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ANALYZING THE PERFORMANCE OF SOUTH AFRICA'S COMMODITY MARKET PRICES THROUGH BUSINESS CYCLE INDICATORS

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ABSTRACT. The soundness of the capital market is crucial in establishing resilient financial market deepening and general economic progress. Equally, the health of the financial market's commodity market is undoubtedly a key determinant of inclusion, equitability, including sustained growth and development, especially in commodity-dependent countries. However, countries worldwide are faced with the continued challenge of falling commodity prices, presenting varied negative effects. Understanding the performance of the commodity market through lenses of fundamental or real-side indicators, other than just micro-specific financial or monetary variables, could prove helpful in constructing better inferences of the commodity market from an industrial, investor and policy standpoint. This study conducted a comprehensive evaluation of South Africa's official component series of the business cycle indicators (BCI), to assess their potential and capacity to serve as explanatory signals for commodity market prices. The study utilized the cross-correlations tests, Granger causality tests, variance decomposition and charting techniques to assess the co-movement and concordance between business cycle component series (regressors) and the All-commodity index (regressand). Monthly observations from June 2003 to November 2017 were employed. Evidence of existing co-movement or concordance was established between the commodity market and most of the BCIs. Significant BCIs were identified as leading, lagging and coincident indicators for the commodity market based on the underlying properties established in the empirical estimates of the study.

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Introduction

Continued low commodity prices pose serious concerns to commodity-producing countries, especially for most developing economies that are highly dependent on the soundness of the commodity market's performance. Unfortunately, these countries have commonly exhibited pressing traits of highly fluctuating, falling and mostly low prices amid increased production and export costs, weak global growth, and volatile global capital markets, as experienced in the 2008-09 financial crisis (Ighobor, 2017). In understanding South Africa's commodity market outcomes, it is essential to consider the existing realities of the country-specific factors, such as the various and mostly overlooked economic indicators, to peruse their likely potential to influence commodity market prices. Unfortunately, much of the present day's research that examines the performance of financial markets are governed by the forecasting of the various capital market segments and money markets through lenses of market-specific or micro-finance variables (Larsen, 2010:1; Rusu & Rusu, 2003:104). This paper objectively shifts the focus towards investigating the potential relationships between South Africa's commodity market prices and the country's official leading, lagging, and coincident business cycle indicators (BCIs) to gauge the latter's usefulness in explicating the performance of the capital market's commodity prices.

Leading, lagging, and coincident indicators are the focal point of economic analysis and forecasting in business cycle analyses. Meanwhile, debates on the predictability of financial times-series largely revolve around traditional and behavioural finance models. Under the efficient market hypothesis (EMH), traditional finance models purport that opportunities for profit-making and market predictability are eliminated due to market time-series random walk stochastic processes (Dupernex, 2007:167). Whereas, behavioural finance theories assert that negative or positive autocorrelations capacitate the predictability of time-series (Abu-Mostafa & Atiya, 1996; Glaser et al., 2004), amid market anomalies arising from cognitive behavioural biases carrying predictable trends, seasonal cycles, turbulence and bubbles (Thomaidis, 2004).

The focus on gauging financial market cycles against real market cycles is an alternative means of establishing if real sector activities can determine South Africa's financial market cycles. It is argued that capital markets, such as the equity market, tend to act as leading indicators of the real business cycle by six months (Moolman, 2003; Pearce, 1983:7-8). Likewise, South Africa's commodity market prices have been identified as one of the country's official real business cycle indicators, characterised as a component series of the composite leading indicator (Venter 2005a:5a). Moolman & Jordaan (2005) posit that despite the ability of component series such as stock market prices to lead the business cycle, other component BCIs tend to lead the business cycle by much longer periods can be used as directional signals of the equity market. Such a notion presupposes that specific component BCIs may lead the business cycle by more extended periods than commodity market prices and can therefore be used to gauge the foreseeable performance of commodity market prices.

Demand and supply forces that govern business cycle fluctuations are relatively suggested to affect the demand and supply of the financial market's credit and assets (Nason & Tallman, 2016). Business cycle and financial cycle linkages may be identified through the credit channel's credit prices, along with equity and housing asset prices (Claessens et al., 2012:178). These linking mechanisms are amplified through the financial accelerator and other channels, including processes within financial markets that involve equity indexes and the real estate, which influence the business cycle (Avouyi-Dovi & Matheron, 2005; Braun & Larrain, 2005:1097; Bosworth et al., 1975:257-258; Carlstrom et al., 2002; Claessens et al., 2012). According to Holmes & Maghrebi (2016:1), potential effects have been identified on the equity market arising from expected economic conditions, while the business cycle is reliably affected by market returns. Moreover, economic recoveries and contractions also tend to cause variations in market volatility and returns (Kvietkauskienė & Plakys, 2017). Henceforth, synchronizations are anticipated in the cyclical movements of business cycles and commodity prices of the capital market based on the aforementioned assertions.

