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Is the Stock Market a Leading Indicator of Economic Activity in Nigeria?

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In an effort to address the lacuna in leading indicator studies of African economies and Nigeria in particular, this paper examines the causal relationships among stock market prices, real GDP and the index of industrial production in Nigeria, using quarterly data from 1984Q1 to 2008Q4. Granger causality tests indicate bi-directional causality between stock prices and GDP but no causality between stock prices and industrial production or between GDP and industrial production. Stock prices and GDP are found to be cointegrated, leading to the estimation of vector error correction models. Out-of-sample forecasts constructed with AR(1), ARIMA, structural ARIMA, and VEC models indicate that stock prices contain information that can be used to improve the accuracy of GDP forecasts and enhance the conduct of macroeconomic policy in Nigeria.

Keywords: Leading indicators; stock index, Granger causality, cointegration, vector error correction models, forecasting GDP, Nigeria

JEL: E32, E37, G15, G17

1.0 Introduction

Policymakers in most advanced and several developing nations use economic indicators to predict the direction of aggregate economic activity. When these economic indicators can reliably signal changes in aggregate economic activity several months or quarters into the future, they facilitate the conduct of macroeconomic policies which must anticipate the future and take corrective action in order to keep the economy growing at, or close to, capacity with price stability. Because of their embodiment of expectations, financial market variables such as equity prices and the yield curve tend to perform well as leading indicators.

Our primary interest in this paper is to investigate whether or not stock prices are leading indicators of economic activity in Nigeria. Equity market prices reflect the expectations of investors and market operators regarding the performance of firms and the economy in general with respect to economic growth, profitability, the level of interest rates and inflation among other variables. To the extent that these expectations are largely correct, stock market prices could be used as an indicator of future economic activity. If stock prices can reliably predict GDP growth, then they can be used to create, along with other indicators, a composite index of leading economic activity. The improvement in forecasting accuracy to be derived from such a composite leading index will enhance the conduct of monetary and fiscal policies, moderate the vagaries of business cycles and significantly enhance economic welfare.

Leading indicators tend to perform better than benchmark autoregressive models in forecasting the future path of economic activity (Stock and Watson, 2003b). However, in order to perform well as leading indicators, Moolman and Jordaan (2005) claim that time series must have a stable relationship with the business cycle, need to be published in a timely manner, must be final data not subject to revisions and should be available on a monthly basis. Stock prices obviously meet three of the four requirements listed by Moolman and Jordan. However, we need to examine their relationship to the business cycle or aggregate economic activity in a rigorous manner in order to establish their suitability as leading indicators. Data constraints currently preclude an examination of the role of the term structure of interest rates as a leading indicator of economic activity in Nigeria.[2] However, few studies have been conducted on the role of stock prices as leading indicators in African countries[3], and this paper attempts to bridge this lacuna with respect to Nigeria.

The paper is organized as follows. Section 2 presents a review of the theoretical literature and empirical evidence on stock prices as leading indicators from advanced and emerging economies. In section 3, the data and methodology are discussed while the results of diagnostic tests, including unit root, Granger causality and Johansen

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[2] A thorough analysis of the information content of the yield curve will become feasible over time as time series data on bond yields accumulate. Long-maturity instruments, such as the 10-year and 20-year bonds, were introduced in Nigeria as recently as August 2007 and March 2009, respectively.
[3] Jefferis, Okeahama and Matome (2001) and Mauro (2003) are among the few studies on African economies.

cointegration, are presented in section 4. In section 5, we present the results of out-of-sample forecasts conducted with and without stock prices as a structural variable. Section 6 concludes the paper.

2.0 Review of Theoretical and Empirical Literature

2.1 Theoretical Bases for Stock Prices as Leading Indicators

There are at least four theoretical bases for the role of stock prices as leading indicators of economic activity—stock prices as aggregators of expectations, the cost of raising equity capital, the financial accelerator and the wealth effect.

The standard valuation model recognizes the value of a share of common stock as the present value of the expected future dividends from owning stocks. The Gordon (1959) , or constant growth, model in equation (1) shows the now familiar relationship between expected dividends, D_1, the required return on equities, r, the anticipated growth rate of earnings, g, and the current price, P_0, of common stocks.

$$P_0 = \frac{D_1}{r - g} \qquad (1)$$

This relationship holds even if an investor has a short time horizon. An investor with a one year horizon will receive D_1 plus P_1upon selling the stock. However, P_1 is a function of D_2 to D_∞. While computationally convenient, the Gordon model is valid only when r > g and when g, the growth rate, is constant (Brigham and Houston, 2007). More generally, the value of a stock today can be expressed at the present value of an infinite stream of dividends:

$$P_0 = \sum_{t=1}^{\infty} \frac{D_t}{(1+r)^t} \qquad (2)$$

If stock prices depend on expected dividends and dividends depend on the profitability of firms, then stock prices should embody expectations held by investors regarding the level of economic activity. This forward-looking property of stock markets suggests that stock prices would perform well as leading indicators, subject to the reliability of investors' forecasts of economic activity and corporate profits. Stock prices should decline if investors anticipate a slow-down in economic activity and rise if they expect an acceleration of economic activity. In short, stock and other asset prices are leading indicators of economic activity because they are forward-looking economic variables (Stock and Watson, 2003a). The behavior of global stock markets in the first three quarters of 2009 indicates that they anticipated the nascent economic recovery by one to two quarters.

Because the optimal capital structure usually involves a mix of debt and equity, the cost of equity capital is a significant portion of most firms' weighted average cost of capital, the hurdle rate for investment projects. Firms issuing equity in order to obtain investment funds must not only consider the required return on their equity but must also take flotation costs into account. Given the high cost of raising external equity, firms may be more willing to issue equity when stock prices are high in order to maximize the proceeds from selling ownership stakes. Even though some scholars [see for example, Ritter (1991), Baker and Wurgler (2000), and Hirshleifer (2001)] claim that firms knowingly sell overvalued equity to investors, thereby violating some of the tenets of the efficient market hypothesis, there is no doubt that higher stock prices are consistent with a lower cost of equity for firms. If a lower cost of equity reduces the weighted average cost of capital and makes more capital projects economically feasible, a positive relationship could develop between stock prices and subsequent economic activity.

The *financial accelerator* channel stems from that fact that rising stock prices lead to an improvement in the balance sheets of firms and households which, in turn, improves their creditworthiness [see Fazzari et al. (1988) and Bernanke *et al*. (1996)]. The increase in creditworthiness reduces borrowing costs and increases the borrowing capacity of firms and households, stimulating investment spending and current consumption. Predictably, the financial accelerator also operates in downturns. According to Bernanke et al., "the theory underlying the financial accelerator suggests that (1) borrowers facing relatively high agency costs in credit markets will bear the brunt of economic downturns (the flight to quality); and that (2) reduced spending, production and investment by high-agency-cost borrowers will exacerbate the effects of recessionary shocks" p. 14. The financial accelerator is similar to the cost of capital channel because both operate through the capital structure of firms and households. However, while the cost of capital channel is conventionally deemed to operate through the issuance of equity and the financial accelerator through the issuance of debt, both channels could conceivable operate through the issuance of both debt and equity.

