated by South Africa's shares exchange (Mahama, 2013). There has been an intensifying number in the JSE's listings of different forms of corporations which have since obtained prominence along the years, incorporating both industrial and non-mining entities. This has been accompanied by the gradual development and expansion of the country's economy. As of 1998, JSE listings rapidly grew to 659 firms from 151 mining, finance and industrial entities, while the mining sector has maintained its significance towards South Africa's financial sector growth and development (Moolman & Du Toit, 2005). As of June 2002, JSE's FTSE/JSE All-Share Index (ALSI) was established (Miller & Ward, 2015:88) as an average price index of listed shares (Van der Wath, 2015), officially recognized as the country's leading shares benchmark comprising of about 165 listed entities (Hunkar, 2018). Figure 2.1 depicts the rise in the price of South Africa's FTSE/JSE All-Share Index (ALSI) from 2002 to 2017 accompanied by a rising average trend.

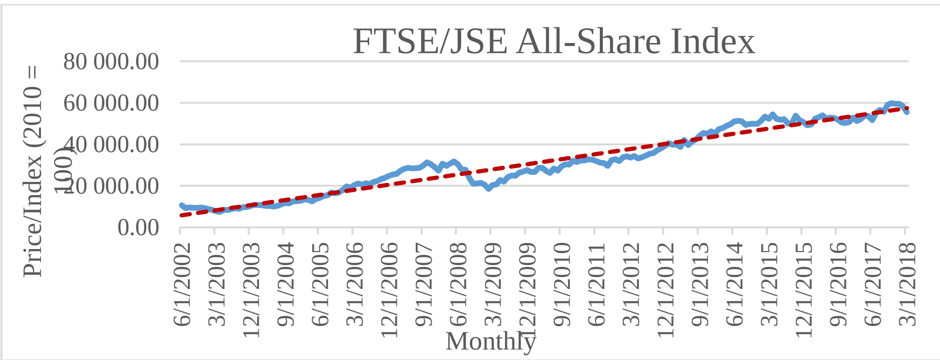

Figure 2.1. FTSE/JSE All-Share Index (ALSI) price (2002 to 2017)

Source: Author Compilation

Past research centred on the analysis of whether stock or equity price movements may be explained by historical information revealed existing inefficiencies in stock prices, particularly, autocorrelations were revealed in the New York Stock Exchange (NYSE) indexes as examined by Poterba and Summer (1988) and Conrad and Kaul (1988). Also, Lo and MacKinlay (1988) analysed the CRSP index, first-order weekly return autocorrelations were found including positive autocorrelations in approximately 423 United Kingdom stocks as analysed by Gębka and Wohar (2013).

Moreover, Lehmann (1990) found weak but significant autocorrelations in the listed securities of American Stock Exchange (AMEX) and the NYSE, similar to findings established by Campbell, Lo and MacKinley (1997).

More recently, Hsing (2014) examined the relationship between pertinent macro-economic variables with stock market performance in Estonia using the GARCH model and the regression from 2000.Q1 to 2013.Q3. Findings revealed that Estonia's stock market index is positively affected by debt/GDP, real GDP, and the German stock market. Meanwhile, Estonia's inflation rate, the exchange rate, domestic interest rates, and the Euro area government bond yield, all had negative effects on Estonia's stock market. A study conducted in Nigeria by Ikoku (2010) using quarterly data from 1984Q1 to 2008Q4 analysed the causal linkages between the industrial production index (IP), real GDP and stock market prices. A bidirectional causal relationship was suggested for stock prices and GDP, whereas, causality between stock prices and the IP with GDP was not established. However, cointegration was revealed between GDP and stock prices. Ikoku (2010) further used the ARIMA, vector error correction model (VECMs), and structural ARIMA and found that stock prices contained properties which may be utilized to enhance the forecasting capacity of GDP.

Dritsaki (2005) used the Johansen cointegration and Granger causality to assess the stock market in Greece. Results insisted that inflation, industrial production and interest rates, exhibit explanatory capacity towards movements in the stock market. Together with a bidirectional association between industrial production and stock returns. Accordingly, Patra and Poshakwale (2006), using bivariate VAR models, found negative effects of inflation and money supply on stock returns from 1990-1999. Upon studying the cyclical features of Greece's macro-economic indicators and its stock market, Leon and Filis (2008) used quarterly data and analysed these features used VAR analysis. Findings established a negative effect of GDP on stock market performance. Based on the Breusch-Godfrey Serial Correlation LM test and the Ljung-Box Q statistics, Tripathy (2011) considered weekly data of the period 2005 to 2011 to examine the causal relationship and market efficiency of India's stock market and macroeconomic variables. Existing autocorrelations in the macro-economic variables and the stock market were found. Also, Granger causality revealed that the exchange rate, inflation rate and interest rates, all influence India's stock market. Tripathy (2011) concluded that India's stock market is not weak-form efficient, thus abnormal profits can be obtained by rational investors through the utilisation of historical data of stock prices and information relating to macro-economic factors.