Review of literature

Commodity prices are known to be exogenous. They are commonly taken as crucial leading market indicators due to their inherent capacity in providing reasonable signals of economic shocks. In contrast, the international market serves as a critical instrument for setting market prices (Rangasamy, 2009). Thanks to the capital market's commodity exchanges, the commodities exchange market makes up a convenient environment for trading precious commodities such as metals, agricultural products, and so forth (Van Zyl et al., 2009:471). These markets are established as efficient and formal platforms where buyers and sellers of commodities engage and interact in executing market activities and are essential for providing improved physical goods marketing and quality management of price risks (Mezui et al., 2013). Reduced price risk, enhanced price discovery, and economic inclusiveness are some of the key benefits of these exchanges, arising from a boost in finance and agricultural linkages, leading to the overall competitiveness and efficiency of the commodity sector (Mezui et al., 2013; Rashid, 2015:2).

The empirical literature on the analysis of potential concordance between macroeconomic or business cycles and financial cycles has been minimal, particularly for the African landscape. Whereas studies on such inter-plays for developing and developed economies have presented mixed findings. In terms of the existing studies, Schaling et al., (2014) established a lack of cointegration and a negative correlation between South Africa's exchange rate and commodity prices from 1996 to 2010. In comparison, strong unidirectional causality was found stemming from commodity prices to the nominal exchange rate. However, having been comparatively weaker than that of countries from the Organization for Economic Co-operation and Development (OECD).

Moreover, using the spline-GARCH framework and the detrending procedure of the generalized least squares (GLS), Karali & Power (2013) examined components of high – and low-frequency volatility of eleven commodities relative to macroeconomic indicators. Results showed that macroeconomic variables in the United States of America had a more significant effect on commodity prices during the bull-and-bear cycle than before, as of 1990-2009. Further highlighting that from 1990 to 2005, common effects of macroeconomic variables on commodity prices were detected, while commodity-specific effects were observed from 2006 to 2009.

Also, results by Smolík et al. (2015) showed that 75.74 per cent of the volatility in monthly averages of daily values for the S & P Goldman Sachs Commodity Index (GSCI) were explained by changes in selected macroeconomic determinants for the period January 2000 to September 2013, using the Boosted Trees method. Among the most significant determinants were the nominal effective exchange rate of the United States Dollar and short-term interest rates. An increase in the S & P GSCI value was accordingly revealed due to the weakening of the US dollar. Smolík et al. (2015) explained that this was due to the short-term nature of speculations in the highly financialised and current commodity exchanges, which coincides with economic development and investors' psychological behavior. Furthermore, results by Bangara & Dunne (2018) revealed existing causality running from Malawi's tobacco prices to various macroeconomic time-series, where positive shocks in tobacco prices had a significant and positive effect on the gross domestic product (GDP), including a decline in the consumer price index and the strengthening of the real exchange rate. This involved quarterly data from 1980Q1 to 2012Q4 based on the structural vector auto-regressive (SVAR) model.

Moreover, the study by Frankel & Rose (2010) revealed the potential for impact of macro-economic variables (i.e., global output and inflation) and micro-economic components (i.e., inventories, volatility, and spot-forward spread) on commodity prices. Where macro-economic factors displayed positive effects and the most effect coming from micro-economic variables. Also, using the factor-augmented vector auto-regression (FAVAR) model, Yin & Han (2016) revealed significant effects of China's macro-economic components on commodity markets. Comparatively, results from the US were not significant. Positive effects of inflation, money supply and output on commodity price bubbles were subsequently showcased in the study by Li *et al.* (2017), while interest rates had a negative effect. The study considered the period 2006 to 2014 and used the Zero-inflated Poisson model, where output and money supply were identified to have had the most significant impact. Lastly, using the error correction model (ECM) and the Auto-regressive Distributed Lag (ARDL) model, for the period January 2001 to June 2012, Jena (2016) found an existing long-run relationship between the agricultural price index and macro-economic series, including a negative relationship between the energy price index and macro-economic variables. However, the metal price index did not show any long-run relationship with the macro-economic variables. Nevertheless, the industrial production index (IPI) and the exchange rate had significant and positive impacts on the agricultural price index and significant impacts on the energy price index.