The *wealth effect* operates via the consumption function, when households consume not only out of earned income but also as a result of perceived increases in the value of their assets, including real estate and equity. Increasing stock market wealth seems to improve consumer sentiment and raise expectations of higher incomes in the future (Otoo, 1999). Case *et al*., (2005) estimated the marginal propensity to consume out of housing wealth in the range of 11 – 17 percent and out of equity wealth of about 2 percent in 14 western nations. Using micro data for the U.S., Bostic et al. (2009) found "an important role for both financial wealth and housing wealth in the determination of household consumption patterns. The results suggest the estimation of significant coefficients in both cases; the implied elasticity with respect to total consumption is .02 percent for financial assets, and .04 percent for house values. House values were much more important for non-durable and food consumption and financial assets were much more important for durable consumption" p. 14. The operation of the wealth effect was palpable in the United States before the financial and economic crises, with households using home equity loans to tap the rising values of their homes to fund consumption spending. The consequent collapse of U.S. consumption expenditures following the decimation of asset prices suggests that the wealth effect operates with rising as well as falling asset values. We must keep in mind, however, that the importance of the wealth effect in determining the role of stock prices as leading indicators depends crucially on the extent of stock ownership in a country. There is more empirical evidence in favor of the wealth effect in the U.S. than in several European nations with lower stock-ownership rates [see Paiella (2007) and Simone (2009)]

2.2 Empirical Evidence on Stock Prices as Leading Indicators

Several studies of advanced economies have found stock prices to be a fairly reliable indicator of GDP growth. Because of its leading role in the use of leading indicators to predict business cycles, most of the studies of the advanced economies have been done on the U.S. economy. The Dow Jones composite index of stock prices was included in the index of leading indicators for the U.S. economy more than seventy years ago by Mitchell and Burns (1938). However, studies of other advanced economies are becoming more prevalent in the literature, as the leading indicator approach becomes more widely adopted. Table 1a summarizes the empirical evidence from the advanced economies.

Leading indicator studies of emerging markets are much less common than studies of the advanced economies. This paucity of studies may be partly due to data inadequacies, as quarterly GDP surveys have only recently begun for many less developed countries. Leading indicator studies of African economies are quite rare and usually part of group studies of several advanced and developing countries. Most studies on African stock markets focus on the role of stock market development, as measured by the ratio of market capitalization to GDP, in economic growth. For example, Osinubi (2004), Adebiyi (2005), and Nurudeen (2009) found that there was a positive link between stock market development and economic growth in Nigeria. However, Akinlo et al. (2009) found weak evidence of this relationship in Nigeria, even though they found that stock market development Granger-caused economic growth in Egypt and South Africa. The focus in leading indicator studies is on the information content of stock prices in terms of their ability to help predict the direction of economic activity in the near future, not on the long run relationship between financialization and economic growth. Table 1b summarizes the empirical evidence from the emerging economies.

The review of the literature indicates that stock prices have a sound theoretical basis for leading economic activity. The empirical evidence is mixed, but mostly supportive of this hypothesis. Among advanced countries, stock markets tend to be stronger leading indicators in countries with Anglo-Saxon backgrounds; this is perhaps due to the fact that stock markets tend to play larger roles in the economies of such nations. Among emerging economies, stock prices tend to become stronger leading indicators as the economy develops and financial markets become larger in relation to GDP. A rigorous investigation of the role of stock markets in predicting economic activity in Nigeria will enhance the body of knowledge in this area as well as provide policymakers with an additional tool with which to manage the Nigerian economy.

Table 1a – Empirical Evidence from Advanced Economies

Study	Nation(s)	Data Range	Periodicity	Findings
Fama (1981)	U.S.	1953 - 1987	Monthly, Quarterly, Annual	Stock prices led all real variables.
Pearce (1983)	Canada, France, Germany, U.K. & U.S.	1955 - 1983	Quarterly	Stock prices tend to rise midway through recession.
Huang and Kracaw (1984)	U.S.	1962 - 1978	Quarterly	Stock prices led GDP by four quarters.
Campbell (1989)	U.S.	1953 - 1989	Quarterly	Stock prices and Yield Curve led GDP.
Lee (1992)	U.S.	1947 - 1987	Monthly	Stock prices Granger-cause industrial production.
Comincioli (1996)	U.S.	1970 - 1984	Quarterly	Stock prices Granger-cause GDP with lags of one to three quarters.
Otoo (1999)	U.S.	1980 - 1999	Monthly	Stock prices are leading indicator.
Choi, Hauser and Kopecky (1999)	Canada, France, Germany, Italy, Japan, U.K. & U.S.	1957 - 1996	Monthly	Stock prices useful for forecasting only in U.S., Canada, U.K. & Japan.
Burgstaller	Austria, Japan & U.S.	1976 - 2002	Monthly	Stock prices had no predictive power; Stock prices weakly affect consumption.
Stock and Watson (2003a)	Canada, France, Germany, Italy, Japan, U.K. & U.S.	1959 - 1999	Monthly, Quarterly, Annual	Inconsistent results from review of sixty-six papers.
Stock and Watson (2003b)	U.S.	1986 - 2002	Quarterly	Stock prices and other leading indicators superior to benchmark AR model.
Gan, Lee, Yong and Zang (2006)	New Zealand	1990 - 2003	Monthly	Stock index caused by GDP (not leading indicator)
Foresti (2007)	U.S.	1959 - 1999	Quarterly	Stock prices had predictive power with lags of up to five quarters.

Table 1b – Empirical Evidence from Emerging Economies

Study	Nation(s)	Data Range	Periodicity	Findings
Leigh (1997)	Singapore	1975 - 1991	Quarterly	Stock prices Granger-cause GDP.
Christoffersen and Slok (2000)	Czech Republic, Hungary, Poland, Russia, Slovakia & Slovenia	1994 - 1999	Monthly	Stock prices led industrial production by one to six months.
Husain and Mahmood (2001)	Pakistan	1959 - 1999	Quarterly	Stock prices lagged GDP (not leading indicator).
Nishat and Shaheen (2004)	Pakistan	1973 - 2004	Quarterly	Stock prices led Industrial Production by one quarter.
Jefferis, Okeahalam and Matome (2001)	Botswana, South Africa & Zimbabwe	1985 - 1996	Quarterly	Stock prices cointegrated with GDP; leading indicator.
Mauro (2003	Argentina, Chile, Greece, India, Mexico, South Korea, Thailand & Zimbabwe	1971 - 1998	Quarterly, Annual	Stock prices in all nations except India led GDP by up to four quarters; signal stronger in nations with high market capitalization.
Amadja (2005)	Indonesia, Malaysia, the Philippines, Singapore & Thailand	1997 - 2003	Monthly	Stock prices Granger-caused GDP in Singapore and Thailand; no causality in Malaysia and the Philippines.
Mun, Siong & Thing (2008)	Malaysia	1977 - 2006	Annual	Stock prices Granger-caused GDP with a lag of up to two years.
Bahadur and Neupane (2006)	Nepal	1988 - 2005	Annual	Stock prices had no impact on GDP. However, market capitalization Granger-caused GDP with a four-year lag.
Pilinkus (2009)	Lithuania	1999 - 2008	Monthly	Stock prices Granger-caused GDP.

3.0 Methodology and Data

3.1 Methodology

Two basic methodological approaches are adopted to determine whether or not the stock market is a leading indicator of economic activity in Nigeria. The first approach is to conduct the familiar test proposed by Granger (1969) in order to determine whether or not changes in nominal or real stock prices precede changes in economic activity (as measured by GDP or IIP). The results of the Granger-causality test are crucial for the use of stock prices as a leading indicator, especially if the lead over economic activity is reliable and of sufficient length to give useful signals to policy makers. It is important to mention here that the Granger-causality test is actually a *test of precedence* and does not imply that changes in stock prices cause changes in economic activity in the conventional sense. In addition to Granger-causality tests, we utilize unit root tests, correlation analysis and cointegration tests to analyze the basic properties of the time series.

The second methodological approach is to determine the usefulness of stock prices in forecasting economic activity. An AR(1) is used as the baseline forecasting model, augmented by an optimized[4] autoregressive integrated moving average (ARIMA) model. Then we build four structural models—two ARIMA models and two Vector Error Correction models (VECMs) employing nominal and real values of the stock index, respectively, as structural variables. We seek to determine whether or not the structural models have superior forecasting ability, in terms of smaller forecast errors, compared to the baseline AR(1) and ARIMA models.

In order to simulate an actual forecasting environment, the 100-quarter sample period is divided into two sub periods—data from 1984Q1 to 2007Q2 (94 percent of the total) are used to estimate models while data from 2007Q3 to 2008Q4 (6 percent of the total) are used for forecast evaluation. As such, the out-of-sample performance of the models can be estimated.