Furthermore, based on the monthly S&P 500 price index, Chen (2009) sought to analyse whether macro-economic variables such as interest rate spreads or yield curves (the difference between the 3-Month Treasury Bill Rate and the 10-Year

Treasury Constant Maturity Rate), money stocks, inflation rates, nominal exchange rates, aggregate output, unemployment, federal funds rates and federal government debt can be used to predict stock market recessions or bear markets in the United States. The study incorporated Diebold and Rudebusch's (1989) Bry-Boschan Method or the probit regression model, and Clark and West's (2007) Markov-switching model, focusing on the period 1957M2 to 2007M12. Non-parametric and parametric methods were used in taking into account periods of recession in the stock market and examined the predictive capacity of variables using in-sample and out-of-sample methods. Results established that the most useful predictors were the yield curve and inflation in both in-sample and out-of-sample estimations. The best predictive capacity was found in macro-economic variables on stock market return bear expansions.

Using the Johansen multivariate cointegration, innovation accounting and Granger causality, MacFarlane (2011) analysed the predictive capacity of South Africa's macroeconomic variables such as the exchange rate, consumer price index (CPI), 10- year government bond yield, GDP, and money supply on South Africa's stock market movements. MacFarlane (2011) showcased that historical information in the respective economic factors does not significantly explain future movements in the FTSE/JSE All-Share Index returns. A study on emerging markets, by Bilson, Brailsford and Hooper (2001), purported that money supply and the CPI both have explanatory capacity towards stock market returns. Glen (2002) and Ritter (2005) subsequently suggested that GDP contains leading properties towards movements in the stock market and acts as a leading indicator of the latter over subsequent periods. Further echoing the findings by Vassalou (2003), of existing explanatory capacity of GDP related news and its ability to lead current stock market price movements. In a similar fashion, movements in stock market return were founded to have been positively influenced by real economic activity among various countries, namely; Sweden, Australia, Norway and Canada. A noteworthy assertion was otherwise projected on the deferred response of stock market movements to variations in GDP. For the European stock market, Errunza and Hogan (1988) established that stock market volatility can be explained by money supply and industrial production, except for Belgium, the UK and Switzerland.

3. Methodology

The primary objective of the research was to investigate whether BCIs are noteworthy gauging signals for capital market analysis and interpretation in South Africa. Specifically, examining the sub-component series of South Africa's composite BCIs which are formally identified as the official leading, lagging and coincident indicators, and their respective individual predictive capacity or properties in leading the stock market price index of the JSE. A quantitative approach was utilised incorporating the period June 2003 to November 2017, with 174 monthly observations of the stock market, and the BCIs. The time-frame was selected according to the availability of the dataset with specialised focus on South Africa's post-apartheid period.

BCIs were selected based on their local and international precedence. The selection of BCIs as suitable signals for the JSE All Share Index (ALSI) was considered in respect to the outlined signaling market criteria outlined by Carriero & Marcellino (2007). The ALSI_t, which served as the dependent variable, was used as the yardstick for South Africa's stock market, while the explanatory independent variables included the sub-series of South Africa's official leading, lagging and coincident indicators of the business cycle. Time-series observations of the ALSI_t were obtained from the JSE, observations pertaining to the business cycle individual component series of the composite BCIs were retrieved from the South African Reserve Bank (SARB).

A cross-correlations test, in tandem with the cross-correlation function (CCF), allow for the analysis of the lead, lag or coinciding relationships between two variables by illustrating the relationship of time-lagged interactions (gap) between the variables (McCoy & Blanchard, 2008). Similar to Burger (2010) and Damos (2016), who analysed the predictive linkages between the financial market and business cycle behavior. The cross-correlations test examines potential relation among two time-series (Mahan, Chorn & Georgopoulos, 2015: 100), indicating the variations in the sequences of the input series gap relative to those of output or reference series (Burger, 2010: 29). In addition, the Granger causality test, when utilised in concurrence with cross-correlations, provides a clear estimation of the sequence of variations among the input and the output series (Burger, 2010). Figure 3.1 illustrates the underlying procedure of analysis.