Methodology

As a primary objective, the study sought to examine the potential for BCI's to affect commodity prices in their capacity to provide meaningful signals for capital market analysis and interpretation. Therefore, the sub-individual components of South Africa's official coincident, leading and lagging composite indicators for the business cycle were examined relative to commodity prices. The study utilized a quantitative research method, with the time-series encompassing about 171 monthly observations spanning from June 2003 to November 2017 for the BCIs. The all-commodity index (ALCI) represented the commodity market prices. This time-frame was selected to consider South Africa's post-apartheid period and the availability of the time-series data-set. The composite BCIs' sub-series were considered as explanatory variables and were chosen due to their local and international superiority, with respect to Carriero & Marcellino's (2007) signaling market criteria. Accordingly, the ALCI was treated as the dependent variable. The ALCI and the BCI sub-series data sets were retrieved from the South African Reserve Bank (SARB).

To gauge the leading, lagging and coinciding properties of the BCI sub-series on the ALCI, this paper employed the cross-correlations test in conjunction with the cross-correlations function (CCF) to illustrate the time-lagged interactions (gap) between the ALCI and the BCI sub-series (McCoy & Blanchard, 2008). This approach is similar to the studies on the financial market and the business cycle by Burger (2010) and Damos (2016). According to Mahan et al. (2015:100), the cross-correlations test is configured to examine potential relationships between two variables. It highlights the changes in the sequences of the gap in the input series relative to those of the reference or output time-series (Burger, 2010: 29). The study subsequently employed the Granger causality test, which estimates the sequences of changes between the input and output variables when used in line with the cross-correlations test (Burger, 2010). The employed steps of analysis are respectively shown in Figure 1.

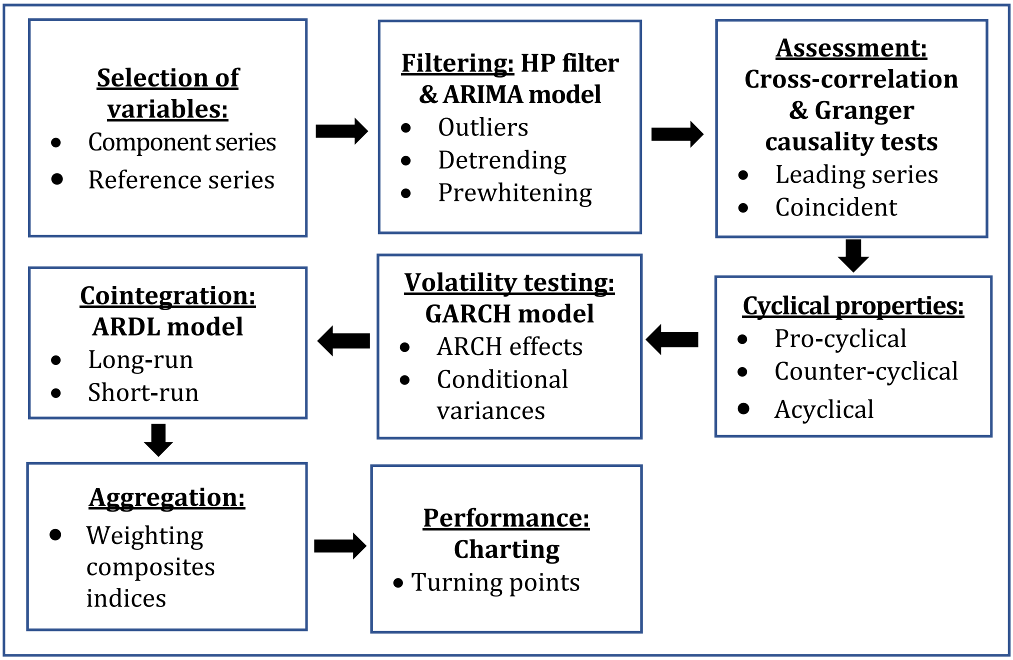

Figure 1. Model framework steps
Source: Author compilation

In order to circumvent potential biases in the cross-correlations test, Gröger & Fogarty (2011) purport that time series should be (i) stationary concerning their means and variance and are (ii) pre-whitened or filtered. Following Gujarati & Porter (2008), the study sought to ensure the absence of unit root in all the time series to certify the stationarity of all the variables based on the Augmented Dickey-Fuller (ADF) test by Dickey & Fuller (1979). Accordingly, for each input series, time series were pre-whitened using the autoregressive integrated moving average (ARIMA) model. All time series were transformed into their natural logarithmic form while considering the cyclical component of each variable, having been detrended using Hodrick & Prescott's (1997) Hodrick-Prescott (HP) filter. The detrended smoothed and deseasonalised series assist in establishing a fairer understanding of the stability and strength of the cycle's co-movement while enhancing the forecasting of turning points and reducing likely falsehoods in signals (Mohanty et al., 2003). Following Probst et al. (2012), equation 1 was estimated to showcase the cross-correlations models, which sought to examine the sensitivity of the state of the dependent variable in the face of pressure caused by the independent variable.