With the combination of formal tests and forecast simulation, we should be able to ascertain the information content of stock prices for the business cycle in Nigeria. Needless to say, the ability to improve forecasts of economic activity is the *raison d'être* of a leading indicator and would indicate whether or not the stock index, in nominal or real terms, should be incorporated in a composite index of leading indicators in Nigeria.

3.2 Data

Because the All Share Index (ASI) of the Nigerian Stock Exchange (NSE) was formulated in January 1984, we use ASI data from the first quarter of 1984 to the fourth quarter of 2008, a total of 100 observations. The ASI is a market-value-weighted index representing all the stocks traded on the floor of the NSE; it is the only stock index with the coverage and vintage required to truly discern the role of the stock market as a leading indicator of economic activity in Nigeria. Nominal values of ASI are deflated with the consumer price index (CPI) to create another variable, real ASI (ASIR). CPI statistics were obtained from the National Bureau of Statistics (NBS).

Real Gross Domestic Product (GDP) and an Index of Industrial Production (IIP) are used as measures of economic activity[5] for the sample period. Both variables are produced through surveys conducted by the National Bureau of Statistics and the Central Bank of Nigeria. Economic activity in Nigeria is dominated by Agriculture, which accounted for 42.1 percent of GDP in 2008. This was followed by Industry (22 percent), Wholesale and Retail Trade (17.3 percent), Services (16.8 percent) and Building and Construction (1.8 percent). Remarkably, the share of Agriculture in Nigeria's GDP increased by 11.6 percentage points during the last twenty five years, from 30.5 percent in 1984 to 42.1 percent in 2008. During the same period, the share of industry in Nigeria's GDP declined from 42.4 percent to 22 percent, a loss of 20.4 percentage points.

4.0 Descriptive Statistics and Diagnostic Tests

4.1 Descriptive Statistics

Figure 1 contains graphical representations of the variables and their quarterly growth rates. ASI, ASIR and GDP exhibit strong upward trends, while IIP seems to exhibit a substantial degree of mean-reversion. Because quarterly

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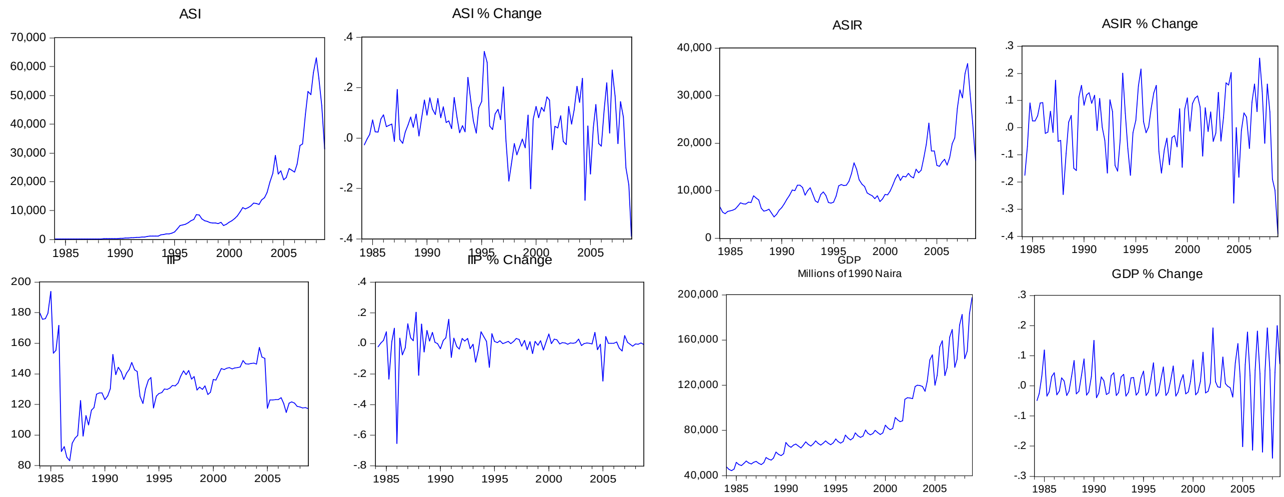
[4] This model is selected on the basis of having the lowest information criteria (i.e., AIC and SIC) values.

[5] While most studies use either GDP or the Index of Industrial Production as the measure of economic activity, a number of studies, for example Fama (1981), utilize both variables. We employ both variables in this paper in the interest of completeness.

GDP surveys by the NBS commenced in 2004, annual GDP data were interpolated between 1984 and 2003 in order to derive quarterly equivalents.

Figure 1 – ASI, ASIR, GDP and IIP (1984 – 2008)



Descriptive statistics for the four time series show that are ASI and ASIR returns and GDP and IIP growth rates are negatively skewed with fat tails, judging by the kurtosis statistics. During the sample period, the ASI turned in mean quarterly returns of 5.7 percent (median of 6.7 percent); the ASIR had mean quarterly returns of 0.9 percent (median of 2.5 percent); the mean quarterly GDP growth rate was 1.43 percent (median of 1.43 percent); and the mean quarterly IIP growth rate was -0.43 percent (median of 0.35 percent). The Jarque-Bera statistics suggest that the null hypothesis of normality would be rejected for all four time series, even though the probability of 0.048 for ASIR is close to the 5 percent threshold.

4.2 Unit Root Tests

Dickey (1976) and Fuller (1976) show that the least squares estimator is biased downward in the presence of unit roots. Since the *Dickey-Fuller bias* can be expected to reduce the accuracy of forecasts, we test for the presence of this bias using the *Augmented Dickey-Fuller* (ADF) test as well as the *Phillips-Perron* (PP) test proposed by Phillips and Perron (1988).

Bierens (2003) shows that an AR (p) process as shown in equation (3):

$$y_t = \beta_0 = \sum_{j=1}^{p} \beta_j y_{t-j} + u_t, \qquad (3)$$

$$u_t \sim iidN(0, \sigma^2)$$

can be written, through recursive replacement with differenced terms, as equation (4):

$$\Delta y_t = \alpha_0 + \sum_{j=1}^{p} \alpha_j \Delta y_{t-j} + \alpha_p y_{t-p} + u_t, \qquad (4)$$

$$u_t \sim iidN(0, \sigma^2)$$

where $\alpha_0 = \beta_0$, $\alpha_j = \sum_{i=1}^{j} \beta_i - 1,\ j = 1, ..., p.$

The ADF tests the null hypothesis that $\alpha_p = 0$ against the alternative hypothesis that $\alpha_p < 0$. If the AR(p) process has a unit root, then $\alpha_p = 0$. On the other hand, if the process is stationary, then $\alpha_p < 0$. In contrast to the ADF, the PP test does not require that the ARIMA process be specified and would, thus, be less subject to misspecification than the ADF test.

Table 2 – Augmented Dickey-Fuller Unit Root Tests

PP Tests - Levels

Null Hypothesis: Variable has a unit root

		Without Trend				With Trend			
Variable:		**ASI**	**ASIR**	**GDP**	**IIP**	**ASI**	**ASIR**	**GDP**	**IIP**
PP test statistics:		-0.9923	1.4539	2.1929	-3.6161	-2.3208	-0.7040	-2.9202	-3.5647
Test critical values:	1% level	-3.4977	-3.5022	-3.4977	-3.4977	-4.0534	-4.0597	-4.0534	-4.0534
	5% level	-2.8909	-2.8929	-2.8909	-2.8909	-3.4558	-3.4589	-3.4558	-3.4558
	10% level	-2.5825	-2.5836	-2.5825	-2.5825	-3.1537	-3.1555	-3.1537	-3.1537
MacKinnon prob-values:		0.7537	0.9991	0.9999	0.0071	0.4186	0.9695	0.1608	0.0382

