Is consumer confidence an indicator of JSE performance?

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ABSTRACT

While most studies examine the impact of business confidence on market performance, we instead focus on the consumer because consumer spending habits are a natural extension of trading activity on the equity market. This particular study examines investor sentiment as measured by the Consumer Confidence Index in South Africa and its effect on the Johannesburg Stock Exchange (JSE). We employ Granger causality tests to investigate the relationship across time between the Consumer Confidence Index and market performance. The results show weak evidence of a contemporaneous relationship; however, significant evidence of a Granger caused relationship is apparent. Further, changes in investor sentiment Granger-cause changes in the two indices used, generally with a lag of 9 and 12 months, but not vice versa. Thus, we find that Consumer Confidence leads JSE performance during our sample period. Our research provides evidence contradicting the common perception of consumer confidence lagging market performance, particularly in the South African context.

KEY WORDS: consumer confidence; financial markets; South Africa; behavioral finance

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Introduction

The aim of conventional finance theory is to provide an understanding of financial markets using models in which investors are viewed as rational. Rationality is seen as having two meanings; first, investors update their beliefs correctly when new information is collected, in alignment with the manner described by Bayes' Theorem (Laplace, 1812) and second, investors make choices that are normatively standard, i.e., they are consistent with Savage's notion of Subjective Expected Utility (Savage, 1954). The simplicity of this concept makes it exceptionally attractive, but disappointment ensues when the data confirm that our basic notions of the share market are not explained by this framework (Barberis & Thaler, 2003).

This particular study examines investor sentiment, proxied by consumer confidence, in South Africa and its effect on the Johannesburg Stock Exchange. Investor sentiment can be described as "a belief about cash flows that is not justified by the facts at hand" (Baker & Wurgler, 2007, p. 129). Additionally, these investor beliefs are gauged relative to some norm or average (Brown & Cliff, 2004), often the true fundamental value of the asset. Investigating these effects is vital: sentiment is seen as playing a critical role in the economy

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because it influences not only the business cycle but also the financial fluctuations within the economic system too (Sehgal, Sood, & Rajput, 2009).

Investor sentiment is measured using the First National Bank and Bureau of Economic Research Consumer Confidence Index (hereafter known as CCI). Currently, the CCI is currently the only formal measure of consumer confidence publicly available in South Africa and is made available by the Bureau on a quarterly basis. It is measured via consumer surveys that provide regular evaluations of consumer attitudes and expectations, which are then used to evaluate economic trends and prospects. The survey is constructed using three questions, each carrying a different weight. The CCI is then computed as the average of the result of the three questions. The CCI is expressed as a net balance, thus revealing changes in consumer expectations. The net balance is derived as the difference between the percentage of respondents expecting an improvement and those expecting a decline (Kershoff, 2000).

The results of this study provide room for further debate on whether market performance can be foretold. Indeed, some studies find that consumer confidence is a lagging indicator of market performance in the United States. This implies that one cannot use this sentiment as a proxy in predicting market movements. However, Lemmon and Portniaguina (2006) and Zouaoui, Nouyrigat and Beer (2011) both provide evidence of how consumer confidence can be used to forecast macroeconomic activity and market crises, respectively. Individual investors may find this information important should they wish to speculate and exploit the perceived biases present in the share market in hopes of earning excess returns.

The remainder of this study is organized as follows: Section 2 presents a review of the literature on this topic, and Section 3 outlines the data and methodology used. Section 4 discusses the results, Section 5 considers the limitations of the studies and the opportunities for further research, and Section 6 concludes. Finally, Appendix A presents the distributional properties of the data used.

Literature Review

Investor Sentiment

There is a growing body of research pertaining to the effect of investor sentiment on the share market as a whole. The study of movements in share prices that are seemingly unjustified by fundamental pricing theories can be attributed to the term "animal spirits," which was made popular by Keynes (1937). An important factor that can be used to explain the cross-section of share returns but whose role was excluded in the development of classic finance theory is investor sentiment (Baker & Wurgler, 2006). Standard finance theory dictates that share prices should reflect the present value of discounted cash flows (Schmeling, 2008); however, the fact that this is not always true highlights the possibility of additional factors, not all of which may be rational, in explaining share price movements.

A consumer confidence index reflects the combined expectations and the beliefs of investors concerning the fundamentals of markets and the economy (Li, 2010). Lemmon and Portniaguina (2006), Qiu and Welch (2004) assert that a confidence index forms a direct measure of the general feelings of investors and that changes can measure the fluctuation of share returns especially for small firms. A common approach in the literature is to use a combined sentiment index consisting of several sentiment proxies. Utilizing such an index, Baker and Wurgler (2006) observe that investor sentiment has a significant effect on the cross section of stock returns.

The importance of studying investor sentiment is somewhat overshadowed by the difficulty in quantifying this concept, a difficulty that is further exacerbated by the fact that investor sentiment may be grouped into direct and indirect investor sentiment. Direct investor sentiment refers to investors' moods or expectations about the future and is usually measured via surveys and questionnaires. Indirect investor sentiment refers to a number of economic variables that are perceived to act as proxies for measuring investor sentiment (Uygur & Taş, 2012). These can include mutual fund flows, trading volume, dividend premia, first-day returns and volumes on Initial Public Offerings, insider trading (Baker & Wurgler, 2007) and closed-end fund discounts (Lee, Shleifer, & Thaler, 1991). Moreover, Baker and Wurgler (2007) address this challenge by describing the "bottom up" approach of measuring investor sentiment, which makes use of biases in investor psychology to explain how investors react to past returns. They then endeavor to develop a contrasting model, namely the "top down" approach, which makes use of aggregate sentiment and its effects on market returns and on individual shares.