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

Where:

r_t represents the cross-correlation coefficient at time lag t;

t represents the time lag between two time-series in terms of months;

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

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

y_2 represents the output series (capital markets - ALCI).

The CCF is used to measure the strength of co-movement between time-series while classifying variables as leading, coinciding or lagging series at separate lag or lead times. Estimating the cross-correlations coefficient at time t establishes the model in eq. 1 (McCoy & Blanchard, 2008:5). The cross-correlation peak of the CCF suggests whether the variable is coincident, leading or lagging indicator. In contrast, the value of τ where the CCF is maximised, provides the lead and lag relationship. The gap of the cross-correlations between the reference series and the component series are configured based on the time (t), the contemporaneous (t = 0), the leads (t – 20 to t – 1) and the lag (t + 1 to t + 20) values for the two series. Whereby the sign of the cross-correlations suggests the type of patterns. A negative (-) sign with an inverse pattern to the reference series would be considered counter-cyclical. Accordingly, positive (+) cross-correlation values with a pattern that resembles the reference series would be considered pro-cyclical, whereas acyclical patterns would be assumed when no definitive pattern is presented (Napoletano et al., 2006).

Moreover, Sugihara et al. (2012) highlight that the cross-correlations test between variables may not imply causation. Henceforth, introducing causality rules to the model would present a more accurate stance for assessing variables to establish if the present correlation is triggered by a common variable or based on mere chance (Damos, 2016). In this case, the Granger causality test was employed to confirm the lag, lead and coinciding relationships after the cross-correlations estimations, similar to Burger (2010). The Granger causality test by Granger (1969) is applied as a reasonable test of causality in order to establish whether a variable can be a significant instrument of presenting forecasts of other time-series by highlighting potential causation, then simply just lag or lead correlations. Following Lin (2008), the Granger causality model is expressed according to equation 2 as follows.

Based on the parameters, if for all *h > 0*, then X_t does not Granger cause Y_t.

$$F(Y_{t+h} \mid \Omega_t) = F(Y_{t+h} \mid \Omega_t - X_t) \quad \text{.........................} \; eq. 2$$

Where:

F represents the conditional distribution;

Ω_t represents all the information concerning the variables; and

X_t and Y_t denote the reference and output series.

According to Burger (2010:30-31), when an output series presents a CCF having a maximum value with the input series. At the same time, the Granger causality test provides statistically significant results. This reveals that the changes in the output variable could either lag or lead to the changes in the input series gap. On the other hand, the gaps in the changes between the input and output series may be regarded as coinciding or contemporaneous series when high cross-correlations are revealed, while none of the findings presented by the Granger causality is statistically significant.

Empirical Analysis and Results

Section 4 and its subcomponents provide established findings of this study in assessing the potential for co-movement within the series of the BCIs and the capital market's commodity prices represented by the ALCI. The likelihood of existing concordance suggested the potential for macro-economic or BCIs to explicate the cyclical performance in the movement of South Africa's commodity prices. Appendix 1 reveals all the considered BCIs, which the South African Reserve Bank has officially identified as key BCIs. The component BCIs were coded/abbreviated to establish simplicity in the paper and were henceforth represented according to the demonstration in Appendix 2.

Unit Root/Stationarity Tests and the ARIMA model estimations

Mahan et al. (2015:97) caution that time-series variables are likely to be auto-correlated, having values that their past values could influence. Non-stationarities in data series may be characterised by drifts or trends over time, resulting in exaggerated correlations which may not exist. Henceforth, Podobnik & Stanley (2008:1) expound on the necessity of utilizing stationary variables for the cross-correlations test to circumvent potential spuriousness in the findings. All time-series were also detrended based on the HP filter in their log-based time-series as necessary transformation methods following Carmona et al. (2012:3). The values of the HP filter were set at "14400" as prescribed for monthly time-series to smooth and extract the cyclical component of each variable (Pollock, 2018:20). Accordingly, results of the ADF test in Appendix 3 revealed that all variables were stationary at "level", having p-values below 0.05, and indicated a lack of unit root in all the time-series and thus, no subsequent differentiating was needed. Moreover, Appendix 4 showcases the ARIMA model's automatically selected order processes in pre-whitening the residuals, captured using Rstudio's auto Arima function (Probst et al., 2012:673).