PP Tests - First Differences

Null Hypothesis: Variable has a unit root

		Without Trend				With Trend			
Variable:		**D(ASI)**	**D(ASIR)**	**D(GDP)**	**D(IIP)**	**D(ASI)**	**D(ASIR)**	**D(GDP)**	**D(IIP)**
PP test statistics:		-4.7602	-7.2805	-10.9273	-12.7637	-4.6346	-7.4848	-13.1681	-12.7458
Test critical values:	1% level	-3.4984	-3.5030	-3.4984	-3.4984	-4.0544	-4.0609	-4.0544	-4.0544
	5% level	-2.8912	-2.8932	-2.8912	-2.8912	-3.4563	-3.4594	-3.4563	-3.4563
	10% level	-2.5827	-2.5837	-2.5827	-2.5827	-3.1540	-3.1558	-3.1540	-3.1540
MacKinnon prob-values:		0.0001	0.0000	0.0000	0.0001	0.0016	0.0000	0.0000	0.0000

Table 2 shows the results of the ADF tests on ASI, ASIR, GDP and IIP. The tests on the levels of the variables, with only a constant and no trend in the equations, show that the null hypothesis of a unit root cannot be rejected for ASI, ASIR and GDP at either the 1 percent, 5 percent or 10 percent levels; their MacKinnon (1996) one-side p-values are 0.9999, 0.9991 and 0.9998, respectively. However, with a p-value of 0.0305, the null hypothesis of a unit root can be rejected at the 5 percent level but not at the 1 percent level for IIP. ADF tests on the first differences of the variables result in a strong rejection of the null hypothesis of a unit root for ASI, ASIR and IIP. However, this is not the case for GDP, which has a p-value of 0.2381. The tests on the levels of the variables with a constant and a linear trend in the equations have similar results to those with a trend except that the p-value for IIP has increased to 0.1179. The ADF test results with first differences are not very sensitive to the addition of a linear trend to the equations, giving essentially the same results for ASI, ASIR and IIP, but with a p-value that decreases to 0.0899 for GDP.

The PP tests shown in table 3 give the same results as the ADF tests with respect to ASI and ASIR, suggesting that both times series are integrated of order one, i.e., I(*1*). With respect to GDP, the PP test is more conclusive than the ADF test, as the series becomes stationary with first differencing, suggesting an I(*1*) process. The PP test on IIP, with no trend in the equation, rejects the null hypothesis of a unit root at levels or first differencing, with p-values of 0.0071 and 0.0001, respectively. However, when a linear trend is added to the equation, the PP test on IIP cannot reject the null hypothesis of a unit root at the 1 percent level on account of the p-value of 0.0382.

Even though unit roots tests are known to have low power, one can reasonably proceed on the assumption that ASI, ASIR and GDP are I(*1*) series, while the IIP could be considered an I(*0*) series based on a 5 percent significance level. ASI, ASIR and GDP are non-stationary but could be made stationary with first differencing while IIP is stationary. Where differencing is not appropriate, ARMA terms could be used to realize white noise errors.

Table 3 – Phillips-Peron Unit Root Tests

ADF Tests - Levels

Null Hypothesis: Variable has a unit root

		Without Trend				With Trend			
Variable:		**ASI**	**ASIR**	**GDP**	**IIP**	**ASI**	**ASIR**	**GDP**	**IIP**
ADF test statistics:		2.1662	1.4539	1.9407	-3.0907	0.1366	-1.1358	-0.2014	-3.0762
Test critical values:	1% level	-3.5039	-3.5022	-3.5022	-3.4984	-4.0620	-4.0609	-4.0597	-4.0544
	5% level	-2.8936	-2.8929	-2.8929	-2.8912	-3.4600	-3.4594	-3.4589	-3.4563
	10% level	-2.5839	-2.5836	-2.5836	-2.5827	-3.1561	-3.1558	-3.1555	-3.1540
MacKinnon prob-values:		0.9999	0.9991	0.9998	0.0305	0.9972	0.9167	0.9922	0.1179

ADF Tests - First Differences

Null Hypothesis: Variable has a unit root

		Without Trend				With Trend			
Variable:		**D(ASI)**	**D(ASIR)**	**D(GDP)**	**D(IIP)**	**D(ASI)**	**D(ASIR)**	**D(GDP)**	**D(IIP)**
ADF test statistics:		-6.6700	-7.3069	-2.1182	-12.8773	-7.1430	-7.5022	-3.2047	-12.8433
Test critical values:	1% level	-3.5039	-3.5030	-3.5022	-3.4984	-4.0620	-4.0609	-4.0597	-4.0544
	5% level	-2.8936	-2.8932	-2.8929	-2.8912	-3.4600	-3.4594	-3.4589	-3.4563
	10% level	-2.5839	-2.5837	-2.5836	-2.5827	-3.1561	-3.1558	-3.1555	-3.1540
MacKinnon prob-values:		0.0000	0.0000	0.2381	0.0001	0.0000	0.0000	0.0899	0.0000

4.3 Correlation Coefficients

Correlation coefficients provide an initial look at the relationship among the variables. In order to explore the effect of the interpolation of GDP between 1984 and 2003, the coefficients were computed for three sub-samples—1984Q1-2003Q4, 2004Q1-2008Q4 and 1984Q1-2008Q4.

ASI, ASIR and GDP are highly and positively correlated. The weakest coefficient between ASI and GDP was 0.4087 in the 2004Q1 to 2008Q4 sample, and the highest was 0.9291 in the 1984Q1 to 2003Q4 sample. Likewise, the weakest coefficient between ASIR and GDP was 0.2162 in the 2004Q1 to 2008Q4 sample, and the highest was 0.8443 in the 1984Q1 to 2008Q4 sample. In contrast, ASI, ASIR and IIP had a weaker and, sometimes, negative relationship. At first glance, the negative correlation between ASI and IIP and ASIR and IIP in the 1984 to 2008 period might call into question the accuracy of IIP as a measure of economic activity. However, industrial production in Nigeria was declining during this period, while the stock market was in the midst of a boom for most of the period.

We conclude that ASI and ASIR were more highly correlated with GDP than with IIP, and that the interpolation of GDP values between 1984 and 2003 did not have an appreciable effect on the relationship among the variables.

4.4 Granger Causality Tests

Granger causality tests were conducted, using bivariate regressions as shown in equations (5) and (6), between ASI and GDP and between ASIR and GDP[6], using 1 to 10 quarterly lags, *l*.

$$\mathrm{ASI}_t = \alpha_0 + \alpha_1 \mathrm{ASI}_{t-1} + ... + \alpha_l \mathrm{ASI}_{t-l} + \beta_1 \mathrm{GDP}_{t-1} + ... + \beta_l \mathrm{GDP}_{t-l} + \varepsilon_t \quad (5)$$

$$\mathrm{GDP}_t = \alpha_0 + \alpha_1 \mathrm{GDP}_{t-1} + ... + \alpha_l \mathrm{GDP}_{t-l} + \beta_1 \mathrm{ASI}_{t-1} + ... + \beta_l \mathrm{ASI}_{t-l} + u_t \quad (6)$$

[6] Granger causality tests conducted between ASI and IPP and between ASIR and IIP showed no causality among the variables.

The null hypothesis is that GDP does not Granger-cause ASI in equation (5) and that ASI does not Granger-cause GDP in equation (6). F-tests was conducted with the joint hypothesis that β_1 through β_{10} are zero. The tests were conducted with the levels and first differences of ASI and GDP and ASIR and GDP.

The results with the variables in levels, shown in table 4, indicate that ASI causes GDP at lags 1 and 2; GDP causes ASI at lags 3 and 4, and there is bi-directional causality between ASI and GDP at lags 5 through 10. With respect to ASIR and GDP, ASI causes GDP at lag 1; GDP causes ASIR at lags 2 to 4 and 7 to 10; and there is bi-directional causality between the two variables at lags 5 and 6.