Poterba and Samwick (1995) argue that the effect of share price movements on investor sentiment can be attributed to two factors. The first is the traditional wealth effect, where changes in share prices cause changes in household wealth and hence influence investor sentiment. The second is the "leading indicator" channel, where share prices may change in response to changes in economic activity. Here, changes in share prices are interpreted as an indicator of future earnings (Bremmer, 2008). A study by Otoo (1999) provides results consistent with the latter reason whereby changes in equity prices are viewed as a leading indicator. These findings are supported by Jansen and Nahuis (2003), who also find that higher share prices are a leading indicator that increase investor sentiment.

Some authors postulate that periods of high sentiment may cause overvaluation and hence inflated returns (Baker & Wurgler, 2007). This hypothesis highlights that it may be possible to predict low future returns on these shares because when sentiment levels drop, the hypothesis shows that prices tend to move towards their fundamental value. Evidence from Fisher and Statman (2000) indicates that there is a negative relationship between the sentiment level of individual investors and S&P 500 returns the following month. This evidence supports the notion that because prices tend to move toward their fundamental values following a period of overvaluation, observed returns are much lower. Da, Engelberg and Gao (2013) construct an index termed the Financial and Economic Attitudes Revealed by Search (FEARS) index, which is based on aggregated search queries on market sentiment indicators such as recession, unemployment and bankruptcy. They find that the FEARS index is correlated with low returns today, but can be used to predict higher returns tomorrow, an effect that is stronger for those shares favored by sentiment investors or those that are difficult to arbitrage. Additionally, increases in the FEARS index prompt mutual fund flows out of equity funds into bond funds, evidence that supports the "noise trading" hypothesis of De Long, Shleifer, Summers and Waldman (1990).

Otoo (1999) finds that consumer sentiment and share prices share a strong positive relationship such that an increase in equity prices boosts consumer sentiment. Further, the use of Granger causality tests show that share prices Granger-cause consumer confidence, but this causality is not observed in the opposite direction. Granger causality considers the direction of the flow of time to determine the causal ordering of the chosen variables (Granger, 1969). Karnizova and Khan (2010) conduct a similar study in Canada and draw a similar conclusion, namely, that share prices Granger-cause consumer confidence. Jansen and Nahuis (2003) extend this study to eleven European countries. In considering the short-run link between equity prices and consumer confidence, Germany is the only country where there is a disconnect between changes in sentiment and share prices. On the other hand, the UK demonstrates the highest correlation between these variables, with the other eight countries revealing lower correlations (Jansen & Nahuis, 2003). These results can be said to reflect the fact that share ownership in continental Europe is significantly lower than in the UK (Boone, Giorno, & Richardson, 1998). The results show that for seven countries, changes in share prices positively affect consumer confidence two weeks later.

South African Studies

Currently, there is no formal evidence pertaining to investor sentiment as measured by the CCI; however, research by Kershoff (2000) examines the relationship between economic cycles and the BER Business Confidence Index (BCI). An important finding for the South African economy is that the BCI has "proven itself historically both as useful indicator of economic growth and as a very good leading indicator of the business cycle in South Africa." (Kershoff, 2000, p. 5). Collins (2001) considers the relationship between a macroeconomic indicator, business confidence surveys, and share market performance. The results show that share market performance is a predictor of business confidence surveys and that this Granger causality is only one-directional.

The research by Collins (2001), although not conducted on the CCI, provides important insight into the drivers of the South African economy and the JSE, as well as providing room for further research in this area. Here, we instead use the CCI to measure the impact of consumer spending in the equities market (proxied by the JSE All Share Index).

Data and Methodology

Sampling Data and Collection

The CCI data are obtained from the Bureau for Economic Research, which is published quarterly. As outlined in Section 1, the CCI is expressed as a net balance and thus reveals changes in consumer expectations. The net balance is derived as the difference between the percentage of respondents expecting an improvement and those expecting a decline. The survey is constructed using three questions, each carrying a different weight, and the CCI is given as the weighted average of the results of the three questions. The three questions are as follows:

1. How do you expect the general economic position in South Africa to develop during the next 12 months? Will it improve considerably, improve slightly, deteriorate slightly, deteriorate considerably or don't know?
2. How do you expect the financial position in your household to develop in the next 12 months? Will it improve considerably, improve slightly, deteriorate slightly, deteriorate considerably or don't know?
3. What is your opinion of the suitability of the present time for the purchase of domestic appliances such as furniture, washing machines, refrigerators etc.? Do you think that for people in general it is the right time, neither a good nor a bad time or the wrong time?

The answers to questions 1 and 2 are weighted as follows: improve considerably (+10), improve slightly (+5), deteriorate slightly (-5) and deteriorate considerably (-10). The responses to question 3 are weighted as follows: right time to buy (+10) and wrong time to buy (-10) (Kershoff, 2000).

JSE monthly price data are obtained from the Findata@Wits database, a financial database used for research maintained by the University of the Witwatersrand. Price data are collected for all companies listed on the JSE during the sample period in question, for a total of 867 companies. Those that delisted during the period were not removed to avoid any survivorship bias in the study.

Description of Overall Research Design

Given the two frequencies of data used, one must first transform one of the datasets to match the frequency of the other. One method by which to do so is to in-terpolate the CCI quarterly data in order to obtain monthly data. However, a potential limitation in using this method is that the interpolated values are not "real" in the sense of being available to an investor. In other words, while solving a statistical problem, the applicability of this method to a real world scenario is diminished. The second and more favorable alternative is to make use of the Time-Averaging method outlined by Armetso, Engemann and Owyang (2010). This method is viewed as superior because it converts the high frequency data (JSE share returns) to match the low frequency data (CCI data). For the purposes of this study, the time averaging method is employed.