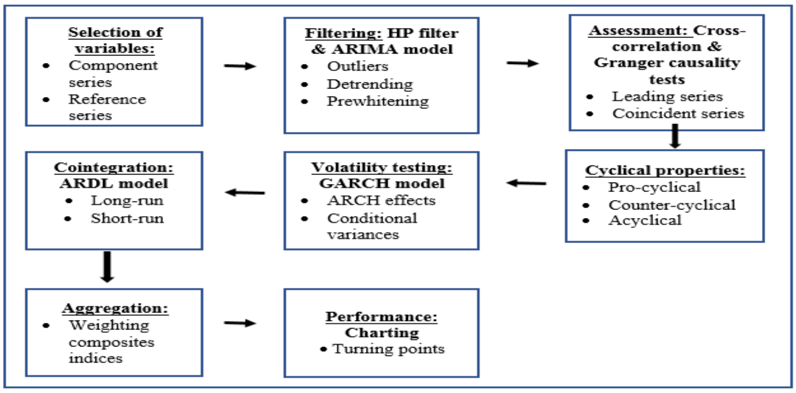

Figure 3.1. Model Framework Steps

Source: Author Compilation

According to Gröger and Fogarty (2011), the cross-correlations test requires that variables are (i) stationary in terms of their mean and variance, and (ii) filtered or pre-whitened to circumvent likely biasness. Stationarity or the lack of unit root among variables was ensured, as emphasised by Gujarati and Porter (2008), using Dickey and Fuller's (1979) Augmented Dickey-Fuller (ADF) test. The pre-whitening of the series was done through the Autoregressive moving integrated moving average (ARIMA) model to each input series. This was undertaken while using the logarithmic transformed detrended or cyclical component of the time-series using the Hodrick-Prescott (HP) filter by Hodrick and Prescott (1997). Upon examining the responsiveness or sensitivity of the specific state of the dependent variables to a particular pressure emanating from the independent variable (Probst *et al.*, 2012), cross-correlations were estimated following Equation 1.

$$r_t = \frac{n^* \sum y_1 y_2 - \sum y_1 \sum y_2}{\sqrt{[n^* \sum y_1^2 - (\sum y_1)]\,[n^* \sum y_2^2 - (\sum y_2)]}} \tag{1}$$

Such that: r_t denotes the coefficient of the cross-correlation at time lag t;

t denotes the time lag between two time-series according to months;

n^* denotes the number of overlapping observations or data points;

y_1 denotes the input series (composite business cycle subcomponents); and

y_2 denotes the output series (capital markets – ALSI, ALBI, ALCI, or REER).

A variable is considered leading, coincident and lagging indicator based on the peak of the cross-correlation. Mohanty *et al.* (2003) note that the application of detrended (trend eliminated), deseasonalised and smoothed datasets to the CCF provides a much fairer conceptualization of the stability and strength of concordance between cycles, and minimizes the potential for false signals and elevates the precision of turning point predictions. The lead and lag relationship are provided according to the value of τ where the CCF is maximized. Where the cross-correlations between the gap of the component and reference series are according to time (t), the lags (t + 1 to t + 20), leads (t – 20 to t – 1) and contemporaneous (t = 0) values of the two series. Clarification of the cross-correlation signs gives insight into the type of occurring patterns. If the cross-correlations of the component variable exhibit positive (+) values while resembling the pattern of the reference series, it is said to be pro-cyclical. A component series with a negative (–) sign whose cross-correlation pattern is inverse to the reference series is deemed as counter-cyclical. Cross-correlations indicative of no definitive cross-correlating patterns between the component and reference series assumes an acyclical pattern (Napoletano, Roventini & Sapio, 2006).

A limitation in assessing the synchrony between two variables based on the cross-correlations test is that correlation does not imply causation (Sugihara, May, Ye, Hsieh, Deyle, Fogarty & Munch, 2012). Implementing rules of causality may give a more accurate mechanism by which variables can be assessed on whether there is existing interaction or the correlation is by mere chance, or there is a common variable causing them both (Damos, 2016). Granger's (1969) Granger causality test is a plausible test of causality which gives an indication of whether a time-series is significant in providing forecasts of another variable with means by which causation is indicated than mere correlations of lead and lag relationships. Lin (2008) highlights the prime assumptions under the Granger causality test, purporting that the past cannot be predicted by the future, however, the future or present moment can be caused by the past. According to Lin (2008), Granger causality can be expressed as follows:

Under the condition that if for all $h > 0$, then X_t does not Granger cause Y_t.

$$F(Y_{t+h} \,|\, \Omega_t) = F(Y_{t+h} \,|\, \Omega_t - X_t \quad (2)$$

Such that: F denotes conditional distribution;

Ω_t signifies all the detail pertaining to the series; and

X_t and Y_t represent the two time-series variables.

Similar to Burger (2010), the study employed the Granger causality test to ascertain the lead, lag and coinciding relationships as a post estimation to the cross-correlation test. Burger (2010) delineates that if an output variable showcases a maximum value of the CCF with the input series, while results of the Granger causality test provide statistically significant findings, this is evidence that variations in the output series either lead or lag variations in the gap of the input series. Nevertheless, if high cross-correlations are displayed, and neither of the Granger causality findings is statistically significant, then the gaps of variations in the two time-series are considered to be contemporaneous or coinciding with one another.

4. Empirical Analysis and Results

The following sections provide the empirical estimations on the analysis of concordance or co-movement between the capital market's stock market and the BCIs component series. **Table A** of the appendix details the log-transformed and codes of all variables used, presented for the sake of convenience and simplicity of representation. Subsequent representation of variables from this point onwards is demonstrated or referred to according to their coded names.

4.1. Unit Root Tests and ARIMA Modelling

The ADF test results in **Table B** of the Appendix suggest that the p-values established for all individual series are indeed below 0.05. This indicates that the null hypothesis marked H_0 of the presence of a unit, root is clearly rejected. A conclusion can be made that all series were stationary at "level" as no unit root was present for all variables. To avoid spurious estimations caused by non-stationarities in the form of trends or drifts over time within time-series (Carmona *et al*., 2012), provided in **Table C** of the Appendix is the ARIMA model which was automatically selected on the HP-filtered variables using the auto.arima function in R-studio as a procedure for the pre-whitening of residual.