Table 4 – Granger Causality Tests – Levels

ASI vs. GDP

# of Lags	From ASI to GDP /1	From GDP to ASI /2	Test Result /3
1	0.0013	0.2429	ASI causes GDP.
2	0.0026	0.0565	ASI causes GDP.
3	0.0622	0.0016	GDP causes ASI.
4	0.1144	0.0036	GDP causes ASI.
5	0.0008	0.0058	Bi-directional causality.
6	0.0036	0.0019	Bi-directional causality.
7	0.0071	0.0005	Bi-directional causality.
8	0.0147	0.0004	Bi-directional causality.
9	0.0029	2.00E-05	Bi-directional causality.
10	0.0458	1.00E-05	Bi-directional causality.

ASIR vs. GDP

# of Lags	From ASIR to GDP /4	From GDP to ASIR /5	Test Result /3
1	0.0428	0.0599	ASIR causes GDP.
2	0.1393	0.0007	GDP causes ASIR.
3	0.1437	0.0001	GDP causes ASIR.
4	0.2157	0.0004	GDP causes ASIR.
5	0.0068	0.0009	Bi-directional causality.
6	0.0289	0.0003	Bi-directional causality.
7	0.1011	4.00E-05	GDP causes ASIR.
8	0.1830	1.00E-06	GDP causes ASIR.
9	0.4448	0.0000	GDP causes ASIR.
10	0.7402	6.00E-05	GDP causes ASIR.

1/ The numbers are p-values for the null hypothesis "ASI does not cause GDP."
2/ The numbers are p-values for the null hypothesis "GDP does not cause ASI."
3/ The test result is based on a 5 percent significance level.
4/ The numbers are p-values for the null hypothesis "ASIR does not cause GDP."
5/ The numbers are p-values for the null hypothesis "GDP does not cause ASIR."

Table 5 shows the results with first differences of the variables. GDP causes ASI at lag 1 while there is bi-directional causality between the variables at lags 2 through 10. ASIR was found to cause GDP at lags 2 and 4 to 6, while GDP was found to cause ASIR at lags 7 though 10.

These results suggest that ASI and ASI could be useful in forecasting GDP with relatively short lags. In addition, the causal relationship between ASI and GDP seems more stable than that between ASIR and GDP.

4.5 Cointegration Tests

According to Engle and Granger (1987), if two variables are both I(*1*), it is generally true that a linear combination of the variables will also be I(*1*). However, a linear combination of the variables may exist that is I(*0*). If the

Table 5 – Granger Causality Tests – First Differences

D(ASI) vs. D(GDP)

# of Lags	From D(ASI) to D(GDP) /1	From D(GDP) to D(ASI) /2	Test Result /3
1	0.1064	0.0338	D(GDP) causes D(ASI).
2	0.0108	0.0050	Bi-directional causality.
3	0.0255	0.0035	Bi-directional causality.
4	0.0002	0.0031	Bi-directional causality.
5	0.0002	0.0002	Bi-directional causality.
6	0.0025	0.0001	Bi-directional causality.
7	0.0089	4.00E-05	Bi-directional causality.
8	0.0059	2.00E-06	Bi-directional causality.
9	0.0233	2.00E-06	Bi-directional causality.
10	0.0473	4.00E-06	Bi-directional causality.

D(ASIR) vs. D(GDP)

# of Lags	From D(ASIR) to D(GDP) /4	From D(GDP) to D(ASIR) /5	Test Result /3
1	0.3186	0.1069	No causality.
2	0.0547	0.2107	D(ASIR) causes D(GDP).
3	0.1794	0.2224	No causality.
4	0.0020	0.2083	D(ASIR) causes D(GDP).
5	0.0054	0.2482	D(ASIR) causes D(GDP).
6	0.0585	0.3109	D(ASIR) causes D(GDP).
7	0.1344	0.0009	D(GDP) causes D(ASIR).
8	0.3056	0.0004	D(GDP) causes D(ASIR).
9	0.6689	0.0003	D(GDP) causes D(ASIR).
10	0.5504	0.0003	D(GDP) causes D(ASIR).

1/ The numbers are p-values for the null hypothesis "D(ASI) does not cause D(GDP)."
2/ The numbers are p-values for the null hypothesis "D(GDP) does not cause D(ASI.)"
3/ The test result is based on a 5 percent significance level.
4/ The numbers are p-values for the null hypothesis "D(ASIR) does not cause D(GDP)."
5/ The numbers are p-values for the null hypothesis "D(GDP) does not cause D(ASIR)."

variables GDP and ASI are I(1), then linear combinations of GDP and ASI will generally also be I(*1*). Nevertheless, if there is a vector such that the linear combination in equation (7)

$$z_t = \text{GDP}_t - \alpha - \beta \text{ASI}_t \tag{7}$$

is I(*0*), then GDP and ASI are cointegrated of order (1,1), i.e., CI(1,1), with (1, -β) termed the cointegrating vector. Cointegration implies that there is a long-run equilibrium relationship between the two variables, and z_t is the equilibrium error.

Having established, with Granger-causality tests, that ASI and ASIR have a strong short-run relationship with GDP but that ASI and ASIR have no statistically significant relationship with IIP, we explore the long-run relationship between ASI, ASIR and GDP using three cointegration tests—the Johansen (1991, 1995) test,[7] the Engle-Granger (1987) test and the Phillips-Ouliaris (1990) test. As required by the Johansen test, ASI, ASIR and GDP are non-stationary and integrated of the same order.

Table 6 shows the results of the Johansen trace and maximum eigenvalue tests, with a linear deterministic trend[8], between nominal and real stock indices and GDP. Between ASI and GDP, both trace and maximum eigenvalue tests reject the null hypothesis of no cointegrating equation at the 1 percent and 5 percent levels, with p-values of 0.0000 for both tests. However, the null hypothesis of at most one cointegrating equation is not rejected by either test, with p-values of 0.4871 for both tests.

Between ASIR and GDP, again both trace and maximum eigenvalue tests reject the null hypothesis of no cointegrating equation at the 1 percent and 5 percent levels, with p-values of 0.0001 and .0000, respectively.

[7] Johansen and Jeselius (1990) applied this technique to money demand in Denmark and Finland.
[8] We examined the sensitivity of the Johansen tests to the trend assumptions on the cointegrating equations. The tests were not sensitive to the trend assumption, indicating the presence of one cointegrating equation in all trend specifications.

Interestingly, the null hypothesis of at most one cointegrating equation is also rejected by both the trace and maximum eigenvalue tests, with p-values of 0.0000 for both tests. The results indicate more than one cointegrating equation between ASIR and GDP.

Table 6 – Johansen Cointegration Tests

D(ASI) and D(GDP)

Trace Test			
Hypothesized		0.05	
# of CE's	Statistic	Critical Value	Prob.**
None*	91.5042	15.4947	0.0000
At most 1	0.48303	3.84147	0.4871

Maximum Eigenvalue Test			
Hypothesized		0.05	
# of CE's	Statistic	Critical Value	Prob.**
None*	91.0212	14.2646	0.0000
At most 1	0.48303	3.84147	0.4871

Normalized Cointegrating Coefficients
(Standard Error in Parenthesis)

D(ASI)	D(GDP)
1.0000	-1.8899
	(0.1488)

D(ASIR) and D(GDP)

Trace Test			
Hypothesized		0.05	
# of CE's	Statistic	Critical Value	Prob.**
None*	109.7725	15.4947	0.0001
At most 1	17.98613	3.84147	0.0000

Maximum Eigenvalue Test			
Hypothesized		0.05	
# of CE's	Statistic	Critical Value	Prob.**
None*	91.7864	14.2646	0.0000
At most 1	17.98613	3.84147	0.0000

Normalized Cointegrating Coefficients
(Standard Error in Parenthesis)

D(ASIR)	D(GDP)
1.0000	-3.4110
	(0.2766)

* Denotes rejection of the hypothesis at the 0.05 level.
**MacKinnon-Haug-Michelis (1999) p-values.

Table 7 shows the outcome of the Engle-Granger and Phillips-Ouliaris cointegration tests. With respect to the Engle-Granger test, the null hypothesis of no cointegration cannot be rejected for ASI and GDP, with p-values of 0.9658 and 0.0196, respectively. However, the null hypothesis that ASIR and GDP are not cointegrated can be rejected at the 5 percent level, with p-values of 0.0000 and 0.0189, respectively. The Phillips-Ouliaris tests strongly reject the null hypotheses of no cointegration between ASI and GDP and between ASIR and GDP, with p-values of 0.0000 throughout.