Using these quarterly returns obtained from the time averaging methodology, an Artificial Market Index (AMI) is created on a price-weighted basis. As a comparable index to this AMI, data for the All Share Index (ALSI) is also obtained. These data are provided by the JSE on a monthly basis and are time averaged as described above.

JSE data are available from 1990 and CCI data from 1982, and the sample period of the study will therefore run from 1992 to 2011 inclusive, a total of 20 years. This sample period is especially important in South Africa due to the numerous historical and world events that took place during that time. Furthermore, this period is sufficiently long to investigate any effects but short enough to ensure a minimal amount of noise enters the study. The JSE and CCI data for the sample period are divided into four quartiles for two reasons:

1. To assist in isolating the socio-economic effects, or the "noise" that enters the study.
2. Using smaller clusters of data provides a more in-depth interpretation of whatever the results may be.

As a preliminary step, the distributional properties of the data are examined. This entails examining the independence and normality assumptions as well as stationarity. Stationarity is highly important in examining time series data because it determines if there is a long run relationship between share prices and investor sentiment. Should the data set be deemed nonstationary, differencing will be used as running tests on non-stationary variables results in spurious results.

To determine if there is a contemporaneous relationship between the CCI and the two indices, a correlation coefficient is calculated. A causal re-

lationship between the CCI and the two indices is determined by conducting Granger causality tests at different lag orders. The test for a contemporaneous and causal relationship is completed for each subsample created. Granger causality involves running bivariate regressions of the following form:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \ldots + \alpha_l y_{t-1} + \beta_1 x_{t-1} + \ldots + \beta_l x_{t-1} + \varepsilon_t$$
$$x_t = \alpha_0 + \alpha_1 x_{t-1} + \ldots + \alpha_l x_{t-1} + \beta_1 y_{t-1} + \ldots + \beta_l y_{t-1} + u_t \qquad\qquad 1$$

for all possible pairs of (x,y) series in the group, where represents the appropriate lag length.

Results and Discussion

Distributional Properties

A correlogram of all three variables – CCI, AMI, and ALSI – is examined in testing for independence. The CCI data exhibit a degree of autocorrelation, indicating that the observations are not necessarily independent of each other. The opposite is observed for the AMI data: no traces of autocorrelation are uncovered, indicating that the observations are independent of each other. Finally, in considering the independence of the ALSI, it may be concluded that the ALSI observations are independent of each other. Details can be found in Appendix A.

Establishing stationarity is highly important for time series data and hence, the Augmented Dickey Fuller (ADF) test is conducted. The test results, shown in Table A4 in Appendix A, demonstrate that all three variables can be deemed stationary.

Correlation Testing

CCI and ALSI

During the period 1992 to 1996, the CCI and ALSI display moderate correlation with the correlation coefficient at the 5% level of significance. These results from Table 1 below indicate that during this period, there was a moderate concurrent relationship between these two variables.

Over the next five year period, 1997 to 2001, there is a very weak correlation between the CCI and the ALSI; nonetheless, this correlation coefficient is statistically insignificant. Thus, from Table 2 below, it may be concluded that there is no concurrent relationship between these two variables during this period.

The next five year period yields results similar to that observed in the previous five years. During the five years between 2002 and 2006, the CCI and ALSI are weakly negatively correlated, and this correlation coefficient is deemed statistically insignificant. Hence, the results from Table 3 below indicate that there is no concurrent relationship present between these variables during this period.

The final five-year block in the sample yields results similar to the majority of the sample. Between 2007 and 2011, the CCI and ALSI exhibit a weak and negative correlation that is statistically insignificant. Consequently, from Table 4 below, no concurrent relationship is found between the CCI and the ALSI during this five year period.

Overall, a moderate and significant concurrent relationship is found during only one time period, from 1992 to 1996. The remaining periods show no evidence of a concurrent relationship, indicating that the evidence for a concurrent relationship is somewhat weak.

CCI and AMI

The correlation coefficient from Table 5 below indicates that between 1992 and 1996, the CCI and AMI demonstrate a moderate correlation. This correlation coefficient is statistically significant, indicating that there is a moderate concurrent relationship between these two variables. This result is similar to that obtained in the same period when considering the correlation between the CCI and ALSI.

Unfortunately, the subsequent five year period – from 1997 to 2001 – provides evidence refuting the presence of a concurrent relationship. Although the CCI and the AMI are weakly negatively correlated during this time period, as seen in Table 6 below, the correlation coefficient is statistically insignificant and for that reason it may be concluded that there is no concurrent relationship between these two variables.

The five years between 2002 and 2006 provide evidence refuting the presence of a concurrent relationship. Table 7 below indicates that the CCI and AMI are negatively correlated, and although this relationship is stronger than those observed previously, it remains somewhat weak. Regardless, this correlation coefficient is statistically insignificant and it may thus be concluded that there is no concurrent relationship between these two variables.

Table 1. CCI/ALSI Correlation 1992-1996

	1992-1996	
	ALSI	CCI
ALSI	1.00	

CCI	0.4785	1.00
	[0.033]*	----

Note: The p-values for the associated correlation coefficients are provided in the square brackets.
* - statistically significant at the 5% level of significance

Table 2. CCI/ALSI Correlation 1997-2001

	1997-2001	
	ALSI	CCI
ALSI	1.00	

CCI	0.0652	1.00
	[0.78]	----

Note: The p-values for the associated correlation coefficients are provided in the square brackets.