4.2. Cross-Correlations Test Results

By definition, cross-correlations with time t are leads (time t-20 to t-1 (negatives)), lags (time t+1 to t+20 (positives)) and contemporaneous (time t=0) values of the input series against the output series (Carmona *et al*., 2012). To identify the lead, lag and contemporaneous properties, correlation coefficients with the highest lags which are statistically significant at 0.05 significance level are selected. Table 4.4 presents the results of the cross-correlations test between business cycle input series and the capital market's ALSI - output series. Results indicate that there is a leading correlation between the gap in the ALSI and the gaps in the series LLEI3, LLEI8, LLEI9, LLAI4, LLAI6 and LLAI7. Cross-correlations between LALSI and the series LLEI7 appears to be absent over the period. The gaps in the series LLEI1, LLEI2, LLEI4, LLEI5, LLEI6, LLEI10, LLEI11, LCOI1, LCOI2, LCOI3, LCOI4, LCOI5, LLAI1, LLAI2, LLAI3 and LLAI5 appears to lag the gap in the ALSI.

Table 4.4. Cross-Correlations between ALSI and Business Cycle Indicators

ALSI								
BCIs	**LLEI1**	**LLEI2**	**LLEI3**	**LLEI4**	**LLEI5**	**LLEI6**	**LLEI7**	**LLEI8**
Max lags	3	5	-1	19	5	13	-	-18
Coeff.	0.183	0.221	0.158	0.191	0.286	-0.185	-	0.164
BCIs	**LLEI9**	**LLEI10**	**LLEI11**	**LCOI1**	**LCOI2**	**LCOI3**	**LCOI4**	**LCOI5**
Max lags	-3	1	10	12	2	7	2	4
Coeff.	0.269	0.286	0.182	-0.227	-0.174	0.205	0.263	0.210
BCIs	**LLAI1**	**LLAI2**	**LLAI3**	**LLAI4**	**LLAI5**	**LLAI6**	**LLAI7**	
Max lags	2	13	13	-11	8	-3	-9	
Coeff.	0.195	0.157	0.189	0.263	0.177	-0.249	-0.172	

Source: Author compilation

Granger causality estimations were subsequently undertaken to confirm the strength and statistical significance of the cross-correlations findings and reported in Table 4.5. Results specified that amongst the suggested leading indicators of the cross-correlations test, only LLEI3, LLEI8, LLEI9, LLAI4 and LLAI6 were statistically significant leading indicators of the ALSI, with unidirectional causal relationships at lags 1, 18, 3, 11 and 3, respectively. This means that these indicators lead the ALSI by 1, 18, 3, 11 and 3 months, respectively. Whereas, the series LLEI1, LLEI2, LLEI5, LLEI6, LLEI10, LLEI11, LCOI1, LCOI2, LCOI3, LCOI4, LCOI5, LLAI1 and LLAI3 were confirmed as lagging indicators of the ALSI. Meanwhile, the suggested lagging series LLEI1, LLEI6, LCOI1, LCOI3 and LLAI3 also exhibit bidirectional causal relationships with the ALSI at both 0.05 and 0.1 significance levels. Lastly, the series LLEI4, LLAI2, LLAI5 and LLAI7 were suggested as coincident indicators of the ALSI.

Table 4.5. Granger Causality Results of the ALSI and Business Cycle Indicators

ALSI								
BCIs	**LLEI1**	**LLEI2**	**LLEI3**	**LLEI4**	**LLEI5**	**LLEI6**	**LLEI7**	**LLEI8**
Max lags	3	5	-1	19	5	13	-	-18
YX	0.027**	0.589	0.037**	0.499	0.561	0.091*	-	0.073**
XY	0.035**	0.021**	0.577	0.190	0.005***	0.095*	-	0.159
BCIs	**LLEI9**	**LLEI10**	**LLEI11**	**LCOI1**	**LCOI2**	**LCOI3**	**LCOI4**	**LCOI5**
Max lags	-3	1	10	12	2	7	2	4
YX	0.001***	0.458	0.004***	0.001***	0.748	0.059*	0.242	0.128
XY	0.712	0.000***	0.134	0.000***	0.048**	0.037**	0.000***	0.003***
BCIs	**LLAI1**	**LLAI2**	**LLAI3**	**LLAI4**	**LLAI5**	**LLAI6**	**LLAI7**	
Max lags	2	13	13	-11	8	-3	-9	
YX	0.798	0.881	0.075*	0.016**	0.774	0.016**	0.235	
XY	0.032**	0.359	0.000***	0.810	0.252	0.665	0.769	

*Source: Author compilation (Note: ***,** and * indicates significance levels at 0.01, 0.05 and 0.1, respectively.*

Table 4.6 is a summary of the results of estimated models of cross-correlations and Granger causality. These results were also echoed by findings of the variance decomposition.