In summary, all three tests indicate that ASIR and GDP are cointegrated, while the Johansen and Phillips-Ouliaris tests indicate that ASI and GDP are cointegrated. Based on the outcome of the tests, one can conclude that there is a long run equilibrium relationship between the nominal and real stock indices and real economic activity in Nigeria.

5.0 Forecasting GDP with Stock Prices

5.1 Univariate Models

In order to ascertain the information content of stock prices for the business cycle in Nigeria, we start by estimating two univariate GDP models—an AR(1) model and an ARIMA model. All the models were estimated with data from 1984Q1-2007Q2.

Table 7 – Engle-Granger and Phillips-Ouliaris Cointegration Tests

Engle-Granger Cointegration Tests

D(ASI) and D(GDP)

Null hypothesis: Series are not cointegrated

Dependent	tau-statistic	Prob.*	z-statistic	Prob.*
D(ASI)	-1.2734	0.9573	-3.7761	0.9658
D(GDP)	-2.8677	0.3432	-29.1963	0.0196

D(ASIR) and D(GDP)

Null hypothesis: Series are not cointegrated

Dependent	tau-statistic	Prob.*	z-statistic	Prob.*
D(ASIR)	-7.5970	0.0000	-73.5708	0.0000
D(GDP)	-2.87284	0.3408	-29.35149	0.0189

*MacKinnon (1996) p-values.

Phillips-Ouliaris Cointegration Tests

D(ASI) and D(GDP)

Null hypothesis: Series are not cointegrated

Dependent	tau-statistic	Prob.*	z-statistic	Prob.*
D(ASI)	-7.6989	0.0000	-84.8174	0.0000
D(GDP)	-14.8054	0.0000	-59.5247	0.0000

D(ASIR) and D(GDP)

Null hypothesis: Series are not cointegrated

Dependent	tau-statistic	Prob.*	z-statistic	Prob.*
D(ASIR)	-7.6289	0.0000	-75.0430	0.0000
D(GDP)	-14.74491	0.0000	-59.56045	0.0000

*MacKinnon (1996) p-values.

The AR(1) model is commonly used as the benchmark for evaluating the accuracy of more sophisticated forecasting models.[9] If a GDP model with a structural variable, such as the ASI or ASIR, were to perform better than the AR(1) model in out-of-sample forecasts, then stock prices are deemed to contain information useful in predicting GDP.

Because the unit root tests conducted above suggest that GDP is I(*1*), we use the first difference of GDP with autoregressive and moving average terms, following Box and Jenkins (1976), to create the ARIMA model. Forty-eight regression models were estimated with a maximum of six AR and MA terms. The Akaike and Schwarz information criteria for the models are shown in table 8. Both model selection criteria suggest an ARIMA (6, 1, 2) model as the best of the forty-eight models estimated, with AIC and SIC statistics of 19.232 and 19.487, respectively.

Table 9 shows the coefficients and other statistics from the univariate and structural models. The highly significant coefficient of 0.9808 on the AR(1) model suggests a high degree of persistence in the GDP series, while the adjusted r-squared of 0.9314 indicates a fairly good fit, even though this may have been inflated as a result of autocorrelation. The ARIMA model shows statistically significant AR(2), AR(4), AR(6) and MA(2) terms and

[9] Stock (2003) suggests a simple rule in forecasting time series “even if your main interest is in more sophisticated models, it pays to maintain benchmark forecasts using a simple model with honest forecast standard errors evaluated using a simulated real time experiment, and to convey the forecast uncertainty to the consumer of the forecast” p. 581.

Table 8 – ARIMA Model Selection Criteria

ARMA Specification	AIC	SIC	ARMA Specification	AIC	SIC
(0, 1)	20.669	20.724	(3, 4)	19.292	19.514
(0, 2)	20.490	20.572	(3, 5)	19.289	19.539
(0, 3)	20.292	20.400	(3, 6)	19.272	19.550
(0, 4)	19.780	19.916	(4, 0)	19.405	19.545
(0, 5)	19.796	19.959	(4, 1)	19.384	19.552
(0, 6)	19.766	19.957	(4, 2)	19.340	19.536
(1, 0)	20.843	20.898	(4, 3)	19.282	19.505
(1, 1)	20.662	20.744	(4, 4)	19.260	19.512
(1, 2)	20.518	20.627	(4, 5)	19.272	19.552
(1, 3)	20.173	20.310	(4, 6)	19.271	19.579
(1, 4)	19.803	19.968	(5, 0)	19.428	19.597
(1, 5)	19.807	19.998	(5, 1)	19.419	19.616
(1, 6)	19.789	20.009	(5, 2)	19.362	19.587
(2, 0)	19.953	20.036	(5, 3)	19.238	19.492
(2, 1)	19.908	20.018	(5, 4)	19.262	19.544
(2, 2)	19.705	19.843	(5, 5)	19.284	19.594
(2, 3)	19.668	19.833	(5, 6)	19.268	19.606
(2, 4)	19.386	19.579	(6, 0)	19.293	19.491
(2, 5)	19.364	19.585	(6, 1)	19.308	19.535
(2, 6)	19.382	19.630	(6, 2)	19.232	19.487
(3, 0)	19.811	19.922	(6, 3)	19.250	19.533
(3, 1)	19.533	19.672	(6, 4)	19.266	19.577
(3, 2)	19.327	19.494	(6, 5)	19.271	19.611
(3, 3)	19.349	19.543	(6, 6)	19.286	19.654

Table 9 – Forecast Models (Excluding VECMs)

	AR(1)		**ARIMA**		**SARIMA - ASI**		**SARIMA - ASIR**	
	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
D(ASI(-2))	-	-	-	-	0.5120	0.0019	-	-
D(ASIR(-2))	-	-	-	-	-	-	0.5688	0.0000
AR(1)	0.9808	0.0000	-0.1319	0.3166	0.2796	0.0511	0.5647	0.0002
AR(2)	-	-	-1.1391	0.0000	-0.1003	0.4753	-0.6814	0.0000
AR(3)	-	-	-0.2895	0.0691	0.1918	0.2048	0.4270	0.0086
AR(4)	-	-	0.5685	0.0008	0.5133	0.0007	0.7174	0.0000
AR(5)	-	-	-0.1812	0.0901	-0.1258	0.4590	-0.5540	0.0008
AR(6)	-	-	0.8269	0.0000	-0.1655	0.3122	0.6380	0.0001
AR(7)	-	-	-	-	-0.0967	0.5015	-0.5294	0.0004
MA(1)	-	-	0.0915	0.5570	-0.4256	0.0000	-0.7096	0.0000
MA(2)	-	-	0.6301	0.0001	-0.3548	0.0005	0.3351	0.0759
MA(3)	-	-	-	-	-0.3361	0.0001	-0.5256	0.0022
MA(4)	-	-	-	-	0.9355	0.0000	0.3350	0.0506
MA(5)	-	-	-	-	-0.3644	0.0000	-0.2560	0.1313
MA(6)	-	-	-	-	-0.3360	0.0001	-0.1848	0.2448
MA(7)	-	-	-	-	-0.2946	0.0001	0.0691	0.6706
MA(8)	-	-	-	-	0.8771	0.0000	0.5810	0.0000
Constant	134184.5	0.1316	1222.9	0.0116	1183.083	0.0219	1342.008	0.0145
Adj. R-squared	0.9314		0.8225		0.8417		0.8594	
F-statistic	1251.02	0.0000	50.8209	0.0000	28.5766	0.0000	32.7143	0.0000
AIC	20.8312		19.2318		19.2327		19.1137	
SIC	20.8857		19.4869		19.7246		19.6057	
LM Test (NR^2)*	0.1855	0.6667	7.0809	0.2147	7.5327	0.4804	7.5962	0.4739

*Breusch-Godfrey Lagrange multiplier test of null hypothesis of no serial correlation up to highest order of ARMA process.

coefficient of determination is lower, at 0.8225, than that of the AR(1) model. However, the ARIMA model's AIC and SIC are lower than those of the AR(1) model, indicating that it is superior to the AR(1) model.