Table 3. CCI/ALSI Correlation 2002-2006

	2002-2006	
	ALSI	CCI
ALSI	1.00	

CCI	-0.2640	1.00
	[0.26]	----

Note: The p-values for the associated correlation coefficients are provided in the square brackets.

Table 4. CCI/ALSI Correlation 2007-2011

	2007-2011	
	ALSI	CCI
ALSI	1.00	

CCI	-0.0379	1.00
	[0.87]	----

Note: The p-values for the associated correlation coefficients are provided in the square brackets.

Table 5. CCI/AMI Correlation 1992-1996

	1992-1996	
	AMI	CCI
ALSI	1.00	

CCI	0.4713	1.00
	[0.036]*	----

Note: The p-values for the associated correlation coefficients are provided in the square brackets.
* - statistically significant at the 5% level of significance

Table 6. CCI/AMI Correlation 1997-2001

	1997-2001	
	ALSI	CCI
ALSI	1.00	

CCI	-0.0116	1.00
	[0.96]	----

Note: The p-values for the associated correlation coefficients are provided in the square brackets.

Table 7. CCI/AMI Correlation 2002-2006

	2002-2006	
	AMI	CCI
ALSI	1.00	

CCI	-0.3297	1.00
	[0.16]	----

Note: The p-values for the associated correlation coefficients are provided in the square brackets.

Table 8. CCI/AMI Correlation 2007-2011

	2007-2011	
	AMI	CCI
ALSI	1.00	

CCI	0.0371	1.00
	[0.88]	----

Note: The p-values for the associated correlation coefficients are provided in the square brackets.

The final five-year period from 2007 to 2001, shown in Table 8 below, provides similar results as those found above. The CCI and the AMI are found to have a positive but weak relationship that is statistically insignificant. Consequently, there is no evidence to support the presence of a concurrent relationship between these two variables during this time.

Overall, a moderate and significant concurrent relationship is found from 1992 to 1996. The remaining period shows no evidence to support a concurrent relationship, an outcome that is consistent with the results of the previous tests.

The outcome of the analyses of the CCI and ALSI and CCI and AMI yield similar results. Evidence of a moderate concurrent relationship is found in the first five years, i.e., changes in the CCI have an impact on changes in the ALSI or changes in the AMI. The remainder of the sample period provides no evidence to support this relationship, and as a result, it may be concluded that the evidence for a concurrent relationship between these two sets of variables is somewhat weak.

Granger Causality Tests

CCI and ALSI

Table 9 shows the results of the Granger causality tests between the CCI and the ALSI at different lag orders for each sub-sample considered.

The results from output (1) show that for all lag orders, there appears to be no statistically significant Granger-causal relationship between the CCI and the ALSI in either direction. This means that from 1992 to 1996, changes in the CCI do not Granger-cause changes in the ALSI, and changes in the ALSI do not Granger-cause changes in the CCI. Output (2) yields similar results in that at all lag orders, there appears to be no statistically significant causal relationship between the CCI and the ALSI in either direction. This means that from 1997 to 2001, changes in the CCI do not Granger-cause changes in the ALSI, and changes in the ALSI do not Granger-cause changes in the CCI.

The results from output (3) indicate that during the period from 2002 to 2006 a statistically significant causal relationship is found at a lag of 9 months; however, while changes in the CCI Granger-cause changes in the ALSI at a 5% level of significance, this relationship is not observed in the opposite direction. Additionally,

at a lag of 12 months, a bidirectional Granger-caused relationship is found at the 10% level of significance – changes in the CCI Granger-cause changes in the ALSI and changes in the ALSI Granger-cause changes in the CCI. The remaining lag orders show no significant causal relationship between changes in the CCI and the ALSI.

Consistent with the previous time period, output (4), which considers the five years between 2007 and 2011, indicates that a statistically significance unidirectional causal relationship is found at a lag of 9 months; changes in the CCI Granger-cause changes in the ALSI at a 5% level of significance. A similar relationship in the same direction is found at a lag of 12 months; however, this relationship is significant at the 10% level of significance. However, there are no statistically significant results uncovered in the opposite direction – changes in the ALSI do not Granger-cause changes in the CCI.

CCI and AMI

Table 10 below shows the results for the Granger causality tests between the CCI and the AMI at different lag orders for each sub-sample considered.

The results from output (1) reveal that at all lag orders between 1992 and 1996, there appear to be no statistically significant causal relationships between the CCI and the AMI in either direction. This means that during these five years, changes in the CCI do not Granger-cause changes in the AMI and changes in the AMI do not Granger-cause changes in the CCI. Output (2) yields results consistent with those observed in output (1). At all lag orders, there appears to be no statistically significant causal relationship between the CCI and the AMI in either direction. This means that during the period from 1997 to 2001, changes in the CCI do not Granger-cause changes in the AMI and changes in the AMI do not Granger-cause changes in the CCI.