Table 4.6. Deduced Findings of Granger Causality and Cross-Correlations Tests

Leading indicators of the ALSI	Coinciding indicators of the ALSI	Lagging indicators of the ALSI	
Interest rate spread: 1-year government bonds less 91-dat Treasury bills	Real M1 money supply (deflated with CPI) * six-month smoothed growth rate	Job advertisement space in the Sunday Times newspaper: Percentage change over twelve months	Total formal non-agricultural employment
RMB/BER Business Confidence Index	Nominal labour cost per unit of production in the manufacturing sector: percentage change over twelve months	Number of residential building plans passed for flats, townhouses and houses larger than 80m’	Value of retail and new vehicle sales at constant prices
A new balance of manufacturers observing an increase in the average number of hours worked per factory worker (half weight)	Value of non-residential buildings completed at constant prices	Index of commodity prices (in US dollar) for a basket of South African-product export commodities	The ratio of gross fixed capital formation in machinery and equipment to final consumption expenditure on goods by households
Predominant prime overdraft rate of banks	The ratio of consumer instalment sale credit to the disposable income of households	A composite leading indicator of South Africa’s major trading partner countries: percentage changes over twelve months	The utilisation of production capacity in manufacturing
The ratio of inventories to sales in manufacturing and trade		The net balance of manufacturers observing an increase in the volume of domestic order received (half weight)	Cement sales (in tons)
Interest rate spread: 1-year government bonds less 91-dat Treasury bills		Number of new passengers	Industrial production index
RMB/BER Business Confidence Index		Gross value added at constant prices, excluding agriculture, forestry and fishing	

Source: Author Compilation

Following Ramos (2003) and Burger (2010), the study proceeded with the analysis of variance decomposition as an extension of the Granger causality test in order to acquire further insights on the sole contribution of each identified leading input series towards the respective capital market series. It gauges a variable's proportion of forecast error variance explained by its own shocks, and those of other variables (Asmah, 2013). To confirm the findings provided by the Granger causality test results in Table D of the Appendix, it shows that from the 1st to the 10th period the shocks in the ALSI are mostly explained by the series LLEI9, which is shown to have the most stable and largest contribution of about 20.3 per cent as of the 20th period. The series LLAI4, despite having experienced a diminishing share of contribution in the shocks of the ALSI in the 3rd period, contributed about 18.6 per cent of variations during the 10th period, second largest to the series LLEI9. Correspondingly, the series LLEI3, LLEI8 and LLAI6 respectively contributed about, 17.0 per cent, 15.2 per cent and 10.8 per cent during the 10th period to variations in the ALSI. The lowest contribution in the variation of the ALSI stemming from series LLAI6.

4.3. Establishing and Testing the Composite Leading Indicators of the Stock Market (ALSI)

The formerly identified leading series established in Section 4.2 were combined to create a composite leading index or signal of the ALSI. A graphical charting was further used to test the significance of the signal to present a more comprehensive estimation of the concordance between the established macro-economic index and the ALSI based on the extraction and charting of turning points belong to both series. Charting, as a means of graphical illustration, is used in technical analysis to depict market prices and historical patterns in analysing chart patterns for future price predictions according to the extent to which they match (Leigh *et al*., 2002). Such features may include spikes, wedges, saucers, head-and-shoulders, pennants, flags, gaps, and various tops and bottoms (Park & Irwin, 2007). Parracho, Neves and Horta (2010) assert that patterns in market prices are able to report the projections of evolutions about the respective security. The methodology used in constructing the composite leading index of the stock market ensued that of SARB (Van der Walt & Pretorius, 1994), which is the official method used by the South African Reserve Bank in establishing composite indicators of the general business cycle. This method is similar to the approach used by The Conference Board (2001), but with minor improvements and adjustments. The year 2015 was underlined as the base year for each of the constructed indexes (2015 = 100).

From the constructed indices, the cyclical component of each time-series and their respective turning points were extracted to assess their relative performance based on descriptive assessments as presented in the figures that follow. The cyclical components and turning points of the capital markets and the leading series were retrieved from R-studio. The resulting variables were aggregated cycles retrieved from the HP-filter with prior cleaning of each series. In the figures that follow, all prime turning points of the indicator and the reference cycle series were identified characterized by cyclical peaks and troughs. Figure 4.1 illustrates the turning points of the ALSI and the established composite leading indicator index. The paired consecutive colour signals indicate the direction of up or down turning points in both the input and output series. In Figure 4.1, the leading series was able to lead turning points of most cycles of the ALSI for the period. In other words, most turning points or fluctuations in the leading series occurred before those of the ALSI following consistently similar patterns. The arrows, based on the same colour coordination, are indicative of the flow of direction of turning points in the two series. Subsequent downturns (upturns) in the leading series ensued a downward (upward) pattern in the ALSI. This reassures that identified composite leading series can provide significant signals of South Africa's ALSI. A noticeable feature amongst the two series is that the turning points of the leading index appear to be relatively more volatile than the ALSI as of the average period.