Cross-correlations findings

The study selected cross-correlation coefficients which exhibited the highest lags found to be statistically significant at 0.05 significance level. Such that time t were lags [t+1 to t+20 (positives)], leads [t-20 to t-1 (negatives)] and contemporaneous (t=0). Table 1 demonstrates the results from the cross-correlation test pertaining to the ALCI output series and the BCI sub-component input series. The findings revealed existing cross-correlation between the gaps of the input and output series, such that the gap leads the LALCI in the following variables; LLEI3, LLEI8, LLEI9, LLEI11, LLAI1 and LLAI7. Furthermore, the gaps in the variables LLEI1, LLEI2, LLEI4, LLEI5, LCOI1, LCOI2, LCOI3, LCOI4, LCOI5, LLAI1, LLAI3 and LLAI4 were identified to lag behind the series LLC. Nevertheless, contemporaneous properties were identified between the LALCI with the series LLEI10 and LLAI6. The series LLEI6, LLAI2 and LLAI5 showed no cross-correlations with LALCI.

Table 1. Results of the Cross-correlations test for the ALCI and business cycle indicators

ALI								
BCIs	**LLEI1**	**LLEI2**	**LLEI3**	**LLEI4**	**LLEI5**	**LLEI6**	**LLEI7**	**LLEI8**
Max lags	17	17	-9	14	1	-	-1	-17
Coeff.	0.177	-0.299	0.172	-0.200	0.268	-	0.188	0.154
BCIs	**LLEI9**	**LLEI10**	**LLEI11**	**LCOI1**	**LCOI2**	**LCOI3**	**LCOI4**	**LCOI5**
Max lags	-8	0	-12	13	10	14	2	4
Coeff.	0.219	0.955	0.189	0.239	0.194	-0.229	0.335	0.244
BCIs	**LLAI1**	**LLAI2**	**LLAI3**	**LLAI4**	**LLAI5**	**LLAI6**	**LLAI7**	**-**
Max lags	-1	-	3	2	-	0	-9	-
Coeff.	0.221	-	0.401	-0.217	-	-0.171	-0.209	-

Source: Author compilation

The study further employed the Granger causality test for the LALCI and the corresponding BCI sub-components, as displayed in Table 2. This was estimated in order to confirm the cross-correlations test findings previously established in Table 1.

Table 2. Results of the Granger causality test between the ALCI and business cycle indicators

ALSO								
BCIs	**LLEI1**	**LLEI2**	**LLEI3**	**LLEI4**	**LLEI5**	**LLEI6**	**LLEI7**	**LEI8**
Lags	17	17	-9	14	1	-	-1	-17
YX	0.113	0.453	0.078*	0.285	0.543	-	0.027**	0.137
XY	0.001***	0.003*	0.374	0.134	0.001***	-	0.343	0.051*
BCIs	**LLEI9**	**LLEI10**	**LLEI11**	**LCOI1**	**LCOI2**	**LCOI3**	**LCOI4**	**LCOI5**
Lags	-8	0	-12	13	10	14	2	4
YX	0.091*	0.000*	0.013**	0.055*	0.218	0.219	0.257	0.089*
XY	0.166	0.000***	0.221	0.000***	0.000***	0.016**	1.47	0.011
BCIs	**LLAI1**	**LLAI2**	**LLAI3**	**LLAI4**	**LLAI5**	**LLAI6**	**LLAI7**	**-**
Lags	-1	-	3	2	-	0	-9	-
YX	0.009***	-	0.482	0.552	-	0.000***	0.053*	-
XY	0.003***	-	5.843	0.011**	-	0.000***	0.771	-

Source: Author compilation

The Granger causality test findings confirmed that input series LLE3, LLEI7, LLEI11, LLAI1 and the LLAI7 exhibited characteristics of leading indicators for the ALCI and had a bidirectional causal relationship. Whereas, lagging series of the ALCI was confirmed to include the series LLEI1, LLEI2, LLEI5, LLEI8, LCOI1, LCOI2, LCOI3, LCOI5 and LLAI4. Exhibiting bidirectional properties between the ALCI and the series LCOI1 and LCOI5. Lastly, the ALCI was found to be contemporaneous to the series LLEI4, LCOI4, LLAI, LLEI10 and LLAI6.