The results from the subsequent five year period – from 2002 to 2006 – given in output (3) show that at a lag of 9 and 12 months, changes in CCI Granger-cause changes in the AMI; these relationships are observed in one direction only and are statistically significant at the 5% level. The remaining lag orders show no statistically significant causal relationship between changes in the CCI and AMI. These results con-

Table 9. CCI/ALSI Granger Causality Tests

	3 months	6 months	9 months	12 months	15 months	18 months
(1) 1992-1996						
CCI doe s not Grange r caus e ALSI	0.67	0.53	0.57	0.85	0.49	0.87
ALSI doe s not Grange r caus e CCI	0.53	0.83	0.71	0.89	0.88	0.72
(2) 1997-2001						
CCI doe s not Grange r caus e ALSI	0.59	0.60	0.57	0.85	0.96	0.99
ALSI doe s not Grange r caus e CCI	0.26	0.56	0.74	0.72	0.92	0.36
(3) 2002-2006						
CCI doe s not Grange r caus e ALSI	0.15	0.31	0.017*	0.063**	0.71	0.87
ALSI doe s not Grange r caus e CCI	0.66	0.17	0.26	0.054**	0.32	0.13
(4) 2007-2011						
CCI doe s not Grange r caus e ALSI	0.14	0.40	0.036*	0.055**	0.24	0.56
ALSI doe s not Grange r caus e CCI	0.74	0.89	0.99	0.91	0.97	0.66

Note: Statistical significance means that the null hypothesis in Column 1 can be rejected

* - statistically significant at the 5% level of significance

** - statistically significant at the 10% level of significance

cur with the results found for the identical time when changes in the CCI and ALSI were considered.

The final five-year block in the sample period – from 2007 to 2011 – provides evidence for a causal relationship between the CCI and AMI. At a lag of 6, 9 and 12 months there is a statistically significant unidirectional causal relationship between changes in the CCI and the AMI; in this case, changes in the CCI Granger-cause changes in the AMI. This result is similar to those found in the identical period when considering the causal relationship between changes in the CCI and ALSI. In accordance with the previous results, no statistically significant relationship is found in the opposite direction – changes in the AMI do not Granger-cause changes in the CCI.

Discussion of Results

It is evident from the above results that there are two distinct periods: between 1992 and 2001, no statistically significant Granger-caused relationships are identified when testing the CCI against both the ALSI

and the AMI. Conversely, from 2002 to 2011, unidirectional, statistically significant Granger-caused relationships are found such that changes in the CCI do Granger-cause changes in the ALSI and AMI, usually at lag orders of three and four and in one case, the relationship was bidirectional. Possible reasons for this distinct separation include both global factors and those unique to the South African environment.

The period from 1992 to 1996 saw South Africa's first democratic election, the world's reacceptance of South Africa and South Africa's acceptance of the world as a trading partner. Nonetheless, the South African economy remained fragile and it is likely that consumers did not adjust their expectations correctly or in a timely manner; more than likely, consumers were uncertain as to whether the current conditions and economic and political reform would continue, and hence behaved in a possibly irrational manner (Simon, 1978). Therefore, the finding of no significant Granger-caused relationship between the two pairs of variables is disappointing, but not entirely surprising.

Table 10. CCI/ALSI Granger Causality Tests

(1) 1992-1996					
	3 months	6 months	9 months	12 months	15 months	18 months
CCI doe s not Grange r caus e AMI	0.25	0.33	0.19	0.42	0.55	0.80
AMI doe s not Grange r caus e CCI	0.27	0.55	0.81	0.89	0.92	0.67
(2) 1997-2001					
	3 months	6 months	9 months	12 months	15 months	18 months
CCI doe s not Grange r caus e AMI	0.57	0.43	0.39	0.64	0.89	0.94
AMI doe s not Grange r caus e CCI	0.40	0.73	0.89	0.85	0.93	0.15
(3) 2002-2006					
	3 months	6 months	9 months	12 months	15 months	18 months
CCI doe s not Grange r caus e AMI	0.11	0.17	0.011*	0.011*	0.19	0.56
AMI doe s not Grange r caus e CCI	0.96	0.26	0.36	0.29	0.27	0.23
(4) 2007-2011					
	3 months	6 months	9 months	12 months	15 months	18 months
CCI doe s not Grange r caus e AMI	0.56	0.016*	0.005*	0.041*	0.18	0.79
AMI doe s not Grange r caus e CCI	0.52	0.75	0.63	0.41	0.53	0.23

Note: Statistical significance means that the null hypothesis in Column 1 is rejected
* - statistically significant at the 5% level of significance
** - statistically significant at the 10% level of significance

Conversely, the period from 1997 to 2001 was a much more prosperous time in South Africa, but not for the rest of the world. The year 1997 was peculiar as the world experienced both the formation of the Internet bubble and a stock market crash due to a global economic crisis scare. The bubble eventually burst in 2000, bringing many countries into a mild economic depression. At that time, South Africa was being built as a democratic and diverse nation and many changes were being implemented. Given the local and global conditions, it is quite surprising that there were no significant Granger-caused relationships identified between the two pairs of variables.

Following from the greater degree of integration between South Africa and the rest of the world, it is reasonable to expect that international financial trends, such as an investor sentiment effect, would become apparent in South Africa (as per Baker, Wurgler & Yuan, 2012). This is exactly the result that was observed in the period from 2002 to 2011: it was found that changes in the CCI Granger-caused changes in both the ALSI and AMI with a lag

of between 6 and 12 months. The lag of 6 months was observed in one scenario, with the most common finding being a lag of 9 and 12 months. There was only one instance of a bidirectional relationship, but overall there was weak evidence that changes in the ALSI or changes in the AMI Granger-caused changes in the CCI.

The evidence of the direction of this relationship contradicts the results found in the United States (Otoo, 1999), Canada (Karnizova & Khan, 2010) and Europe (Jansen & Nahuis, 2003). Evidence from these studies finds that share returns Granger-cause consumer confidence, but no causality is detected in the opposite direction. The contradiction in these results could be due to the frequency of the data used and, by implication, the lag order observed, or on a more macroeconomic level, the unique characteristics of the South African share market. Another possibility is the nature of the questions asked in the different consumer confidence indices used in different countries.