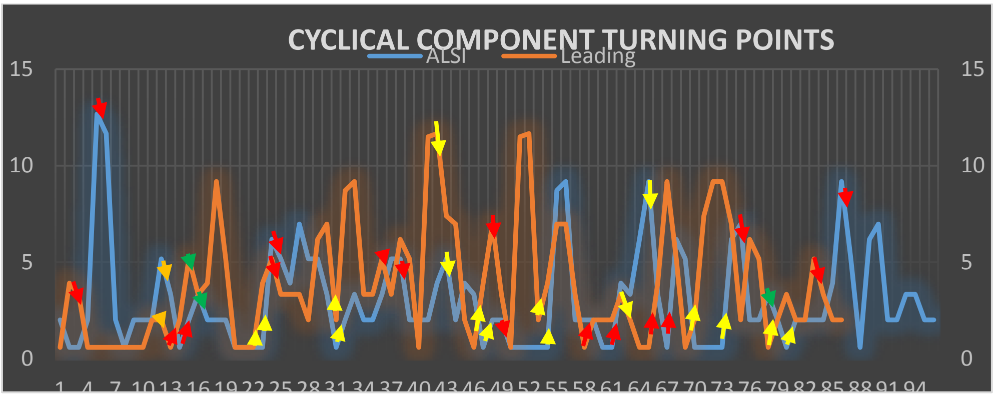

Figure 4.1. Turning Points of the All-Share Index and the Constructed Composite Leading Indicator Index (2015 = 100)

Source: Author compilation

5. Discussion of Results

Business cycle component series or fundamentals (Regressors), were tested against the shares market to ascertain their potential in providing signals of the latter. Underlying their identification as either leading, lagging or coincident indicators, accompanied by the analysis of turning points of the identified leading index with the ALSI back testing the usefulness of the leading index. Methodological frameworks included the cross-correlation tests (a post-estimation to ARIMA modelling), Granger causality and variance decomposition. Findings identified various business cycle component series as significant signals for capital market prices suggesting that turning points in business cycle indicators are closely related to financial market cycles. The selection of various individual indicators to form a common composite series is necessary to project a more coherent reflection of movements in the reference cycle, as similarly shown by Venter (2005), Van Ruth (2010), Bujosa, García-Ferrer, De Juan and Martín-Arroyo (2018). The constructed composite leading indices verify their ability to explain the gaps in turning points of capital markets as movements in the former precede those of capital markets. However, these findings contrast the preceding assertions of the traditional neoclassical finance theory. Malkiel and Fama's (1970) efficient market hypothesis (EMH) suggests that prices fluctuate randomly, incorporate all market information, and are accurately valued, making the attainment of abnormal profits and their prediction impossible via historical information (Del Águila, 2009). Findings revealed, in part, a fair degree of capital market predictability through input variables in contrast to the EMH's random walk behaviour of market series. Such findings under EMH would not be possible as historical information is publicly available and reflected in market prices, making it futile for prediction (Illiashenko, 2017). Wright, Smithers, Warburton, Pepper, Goldberg, Brodie, Riley and Napier (2013) underscore that an indicator of value should be able to assist in forecasting future movements.

Contrary to the EMH, Glaser (2004) purported that market anomalies, which secures the predictability of prices and returns based on specific or event-based forecasts, can translate from wrong asset pricing models or inefficiencies. Event-based forecasts can be advanced through earnings announcements or stock splits. Glaser (2004) also highlights that a body of research exists which document that markets can be predicted based on input series which exhibit positive or negative autocorrelations of short-term returns. Decision-makers' bounded rationality induced cognitive errors or biases within behavioural finance theory are responsible for anomalies and irregularities in financial markets which present seasonal cycles, bubbles, turbulence, and predictable trends (Thomaidis, 2004). Accroding to Abu-Mostafa and Atiya (1996), existing autocorrelations and price trends are amongst the key pieces of evidence against the EMH. For this reason, theoretical and empirical arguments against the EMH has resulted in the shift of focus towards behavioural and psychological elements of market participants from the EMH (Naseer & Bin Tariq, 2015). Unlike the traditional neoclassical theory, behavioural finance recognises that the behaviour of market participants is systematic and can, therefore, be modelled (Illiashenko, 2017). Rachev, Stoyanov, Mittnik, and Fabozzi (2017) also underscore that differing conditional variances relative to the event ensue that a positive fraction of market returns can be forecasted, deeming markets as inefficient. Willman, O'Creevy, Nicholson and Soane (2001) make a case that traders do possess perfect information and financial markets are not perfect.

Findings of co-movement between the ALSI and BCIs resonate with that of Glen (2002), Ritter (2005), Ikoku (2010), and Tripathy (2011) for developing countries, as well as Gjerde and Saettem (1999), Dritsaki (2005), Leon and Filis (2008), Chen (2009), and Hsing (2014), for developed countries. Results in some developing and developed countries has shown that macroeconomic variables are correlated and cointegrated with stock market movements in these countries. Ikoku (2010) reassures the existing causal properties for fundamentals such as GDP in causing movements in Nigeria's stock market, with a corresponding bi-directional relationship. Amongst the twenty-three variables obtained from South Africa's official component business cycle series, only the variable "Gross operating surplus as a percentage of gross domestic product" was indicated as not having led, coincided or lagged with movements in the ALSI. This is similar to findings by Errunza and Hogan (1998), as well as MacFarlane (2011), who found that past information in macroeconomic variables was not successful in explaining stock market performance, respectively for the UK, Belgium and Switzerland, as well as for South Africa.