Correspondingly, these results were reverberated by the estimations of the variance decomposition as showcased in Table 3. It was purporting that the identified leading variables tend to explain variations in the ALCI over time. The variable LEI9 was shown to have had the highest contribution of about 27.1 per cent for the 10th period in the variations in the ALCI series. Also, about 11.1 per cent, 10.7 per cent and 7.9 per cent of variations or shocks in the ALCI were explained by the series LLAI7, LLAI1 and LLEI11, respectively, in the 10th period. The series LLEI3 and LLEI7 had the lowest contributions of about 0.32 per cent and 4.7 per cent, respectively.

Table 3. Variance decomposition results

Period	LALCI					
	LLEI3	**LLEI7**	**LLEI9**	**LLEI11**	**LLAI1**	**LLAI7**
1	0.000	0.000	0.000	0.000	0.000	0.000
2	0.045	1.347	0.157	1.708	1.888	0.305
3	0.114	3.631	0.665	3.237	2.142	1.661
4	0.180	4.499	1.356	3.732	2.865	3.601
5	0.232	4.089	3.444	4.485	4.029	4.683
6	0.269	3.453	5.298	4.854	5.624	6.747
7	0.294	3.337	9.069	5.856	7.162	9.039
8	0.309	3.779	13.413	6.638	8.529	10.569
9	0.319	4.297	19.749	7.246	9.705	11.028
10	0.324	4.714	27.136	7.911	10.737	11.058

Source: Author compilation

Table 4 presents a summary of the identified leading, lagging, and coincident indicators based on the findings of the cross-correlations and the Granger causality tests.

Table 4. Summary of established leading, lagging and coincident variables of the ALCI from the Granger causality and cross-correlations tests

Leading indicators	**Lagging indicators**	**Coincident indicators**
The ratio of consumer instalment sale credit to the disposable income of households	Job advertisement space in the Sunday Times newspaper: Percentage change over twelve months	Real M1 money supply (deflated with CPI) * six-month smoothed growth rate
Gross operating surplus as a percentage of gross domestic product	Number of residential building plans passed for flats, town houses and houses larger than 80m'	The net balance of manufacturers observing an increase in the volume of domestic order received (half weight)
The new balance of manufacturers observing an increase in the average number of hours worked per factory worker (half weight)	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
Number of new passengers	RMB/BER Business Confidence Index	Industrial production index

Leading indicators	Lagging indicators	Coincident indicators
Interest rate spread: 1-year government bonds less 91-day Treasury bills	Gross value added at constant prices, excluding agriculture, forestry and fishing	Predominant prime overdraft rate of banks
Cement sales (in tons)	Total formal non-agricultural employment	
	Value of retail and new vehicle sales at constant prices	
	The utilisation of production capacity in manufacturing	
	The ratio of inventories to sales in manufacturing and trade	

Source: Author compilation

Constructing and testing the commodity market's (ALCI) leading indicator

The use of BCIs as instruments for measuring market cycles' changes was first instigated to detect the business cycle's reference turning points in terms of troughs and peaks. Several individual BCIs are consolidated to form a single series as a coincident, lagging or leading composite index. This is done in order to offset variations in the different series (Provincial treasury, 2012; Venter, 2005b:1-5b). Henceforth, the study sought to combine the formerly identified individual leading indicators by constructing a single composite indicator that weights and consolidates all the identified individual leading series of the ALCI into a single variable. Similar to the method utilised by The Conference Board (2001), yet with minor modifications, the study adopted the official approach used by the SARB to construct the composite leading index for the business cycle (Van der Walt & Pretorius, 1994). Accordingly, 2015 (2015 = 100) was considered the base year for the composite leading index. To test the significance or relevance of the composite signal, the cyclical component and turning points of the ALCI and the constructed composite signal were extracted and compared to verify the concordance of the series using the charting technique. This method illustrated and analyses historical price patterns in both series for future forecasting based on the degree of co-movement (Leigh et al., 2002).

Figure 2 exhibits the cyclical components' turning points for the ALCI and the constructed leading indicator. Turning points of the minimum and maximum, or peaks and troughs, were observed throughout the sample period. A similar movement was confirmed between the two series. Evidently, turning points of the leading series were shown to precede those of the ALCI with the corresponding direction, carrying a primarily positive correlation. This illustration suggested that some business cycle series have the properties and the capacity to lead financial cycles. Albeit, the ALCI appeared to be relatively more volatile than the leading indicator.