5.2 Structural ARIMA Models

We estimated two structural models by adding ASI and ASIR to the optimized ARIMA model discussed above. The structural ARIMA (SARIMA) models build on the ARIMA framework by adding more AR and MA terms, and the first differences of ASI and ASIR, lagged two periods.

Table 9 shows that, in the SARIMA models, the coefficient on D(ASI(-2)) is 0.5120 with a p-value of 0.0019, while the coefficient on D(ASIR(-2)) is 0.5688 with a p-value of 0.0000. In addition, the r-squared statistics of the SARIMA-ASI and SARIMA-ASIR models are quite similar at 0.8417 and 0.8594, respectively. While lower AIC and SIC of the SARIMA-ASIR suggest that it might be the superior model, we shall see that this is not borne out by out-of-sample forecast performance.

Table 10 – Vector Error Correction Models – ASI and GDP

Cointegrating Equations

	VECM (3)	VECM (4)
D(GDP(-1))	1.0000	1.0000
D(ASI(-1))	-2.0259 **	-1.9318 **

Error Correction Equations

	VECM (3)		VECM (4)	
	D(GDP)	D(ASI)	D(GDP)	D(ASI)
CointEq1	-0.8032 **	0.1843	-0.9781 **	0.2679 *
D(GDP(-1),2)	-0.2960 *	-0.1804 *	-0.0291	-0.3835 **
D(GDP(-2),2)	-0.6872 **	-0.1767 **	-0.4338 *	-0.3751 **
D(GDP(-3),2)	-0.8296 **	-0.0711	-0.6087 **	-0.2658 **
D(GDP(-4),2)	-	-	0.1929	-0.1881 **
D(ASI(-1),2)	-1.4237 **	-0.3757	-1.5553 **	-0.3620
D(ASI(-2),2)	0.0149	0.2380	-0.1019	0.2109
D(ASI(-3),2)	0.0915	0.2332	-0.3563	0.4918 *
D(ASI(-4),2)	-	-	-0.4308	0.2229
R-squared	0.9205	0.5069	0.9227	0.556349
Adj. R-squared	0.9147	0.4708	0.9149	0.5114
F-statistic	158.2144	14.0480	117.8737	12.3835
Akaike AIC	19.2045	17.7496	19.2301	17.7024
Schwarz SC	19.4003	17.9454	19.4835	17.9558

* Significant at the 5% level. ** Significant at the 1% level.

The correlograms and Q-statistics of the residuals of the ARIMA and SARIMA models suggested white noise error terms. The Breusch-Godfrey Lagrange multiplier tests on the residuals indicate that the null hypothesis of no serial correlation, up to the highest order of ARMA process, cannot be rejected for either the univariate or the SARIMA models.

5.3 Vector Error Correction Models

Engle and Granger (1987) show that if two variables, y_{1t} and y_{2t}, are CI(1,1), then there exists a vector error correction model (VECM) governing the behavior of the variables as shown in equations (8) and (9):

$$\Delta y_{1t} = \theta_{10} + \theta_{11} z_{t-1} + \sum_{1=1}^{p1} \theta_{12,i} \Delta y_{1,t-1} + \sum_{i=1}^{p2} \theta_{13,i} \Delta y_{2,t-1} + \varepsilon_{1t} \tag{8}$$

$$\Delta y_{2t} = \theta_{20} + \theta_{21} z_{t-1} + \sum_{1=1}^{p3} \theta_{22,i} \Delta y_{1,t-1} + \sum_{i=1}^{p4} \theta_{23,i} \Delta y_{2,t-1} + \varepsilon_{2t} \tag{9}$$

where Δ represents the first difference of the variables, p_i are the lag lengths, and the error terms ε_{1t} and ε_{2t} are iid (0, ∑). The z_{t-1} terms represent the degree to which y_{1t} and y_{2t} deviate from their equilibrium levels in the previous period, while the θ_{11} and θ_{21} are the speed of adjustment parameters.[10] According to Engle and Granger, "for a two variable system a typical error correction model would relate the change in one variable to past equilibrium errors, as well as to past changes in both variables" (p. 254).

Table 11 – Vector Error Correction Models – ASIR and GDP

Cointegrating Equations

	VECM (3)	VECM (4)
D(GDP(-1))	1.0000	1.0000
D(ASIR(-1))	-3.7488 **	-2.9483 **

Error Correction Equations

	VECM (3)		VECM (4)	
	D(GDP)	D(ASIR)	D(GDP)	D(ASIR)
CointEq1	-0.3431 **	0.2144 **	-0.4913 **	0.2260 **
D(GDP(-1),2)	-0.6354 **	-0.1879 **	-0.4820 **	-0.2469 **
D(GDP(-2),2)	-0.9038 **	-0.1457 **	-0.7714 **	-0.2018 **
D(GDP(-3),2)	-0.9278 **	-0.0694 *	-0.8361 **	-0.1295 *
D(GDP(-4),2)	-	-	0.0611	-0.0616
D(ASIR(-1),2)	-1.1800 **	0.0389	-1.3241 **	-0.1284
D(ASIR(-2),2)	0.2555	0.2601	0.1130	0.1106
D(ASIR(-3),2)	0.2397	0.0838	0.0287	0.0073
D(ASIR(-4),2)	-	-	-0.2415	-0.0904
R-squared	0.9126	0.4263	0.9137	0.4393
Adj. R-squared	0.9062	0.3843	0.9049	0.3825
F-statistic	142.7476	10.1551	104.4866	7.7360
Akaike AIC	19.2988	17.5270	19.3408	17.5626
Schwarz SC	19.4945	17.7227	19.5942	17.8160

* Significant at the 5% level. ** Significant at the 1% level.

Given that ASI, ASIR and GDP were found to be I(1) and cointegrated, VECMs[11] were indicated. VECMs with lags lengths of 3 and 4 were estimated using both ASI and ASIR[12]. Table 10 shows the VECMs using ASI and GDP while table 10 shows the VECMs with ASIR and GDP. The coefficients in the 3-lag and 4-lag specifications are quite similar but we chose the 3-lag specifications for forecast performance testing due to their smaller information criteria statistics.

An area in which the VECMs with ASI and GDP differ significantly from those with ASIR and GDP is the estimated speed of adjustment parameters, the CointEq1 coefficients in tables 10 and 11. The coefficients are -

[10] Dolado, Gonzalo and Marmol (2003) claim that the requirement that at least one of the speed of adjustment parameters is nonzero implies "the existence of Granger causality in cointegrated systems in at least one direction" p. 638.
[11] This is a restricted version of the Vector Autogression (VAR) models described in Sims (1980) and Lutkepohl (1991), with the cointegrating equation as the restriction.
[12] The SIC suggested a lag length of four while other criteria, including the LR, FPE, AIC and HQ, suggested a lag length of twelve. In the interest of parsimony, we estimated 3-lag and 4-lag VECMs.

.8032 and -.9781 for the 3-lag and 4-lag VECMs using ASI and GDP, respectively. For the VECMs run with ASIR and GDP, the coefficients are -.3431 and -.4914 on the 3-lag and 4-lag specifications, respectively. This suggests that the speed of adjustment from deviations from long-run equilibrium in the models with nominal stock prices is approximately double that of the models with real stock prices. This property may make the models with ASI more suitable for short to medium term forecasting than the models with ASIR.

5.4 Performance of Forecast Models

We use progressively longer horizons to gauge the out-of-sample performance of the six models—AR(1), ARIMA, SARIMA-ASI, SARIMA-ASIR, 3-Lag VECM-ASI and 4-Lag VECM-ASIR. The horizons are 2007Q3-2007Q4 (two periods), 2007Q3-2008Q2 (four periods), and 2007Q3-2008Q4 (six periods). Thus, we hope to capture the short to medium term out-of-sample performance of the forecast models.