The five years between 2002 and 2006 were filled with many significant political, social and economic

developments both internationally and domestically, ranging from financial occurrences (the introduction of the euro) to natural disasters. While these events did occur during this time period, it is arguable that the events that influence economic activity would have a greater effect on investor sentiment than those that do not (as seen in the literature discussed previously). During this five-year period in South Africa, real GDP and the unemployment rate experienced a compound annual growth rate (CAGRs) of 6.8% and -1.5%, respectively – that is to say, real GDP increased while the unemployment rate fell. Although these are only two of the several indicators used to describe the state of a country, evidence has shown that macroeconomic indicators play a key role in investors' expectations, beliefs and actions (Da, Engelberg, & Gao, 2013). Overall, it appears that the numerous local and global events described above had an impact on this causal relationship.

Over the five years from 2007 to 2011, the most notable event was the onset of the global financial crisis. Fortunately, South Africa was less heavily affected due to its well-developed and stringent regulations and governance practices. The country was affected indirectly, however, through business and trade partnerships that came under severe pressure. The indirect effects included CAGRs of -9.4% and 2.2% for real GDP and the unemployment rate, respectively (Padayachee, 2011). Aside from these unfavorable local effects and the global financial crisis, numerous other political and economic events occurred around the world (such as the oil price bubble and the election in the United States of the first African American president). Once again, it is possible that the events that occurred during these five years influenced South African investors with a significant delay and that economic transactions were concluded based upon their revised expectations.

The results showed a delay in the conclusion of economic transactions of 9 and 12 months. We hypothesise that the delay with which consumers' expectations and beliefs were translated into action can be attributed to a variety of psychological factors, as well as being due to the nature of the measure of investor sentiment. First, this can be due to investor irrationality where expectations are not adjusted timeously, leading to significant delays in concluding financial decision. The literature shows that this is exacerbated by

a confirmation bias where investors tend to search for confirmation instead of disconfirmation, which causes them to selectively search and analyze financial information with the hopes of finding evidence to support their original intentions (Nickerson, 1998).

Secondly, apart from confirmation bias, investors tend to value certainty and may therefore be hesitant to immediately alter their expectations and spending patterns because they are uncertain of the outcome of the change. This degree of risk aversion may also be that much higher for those who must consider how they will justify their position or expenditures to others (Hilton, 2001). The degree of risk aversion as well as the accountability and justification associated with decision-making may shed some light on the delay observed in these results.

Lastly, the CCI, by definition, measures the change in the expectations of seemingly uninformed investors over the next 12 months. Therefore, not only is the delay observed in the results appropriate, it is expected, as investors must familiarize themselves with the information required to make informed financial decisions.

The evidence pertaining to the causal relationship thus begs the question of whether investor sentiment is a leading or lagging market indicator. Foundational evidence has shown that changes in investor sentiment are seen as a leading indicator of the economy and that the market is also seen as a leading indicator of the economy (Otoo, 1999); however, are changes in investor sentiment seen as a leading indicator of the market? There is evidence to suggest that this relationship does indeed exist and that investor sentiment is often used as one of the variables that assists forecasters in avoiding forecasting errors (Vuchelen, 2004). Lemmon and Portniaguina (2006) uncover evidence showing that investor sentiment does exhibit forecasting power not only for macroeconomic activity but also for the returns on small stocks and stocks held by individuals. This predictive relationship also holds when anticipating stock market crises (Zouaoui, Nouyrigat, & Beer, 2011). The authors find that investor sentiment could positively influence the probability of the occurrence of stock market crises within a one-year horizon, a relationship that is stronger in countries that are more prone to herd-like behaviour and those with inefficient regulatory institutions. Finally, the connection

between consumer spending and stock market activity has been documented and the relationship explained using simple economics: when consumer spending increases, a part of this spending is directed toward the stock market. Huth, Eppright and Taube (1994) uncover evidence indicating that a number of consumer confidence indices are useful in predicting future values of aggregate consumer spending, as well and business and economic activity. This predictive property of investor sentiment provides evidence that it is indeed a leading indicator of the market, a relationship that is useful to many financial market participants.

Limitations and Opportunities for Further Research

This study is limited by the use of quarterly data, which led to a limitation in the number of observations used in the sample. Therefore, as with any empirical study, an improvement can be made by employing a larger data set, which can be achieved either by increasing the sample period or using a higher frequency data set. One must also bear in mind that increasing the sample period allows for a greater degree of noise to enter the study, and isolating any relationships or effects thus becomes a greater challenge.

Finally, although Granger causality is the most common method of testing for a causal relationship, other methods may yield robust results under different circumstances. The decision regarding which causality test to use should be made bearing in mind the type of data used, the frequency of the data and finally, the sample size.

The object of this paper was simply to determine if there is in fact a causal relationship between investor sentiment and JSE performance; however, many opportunities exist for further research with the goal of expanding on current knowledge. Considering that South Africa currently has one measure of investor sentiment available to the public – the Consumer Confidence Index – it would be beneficial to create a sentiment index using proxies for investor sentiment as the explanatory variables, as in Baker and Wurgler (2007), and then investigate the presence of a causal relationship between that index and share market performance. A further avenue to pursue would be to determine which types of shares are particularly susceptible to the effects of investor sen-

timent; this would be particularly useful in South Africa due to the nature of the JSE. Finally, investigating the nature of the causal relationship – either direct or indirect – would make a valuable contribution to the topic of behavioral finance.