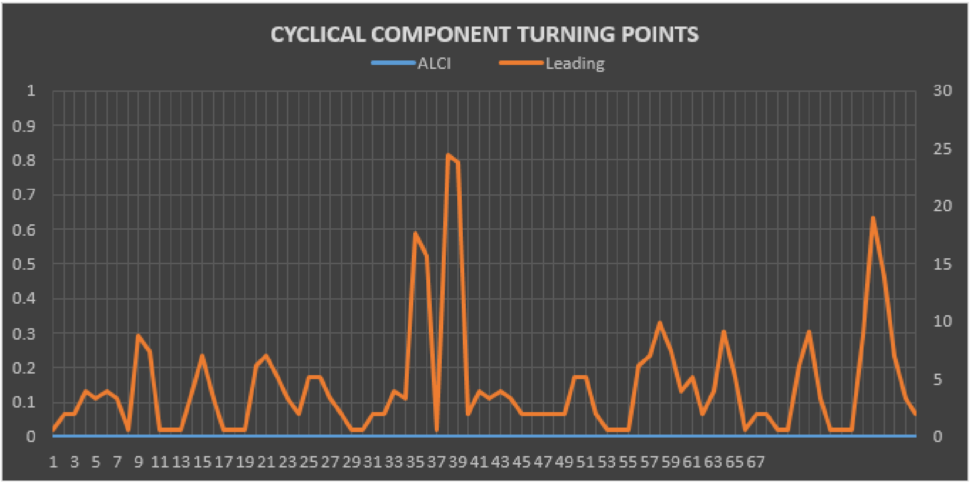

Figure 2. Cycle component turning points of the constructed composite leading indicator and the All-Commodity Index (2015 = 100)
Source: Author compilation

Discussions of results

The SARB's official BCIs were assessed as potential regressors for the capital market's All-commodity index (regressand) in gauging the prospects of establishing leading, lagging and coincident signals of the latter. The study focused on constructing and assessing the significance of the composite leading indicator to predict the All-commodity index. The methods used in achieving the study objectives comprised of the approaches used by Bergman et al. (1998), Burger (2010), Gavin and Kydland (2000), Izani et al. (2004) and Kydland and Prescott (1990). Such methods comprised the cross-correlations test that followed estimations of the ARIMA model, the Granger causality test (a post estimation to the cross-correlations test), and the variance decomposition approach. Moreover, concordance between the study's established composite leading index and the All-commodity index were assessed using charting techniques and revealed that the signals in the composite leading indicator displayed significant leading properties of the turning points in the All-commodity index.

Having been conducted insight of the classical (or traditional) and behavioural financial theories, the study provided evidence that some features of predictability characterise the capital market performance of South Africa's All-commodity index through the lenses of some BCIs following the various empirical estimations. Accordingly, Wright et al. (2013:36) highlight that a valuable indicator is one with the capacity to provide information regarding prospective returns of market prices. The composite leading indicators were shown to have been able to predict the direction of the turning points in the All-commodity index, providing sufficient and reassuring evidence that macro-economic indicators, other than just micro-finance indicators such as credit and savings, are closely associated with financial market cycles.

Moreover, about three-component variables did not show significant leading, lagging and coinciding properties to the All-commodity index, specifically, the "value of non-residential buildings completed at constant prices", "nominal labor cost per unit of production in the manufacturing sector: percentage change over twelve months", and the "composite leading indicator of South Africa's major trading partner countries: percentage changes over twelve months". These findings are similar to the empirical study by Jena (2016) and Schaling et al. (2014). They showed in their studies that some macro-economic series have no short-or long-run cointegration with commodity prices. Nevertheless, results of existing relationships between macro-economic series and the commodity market resonate with empirical evidence of various authors, namely; Bangara & Dunne (2018), Li *et al*. (2017), Yin & Han (2016), on developing countries, including Frankel & Rose (2010), Karali & Power (2013), and Smolík et al., (2015) on developed economies.

The findings of this paper are in contrast with the assertions of non-predictability of financial cycles made by the traditional or neoclassical finance theory according to the random walk nature in market prices (Illiashenko, 2017:44). The current paper's findings are supported by Glaser et al. (2004), who administered the discussion that markets have the ability to be forecasted by input series which have short-term returns characterized by negative or positive autocorrelations. Likewise, Abu-Mostafa & Atiya (1996) motivate that these auto-correlations and price trends serve as one of the paramount pieces of evidence against the traditional or neoclassical finance theory's EMH. Thomaidis (2004:2), also mentions that the behavioral finance theory's rationally-induced biases or errors are the reasons for financial market irregularities or anomalies which result in predictable trends, seasonal cycles, turbulence and bubbles. In line with behavioural finance, market participants' behavior is systematic and thus open to modeling (Birău, 2012:48; Illiashenko, 2017:30); Jolls, et al., 1998:1475). The inefficiency of markets due to the varying conditional variances associated with the event suggests that a significant segment of the market can be forecasted (Rachev et al., 2017:20), as financial markets are not perfect and traders do not possess perfect information making them susceptible to behavioral biases or irrationality (Willmanet al., 2001:906).