6. Conclusion and Recommendations

Findings from a theoretical and empirical standpoint identified key recommendations for maintaining the soundness and stability of the financial market and the general economic environment. The identified leading, lagging and coinciding signals provide crucial avenues for assessing South Africa's market outlook and curbing potential market disruptions via the provision of relevant policy safety-nets and measures. South Africa's finance sector is a key driver of the country's overall growth performance, making it one of the prime backbones for various economic and social value chains. Below are some notable strategies and recommendations for traders (investors), individual economic decision-makers, and policy practitioners. These recommendations may secure the maintenance of ideal market sentiments and performance, the harnessing of, and the capitalising of potential market profitability by investors and speculators, including savvy decision-making by regular consumers and fund depositors. Important inferences and lessons, although not limited to the country's policy formulation and analysis can be summarised as underscored.

Efforts must encourage the utilisation of both real side indicators and pure finance signals for financial market analysis, interpretation and policy formulation. Using both finance and real side signals in forming inferences of financial market performance could present extensively robust options and insights to policy practitioners, investors and scholars. The emphasis of additional consideration of mere real-side economic or business cycle indicators for financial market analysis needs to be heightened, as the risk of solely using purely finance signals could be highly costly on a macro and micro level. Using both finance-related indicators and business cycle signals can provide an overarching overview of potential financial market contingencies and thus the provision of relevant policy safety-nets as well as robust investor or consumer decision-making.

Adoption of quantitative tightening monetary policy options amidst signalled expectations of further stock price increases and investor euphoria, or the application of quantitative easing in a demanding situation based on business cycle indicator analysis. The ratio of inventories to sales in manufacturing and trade as one of the identified leading variables of the stock market can assist policy-makers in cushioning the market and related sectors from potentially uncontrollable growth outcomes. South Africa's component series of the composite BCIs are statistically significant explanatory signals of the stock, bond, commodity and exchange rate market. Through various means of analyses, mere economic indicators have shown their explanatory capacity of behavioural time-series patterns of capital markets for analysis and interpretation. Such a revelation provides statistical evidence that the real and financial sectors and variables do not operate in isolation of each other, notwithstanding their operative idiosyncrasies. Macroprudential analysis of financial systems through the lens of both micro-finance specific indicators and business cycle indicators can establish useful inferences for monetary policy formulation. This includes the formulation of safety-nets for financial market disruptions through observable business cycle interpretation of economic indicators in preventing or lessening the impact of potential financial market instability.

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Appendix

Table A. Representation of Variables and Transformed Time Series to Logged Series

Variable	Log Series	Representation
All share index	LALSI	Log of the All-Share Index
Job advertisement space in the Sunday Times newspaper: Percentage change over twelve months	LLEI1	Log of Leading Indicator 1
Number of residential building plans passed for flats, townhouses & houses larger than 80m’	LLEI2	Log of Leading Indicator 2
Interest rate spread: 1-year government bonds less 91-dat Treasury bills	LLEI3	Log of Leading Indicator 3
Real M1 money supply (deflated with CPI) * six-month smoothed growth rate	LLEI4	Log of Leading Indicator 4
Index of commodity prices (in US dollar) for a basket of South African-product export commodities	LLEI5	Log of Leading Indicator 5
A composite leading indicator of South Africa’s major trading partner countries: percentage changes over twelve months	LLEI6	Log of Leading Indicator 6
Gross operating surplus as a percentage of gross domestic product	LLEI7	Log of Leading Indicator 7
RMB/BER Business Confidence Index	LLEI8	Log of Leading Indicator 8
The new balance of manufacturers observing an increase in the average number of hrs. worked per factory worker (half weight)	LLEI9	Log of Leading Indicator 9
The net balance of manufacturers observing an increase in the volume of domestic order received (half weight)	LLEI10	Log of Leading Indicator 10
Number of new passengers	LLEI11	Log of Leading Indicator 11
Gross value added at constant prices, excluding agriculture, forestry & fishing	LCOI1	Log of Coincident Indicator 1
Total formal non-agricultural employment	LCOI2	Log of Coincident Indicator 2
Value of retail & new vehicle sales at constant prices	LCOI3	Log of Coincident Indicator 3
Industrial production index	LCOI4	Log of Coincident Indicator 4
The utilisation of production capacity in manufacturing	LCOI5	Log of Coincident Indicator 5

Variable	Log Series	Representation
Cement sales (in tons)	LLAI1	Log of Lagging Indicator 1
Value of non-residential buildings completed at constant prices	LLAI2	Log of Lagging Indicator 2
The ratio of gross fixed capital formation in machinery & equipment to final consumption expenditure on goods by households	LLAI3	Log of Lagging Indicator 3
The ratio of inventories to sales in manufacturing & trade	LLAI4	Log of Lagging Indicator 4
Nominal labour cost per unit of production in the manufacturing sector: percentage change over twelve months	LLAI5	Log of Lagging Indicator 5
Predominant prime overdraft rate of banks	LLAI6	Log of Lagging Indicator 6
The ratio of consumer instalment sale credit to the disposable income of households	LLAI7	Log of Lagging Indicator 7