Conclusion

Conventional finance theory aims to provide an understanding of financial markets; under these theories, investors are assumed to be rational. However, as simple the concept of rationality may seem, this framework cannot explain basic ideas of financial markets. The shortcomings of standard finance theory allow for the development of new elements of research with the goal of providing a holistic understanding. One of these elements of research is the effect of investor sentiment on the share market. International research has established a causal relationship between investor sentiment and share market performance, with some analyses even delving deeper into the topic. Considering that there are no South African studies that investigate the link between these two variables, this paper investigates whether there is any relationship between investor sentiment – as measured by the Consumer Confidence Index – and JSE performance.

Statistical testing is conducted on three levels: determining first if there was a concurrent relationship, second, if there was a causal relationship, and finally, investigating the industry determinants of the CCI.

The evidence of a concurrent relationship is somewhat weak, and in each case a concurrent relationship is found in only one period, from 1992 to 1996. During this period, the concurrent relationship between changes in the CCI and changes in the ALSI or changes in the AMI are moderate. The remaining periods show no evidence to support a concurrent relationship, and it can therefore be concluded that there is very weak evidence of a concurrent relationship.

The results from the Granger causality tests create two distinct periods. The first two sub- samples – 1992 to 1996 and 1997 to 2001 – show no evidence of a causal relationship between the CCI and the ALSI or the AMI. In the later sub-samples, however – 2002 to 2006 and 2007 to 2011 – the Granger causality tests show that changes in the CCI Granger-cause changes in the AMI, usually with a lag of 9 or 12 months. However, this relationship is purely unidirectional. The evi-

dence also indicates that during this period, changes in the CCI Granger-cause changes the ALSI, also with a lag of 9 or 12 months. A bidirectional relationship is observed in one instance; however, the remaining relationships are unidirectional. Consequently, it can be concluded that a Granger causal relationship does exist. In answer to the question asked of this paper, we find that consumer confidence can be seen as a predictor of JSE performance with a lag of 9 or 12 months. Our results suggest that the CCI can be considered a leading indicator of the ALSI.

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Appendix A

This appendix provides the tools used to examine the distributional properties of the CCI, AMI and the ALSI. Before proceeding with any statistical testing, it is necessary to test for the independence and stationarity of the three data sets being used.

Independence will be determined using correlograms for the three data series, provided in Figures A1, A2 and A3 below. Independence is tested by testing for autocorrelation – that is, correlations between the observations in one series. If there is no autocorrelation, the autocorrelations and partial autocorrelations

at all lags should be close to zero and all the Q-statistics should be statistically insignificant at the appropriate confidence interval.

Stationarity will be determined by conducting the Augmented Dickey Fuller test. The Phillips-Perron and Kwiatkowski-Phillips-Schmidt-Shin tests can also be used; however, they test for essentially the same thing. Stationarity is highly important, especially when using time series data as it must be determined if the variables in question have a significant causal relationship or if it merely appears that way due to the variables trending over time.

Figure A1. Correlogram of CCI Data

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
***| . |	***| . |	1	-0.433	-0.433	15.566	0.000
.|*. |	.|. |	2	0.147	-0.049	17.390	0.000
.|. |	.|. |	3	-0.030	0.019	17.465	0.001
.*|. |	.*|. |	4	-0.088	-0.107	18.127	0.001
.|*. |	.|*. |	5	0.185	0.128	21.126	0.001
.*|. |	.*|. |	6	-0.202	-0.080	24.749	0.000
.*|. |	**|. |	7	-0.088	-0.279	25.448	0.001
.|*. |	.|. |	8	0.127	-0.005	26.908	0.001
.|. |	.|*. |	9	-0.015	0.116	26.930	0.001
.*|. |	**|. |	10	-0.144	-0.234	28.885	0.001
.|** |	.|*. |	11	0.215	0.132	33.283	0.000
**|. |	.*|. |	12	-0.268	-0.101	40.214	0.000
.|** |	.|. |	13	0.278	0.003	47.757	0.000
.*|. |	.*|. |	14	-0.191	-0.079	51.395	0.000
.|. |	.|. |	15	0.027	0.017	51.466	0.000
.|. |	.*|. |	16	-0.019	-0.189	51.505	0.000
.|. |	.|. |	17	-0.036	-0.041	51.641	0.000
.|. |	.|. |	18	0.030	-0.024	51.733	0.000
.|. |	.|. |	19	-0.018	-0.045	51.766	0.000
.|. |	.|. |	20	0.009	-0.027	51.774	0.000
.|. |	.|. |	21	-0.012	0.006	51.791	0.000
.|*. |	.|. |	22	0.110	0.003	53.161	0.000
.*|. |	.|. |	23	-0.127	-0.041	55.011	0.000
.|*. |	.|. |	24	0.159	0.035	57.988	0.000
.*|. |	.*|. |	25	-0.173	-0.073	61.543	0.000
.|*. |	.*|. |	26	0.083	-0.107	62.385	0.000
.*|. |	.*|. |	27	-0.099	-0.109	63.605	0.000
.|. |	.*|. |	28	-0.021	-0.119	63.659	0.000
.|. |	.*|. |	29	-0.012	-0.135	63.677	0.000
.|. |	.*|. |	30	-0.010	-0.067	63.690	0.000
.|*. |	.|*. |	31	0.110	0.092	65.323	0.000
.|. |	.|. |	32	0.003	0.062	65.324	0.000
.|. |	.|. |	33	0.011	-0.058	65.341	0.001
.|. |	.|. |	34	-0.020	-0.016	65.399	0.001
.|. |	.*|. |	35	0.001	-0.165	65.400	0.001
.*|. |	**|. |	36	-0.089	-0.218	66.576	0.001