Conclusion and recommendations

The majority of BCIs have been revealed to be statistically significant indicators or explanatory signals of the commodity market and are useful for analysis and interpretation, having exhibited explanatory capacity of behavioral time-series movements of the capital market. Reassurance is given that the financial sector is not isolated from the real sector, notwithstanding their operational idiosyncrasies. Most of the considered BCIs were revealed to exhibit forms of leading, lagging and coinciding properties respective to the All-commodity index. Results of the study proved to be significant and corresponded with various backgrounds of the empirical literature on predictability, co-movement or concordance.

These findings are crucial to how market analysts, investors, traders, scholars, including fiscal and monetary policymakers, view and build inferences on the markets. The SARB (2018:3) also acknowledged existing and important linkages between financial stability and the real markets. Thus a stable financial system can be founded by sustainable growth prospects and vice versa. Such that real market developments can influence financial stability and performance. They identified signals or other variables that can display co-movement with the All-commodity index. They can be used to assess South Africa's outlook of its financial market and, therefore, assist in curbing likely market disruptions or lessening their impact by realizing suitable measures or safety-nets. This study encourages the utilization of BCIs or real side variables in conjunction with micro-finance variables to analyze, interpret and formulate economic policy for financial sustainability and stability. The use of real and finance variables improves the accuracy in estimation and macro-prudential analysis. Therefore, investors and traders seeking to make profits in South Africa's capital markets may also attain quality inferences by looking at both real and monetary side factors.

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APPENDIXES

Appendix 1:

South Africa's official composite business cycle indicators

Component time series of the composite business cycle indicators		
Leading indicator	**Coincident indicator**	**Lagging indicator**
Job advertisement space in the *Sunday Times* newspaper: percentage change over twelve months	Gross value added at constant prices, excluding agriculture, forestry and fishing	Cement sales (in tons)
Number of residential building plans passed for flats, townhouses and houses larger than 80m'	Total formal non-agricultural employment	Value of non-residential buildings completed at constant prices
Interest rate spread: 10-year government bonds less 91-dat Treasury bills	Value of retail and new vehicles sales at constant prices	Ratio of gross fixed capital formation in machinery and equipment to final consumption expenditure on goods by households
Real M1 money supply (deflated with CPI)" six-month smoothed growth rate	Industrial production index	Ratio of inventories to sales in manufacturing and trade
Index of commodity prices (in US dollar) for a basket of South African-produced export commodities	Utilisation of production capacity in manufacturing	Nominal labour cost per unit of production in the manufacturing sector: percentage change over twelve months
Composite leading business cycle indicator of South Africa's major trading partner countries: percentage changes over twelve months	n/a	Predominant prime overdraft rate of banks
Gross operating surplus as a percentage of gross domestic product	n/a	Ratio of consumer instalment sale credit to disposable income of households
RMB/BER Business Confidence Index	n/a	n/a

Component time series of the composite business cycle indicators		
Leading indicator	**Coincident indicator**	**Lagging indicator**
New balance of manufacturers observing an increase in the average number of hours worked per factory worker (half weight)	n/a	n/a
Net balance of manufacturers observing an increase in the volume of domestic order received (half weight)	n/a	n/a
Number of new passenger vehicles sold: percentage change over twelve months	n/a	n/a

Appendix 2:
Representation of variables and transformed time series to logged series

Variable	Log Series	Representation
All commodity index	LALCI	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

Variable	Log Series	Representation
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
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

Appendix 3:
ADF unit root results for All-commodity index and business cycle indicators

Variables	Level				First Difference		Order of Integration
	With intercept & without trend		With intercept & trend		Without trend		
	t-stat	P-value	t-stat	P-value	t-stat	P-value	
LACI	-4.150	0.001**	-4.138	0.007	-6.963	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	-11.607	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)

Variables	Level				First Difference		Order of Integration
	With intercept & without trend		With intercept & trend		Without trend		
	t-stat	P-value	t-stat	P-value	t-stat	P-value	
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)
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

Appendix 4:

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