Source: Author compilation

Table B. ADF Unit Root Results for Capital Markets and Business Cycle Indicators

Variables	Level				First Difference		
	With intercept & without trend		With intercept & trend		Without trend		Order of Integration
	t-stat	P-value	t-stat	P-value	t-stat	P-value	
LALSI	-3.428	0.011*	-3.417	0.053	-14.864	0.000	I(0)
LLEI1	-4.291	0.001**	-4.278	0.004	-10.527	0.000	I(0)
LLEI2	-3.018	0.035*	-3.008	0.133	-14.009	0.000	I(0)
LLEI3	-4.392	0.000**	-4.378	0.003	-13.432	0.000	I(0)
LLEI4	-3.962	0.002**	-3.951	0.012	-4.870	0.000	I(0)
LLEI5	-1.607	0.000**	-11.571	0.000	-9.816	0.000	I(0)
LLEI6	-3.657	0.006**	-3.643	0.029	-6.874	0.000	I(0)
LLEI7	-3.873	0.003**	-3.837	0.017	-4.742	0.000	I(0)
LLEI8	-4.802	0.000**	-4.804	0.001	-10.655	0.000	I(0)
LLEI9	-6.873	0.000**	-6.861	0.000	-11.812	0.000	I(0)
LLEI10	-4.104	0.001**	-4.093	0.008	-7.112	0.000	I(0)
LLEI11	-6.678	0.000**	-6.658	0.000	-6.423	0.000	I(0)
LCOI1	-3.821	0.003**	-3.808	0.018	-4.502	0.000	I(0)
LCOI2	-3.985	0.002**	-3.976	0.011	-3.879	0.003	I(0)
LCOI3	-2.740	0.029*	-2.723	0.229	-17.396	0.000	I(0)
LCOI4	-5.695	0.000**	-5.678	0.000	-17.387	0.000	I(0)
LCOI5	-4.776	0.000**	-4.766	0.001	-4.668	0.000	I(0)

Variables	**Level**				**First Difference**		
	With intercept & without trend		**With intercept & trend**		**Without trend**		**Order of Integration**
	t-stat	**P-value**	**t-stat**	**P-value**	**t-stat**	**P-value**	
LLAI1	-4.690	0.000**	-4.675	0.001	-11.137	0.000	I(0)
LLAI2	-12.182	0.000**	-12.144	0.000	-11.315	0.000	I(0)
LLAI3	-5.100	0.000**	-5.083	0.000	-4.481	0.000	I(0)
LLAI4	-6.521	0.000**	-6.498	0.000	-18.179	0.000	I(0)
LLAI5	-4.514	0.000**	-4.495	0.002	-8.540	0.000	I(0)
LLAI6	-4.514	0.000**	-4.530	0.002	-7.260	0.000	I(0)
LLAI7	-3.09	0.029 *	-3.081	0.114	-11.053	0.000	I(0)

Source: Author compilation

Table C. Selection of ARIMA Model for Prewhitening of Residuals

Time series	**ARIMA Order**			**AIC**
	p	*d*	*q*	
LLEI1	1	0	2	417.42
LLEI2	1	0	0	49.78
LLEI3	1	0	2	430.2
LLEI4	5	0	3	687.5
LLEI5	0	0	0	117.39
LLEI6	2	0	5	132.74
LLEI7	2	0	2	1617.8
LLEI8	2	0	1	486.89
LLEI9	1	0	0	38.16
LLEI10	2	0	0	698.85
LLEI11	2	0	1	638.27
LCOI1	3	0	2	1891
LCOI2	4	0	2	1950.81
LCOI3	1	0	1	981.24
LCOI4	1	0	1	925.12
LCOI5	5	0	0	1592.11
LLAI1	1	0	1	729.07
LLAI2	0	0	0	55.85
LLAI3	4	0	1	1109.71
LLAI4	3	0	1	1021.83
LLAI5	2	0	2	289.57
LLAI6	2	0	1	1014.96
LLAI7	2	0	2	1199

Source: Author compilation

Table D. Variance Decomposition Results of the ALSI for Identified Leading Indicators

Period	LALSI				
	LLEI3	**LLEI8**	**LLEI9**	**LLAI4**	**LLAI6**
1	0.000	0.000	0.000	0.000	0.000
2	1.170	1.529	3.151	4.02E-1	0.385
3	3.224	6.314	6.174	0.031	0.513
4	5.625	13.999	17.099	0.886	2.696
5	8.039	14.112	19.324	1.171	3.235
6	10.295	14.562	20.016	5.511	5.523
7	12.321	15.246	20.262	9.972	7.953
8	14.104	15.480	20.357	12.933	9.932
9	15.656	15.279	20.267	17.216	10.430
10	17.002	15.195	20.292	18.621	10.768

Source: Author compilation