Figure A2. Correlogram of AMI Data

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|*. |	.|*. |	1	0.149	0.149	1.8388	0.175
.*| . |	.*| . |	2	-0.127	-0.153	3.2008	0.202
.*| . |	. | . |	3	-0.086	-0.043	3.8239	0.281
.|*. |	.|*. |	4	0.119	0.126	5.0381	0.283
. | . |	. | . |	5	0.026	-0.034	5.0977	0.404
. | . |	. | . |	6	-0.035	-0.009	5.2064	0.518
.*| . |	. | . |	7	-0.080	-0.057	5.7776	0.566
. | . |	. | . |	8	0.000	0.001	5.7776	0.672
. | . |	.*| . |	9	-0.044	-0.067	5.9601	0.744
. | . |	. | . |	10	0.012	0.029	5.9742	0.817
. | . |	. | . |	11	-0.034	-0.040	6.0843	0.868
.*| . |	.*| . |	12	-0.135	-0.139	7.8319	0.798
. | . |	. | . |	13	-0.025	0.029	7.8938	0.850
. | . |	.*| . |	14	-0.056	-0.113	8.2102	0.878
. | . |	. | . |	15	0.046	0.064	8.4213	0.906
.*| . |	**| . |	16	-0.182	-0.219	11.810	0.757
.*| . |	. | . |	17	-0.088	-0.018	12.608	0.762
. | . |	. | . |	18	0.030	0.009	12.702	0.809
.|*. |	. | . |	19	0.117	0.038	14.183	0.773
.*| . |	.*| . |	20	-0.144	-0.158	16.463	0.688
. | . |	. | . |	21	-0.040	0.019	16.645	0.732
. | . |	. | . |	22	0.018	-0.007	16.680	0.781
.|*. |	. | . |	23	0.096	-0.004	17.736	0.772
.|*. |	.|*. |	24	0.095	0.122	18.783	0.763
.*| . |	.*| . |	25	-0.093	-0.184	19.818	0.756
. | . |	. | . |	26	-0.045	0.032	20.062	0.789
.*| . |	.*| . |	27	-0.097	-0.179	21.217	0.776
.*| . |	**| . |	28	-0.141	-0.215	23.729	0.696
. | . |	. | . |	29	-0.052	-0.037	24.075	0.725
. | . |	.*| . |	30	0.010	-0.096	24.089	0.768
. | . |	. | . |	31	-0.052	-0.051	24.450	0.792
.|*. |	.|*. |	32	0.122	0.082	26.495	0.741
. | . |	.*| . |	33	-0.001	-0.076	26.495	0.781
. | . |	.*| . |	34	0.015	-0.066	26.529	0.816
.*| . |	. | . |	35	-0.110	-0.059	28.277	0.782
.|*. |	. | . |	36	0.120	0.054	30.438	0.730

Figure A3. Correlogram of ALSI Data

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|.	.|.	1	-0.021	-0.021	0.0377	0.846
.|.	.|.	2	-0.035	-0.035	0.1385	0.933
.|.	.|.	3	-0.018	-0.020	0.1664	0.983
.|.	.|.	4	0.044	0.042	0.3337	0.988
.*|.	.*|.	5	-0.204	-0.204	3.9781	0.553
.|.	.|.	6	0.052	0.050	4.2217	0.647
.|.	.|.	7	-0.029	-0.043	4.2963	0.745
.|.	.|.	8	-0.027	-0.036	4.3645	0.823
.|.	.|.	9	-0.041	-0.027	4.5227	0.874
.|.	.|.	10	0.011	-0.041	4.5350	0.920
.|.	.|.	11	0.023	0.045	4.5867	0.950
.*|.	.*|.	12	-0.090	-0.114	5.3685	0.945
.*|.	.*|.	13	-0.123	-0.136	6.8446	0.910
.*|.	.*|.	14	-0.093	-0.123	7.6964	0.905
.|.	.|.	15	0.057	0.030	8.0295	0.923
.*|.	.*|.	16	-0.094	-0.103	8.9400	0.916
.|.	.|.	17	0.066	0.021	9.3991	0.927
.*|.	.*|.	18	-0.080	-0.140	10.070	0.930
.|.	.|.	19	0.013	-0.041	10.089	0.951
.|.	.|.	20	0.025	0.031	10.156	0.965
.|.	.*|.	21	-0.017	-0.119	10.187	0.976
.|.	.|.	22	-0.001	0.014	10.187	0.985
.|*.	.|*.	23	0.158	0.095	13.044	0.951
.|*.	.|**	24	0.189	0.216	17.213	0.839
.|.	.|.	25	-0.025	-0.022	17.284	0.871
.|.	.|.	26	0.009	-0.042	17.295	0.900
.*|.	**|.	27	-0.163	-0.212	20.581	0.806
.*|.	.*|.	28	-0.116	-0.133	22.279	0.768
.*|.	.*|.	29	-0.093	-0.074	23.393	0.758
.|*.	.|.	30	0.109	0.039	24.948	0.728
.|.	.|.	31	-0.049	-0.027	25.267	0.756
.|*.	.|.	32	0.100	0.048	26.639	0.735
.*|.	.*|.	33	-0.103	-0.115	28.109	0.709
.|.	.*|.	34	0.000	-0.130	28.109	0.751
.*|.	.*|.	35	-0.075	-0.114	28.934	0.755
.|.	.|.	36	0.020	0.005	28.995	0.790

Table A1. Stationarity Tests on CCI, ALSI and AMI

	Stationarity Tests	
	T-s tat	P-Value
Consumer Confidence Index	-13.8614	0.0001
All Share Index	-8.8933	0.0000
Artificial Market Index	-7.5011	0.0000

Note: * denotes statistical significance at the 5% level of significance; the critical value used above was -3.4677.