Table 12 shows the performance statistics, including the Root Mean Squared Error (RMSE), Mean Absolute Percent Error (MAPE) and Theil Inequality coefficients (TIC)[13].

Table 12 – Model Performance by Forecast Horizon

	Two Quarters (2007Q3 - 2007Q4)	Four Quarters (2007Q3 - 2008Q2)	Six Quarters (2007Q3 - 2008Q4)
AR(1) Model			
Root Mean Squared Error	35544.6	25456.2	35091.5
Mean Abs. Percent Error	19.7459	11.4095	16.0499
Theil Inequality Coefficient	0.1109	0.0833	0.1113
ARIMA Model			
Root Mean Squared Error	8785.7	6653.1	14131.6
Mean Abs. Percent Error	4.8437	3.5666	6.2209
Theil Inequality Coefficient	0.0253	0.0206	0.0421
Structural ARIMA (ASI) Model			
Root Mean Squared Error	2772.5	4107.4	6117.7
Mean Abs. Percent Error	1.5528	2.3998	2.8043
Theil Inequality Coefficient	0.0079	0.0126	0.0178
Structural ARIMA (ASIR) Model			
Root Mean Squared Error	7372.7	9376.7	14122.7
Mean Abs. Percent Error	4.1479	5.7757	7.2867
Theil Inequality Coefficient	0.0212	0.0286	0.0615
3-Lag VECM - ASI			
Root Mean Squared Error	23339.2	25633.7	37525.1
Mean Abs. Percent Error	11.4109	13.6297	16.3664
Theil Inequality Coefficient	0.0616	0.0729	0.0981
3-Lag VECM - ASIR			
Root Mean Squared Error	13549.8	12459.4	16859.9
Mean Abs. Percent Error	7.0370	6.9352	8.2257
Theil Inequality Coefficient	0.0367	0.0368	0.0465

The performance statistics are computed thus:

[13] The TIC, which lies between zero and one, is computed as the sum of the forecast error variance divided by the sum of a naïve forecast variance, where the naïve forecast is the previous period's value of the forecast object (this could be a random walk model). A value of zero indicates a perfect fit for the forecast model while a value of one indicates that the model is not better than the naïve forecast. The bias, variance and covariance proportions decompose the forecast error into the distance between the mean of the forecast compared the mean of the forecast object, the distance between the variation of the forecast compared to that of the forecast object, and the remaining unsystematic error, respectively. A "good" forecast would have a low TIC and a higher covariance proportion than bias or variance proportions. See Theil (1966), Armstrong and Fildes (1995) and Diebold (2007).

$$\text{RMSE} = \sqrt{\sum_{t=T+1}^{T+h} (\hat{\text{GDP}}_t - \text{GDP}_t)^2 \ / \ h} \tag{10}$$

$$\text{MAPE} = 100 \sum_{t=T+1}^{T+h} \left| \frac{\hat{\text{GDP}}_t - \text{GDP}_t}{\text{GDP}_t} \right| / \ h \tag{11}$$

$$\text{TIC} = \frac{\sqrt{\sum_{t=T+1}^{T+h} (\hat{\text{GDP}}_t - \text{GDP}_t)^2 \ / \ h}}{\sqrt{\sum_{t=T+1}^{T+h} \hat{\text{GDP}}_t^{\,2}} + \sqrt{\sum_{t=T+1}^{T+h} \text{GDP}_t^{\,2}}} \tag{12}$$

where the forecast sample is T + h, with h (the forecast horizon) taking the values of 2, 4 and 6, and the forecast and actual values in period t are GDP_t – hat and GDP_t, respectively.

Table 13 – Ranking of Forecast Models*

Rank	**Two Quarters** (2007Q3 - 2007Q4)	**Four Quarters** (2007Q3 - 2008Q2)	**Six Quarters** (2007Q3 - 2008Q4)
1	SARIMA-ASI	SARIMA-ASI	SARIMA-ASI
2	SARIMA-ASIR	ARIMA	ARIMA
3	ARIMA	SARIMA-ASIR	SARIMA-ASIR
4	VECM-ASIR	VECM-ASIR	VECM-ASIR
5	VECM-ASI	AR(1)	AR(1)
6	AR(1)	VECM-ASI	VECM-ASI

* Using mean absolute percentage error (MAPE) as the ranking criterion.

Within the two-quarter horizon, the ARIMA model improves substantially on the performance of the AR(1) model, with a MAPE of 4.84 percent versus 19.75 percent for the AR(1) model. The SARIMA-ASI model performs better than either the AR(1) or the ARIMA model, with a MAPE of 1.55 percent; this is 92.14 percent and 67.94 percent lower than the MAPEs of the AR(1) and ARIMA models, respectively. The SARIMA-ASIR model, with a MAPE of 4.14 percent, performed better than the AR(1) and ARIMA models, but not as well as the SARIMA-ASI model. The VECMs outperformed the AR(1) model but had higher error rates than the ARIMA and SARIMA models.

Over four quarters, the ARIMA model, with a MAPE of 3.57 percent outperforms the AR(1) model which has a MAPE of 11.41 percent. However, the SARIMA-ASI model outperforms both models with a MAPE of 2.39 percent. The SARIMA-ASIR model outperformed the AR(1) model and VECMs but had higher error rates than the ARIMA and SARIMA-ASI models. With a MAPE of 6.94 percent, the VECM-ASIR outperformed the AR(1) model but the VECM-ASI had a MAPE of 13.63 percent versus the AR(1) model's 11.41 percent.

The results over a six-quarter horizon mirror those for the four-quarter; the SARIMA-ASI model has the lowest MAPE of 2.80 percent, followed by the ARIMA model's 6.22 percent, the SARIMA-ASIR model's 7.29 percent, the VECM-ASIR's 8.23 percent, the AR(1) model's 16.05 percent and the VECM-ASI's 16.37 percent.

We summarize the out-of-sample forecast performance of the models in table 13, which ranks the models by MAPE. Regardless of the forecast horizon, the SARIMA-ASI model consistently outperforms the other five models. In addition, the VECM-ASI model ranked fifth over the two-quarter horizon and last over the other horizons. The results suggest that stock market prices contain information that could be used to improve GDP forecasts in the short- to medium term and that a structural ARIMA specification with the nominal stock index is likely to perform better than an ARIMA specification with a deflated stock index or a VECM with either the nominal or real stock index.

6.0 Conclusions and Policy Implications

The goal of this paper was to determine whether or not stock prices contained information which could be used to improve predictions of economic activity in Nigeria. Granger causality tests indicated that the All Share Index is a leading indicator of real GDP but had no relationship with the Index of Industrial Production. In addition, no causality was found between GDP and IIP. Johansen cointegration tests also suggested a long-run equilibrium relationship between nominal and real stock prices and real GDP in Nigeria.

The finding of bi-directional causality between stock prices and GDP is not surprising in light of the fact that, while stock prices reflect the expectations of investors, they ultimately must also reflect economic fundamentals. A high rate of economic growth will lead to an increase in firms' earnings and higher earnings will buoy stock prices. Thus, there is evidence that the stock market in Nigeria is not only a leading indicator of the real economy but that Nigerian stock prices are, at least partly, based on economic fundamentals. Other studies, including Pilinkus (2009), have found bi-directional causality between stock prices and economic activity.

Figure 2 shows average price-earnings (PE) ratios of Nigerian stocks between January 2001 and December 2009. Nigerian stocks seemed to have become decoupled from fundamentals during the boom that began around January 2007; the average PE ratio reached an all-time high of 48.9 in February 2008 before the ensuing crash. However, by December 2009, the average PE ratio had fallen to 19.30, which is quite close to the nine-year average of 18.37. As such, the evidence suggests that, while the Nigerian stock market is not immune to bubbles, it is, to a large extent and in the long run, governed by economic fundamentals.

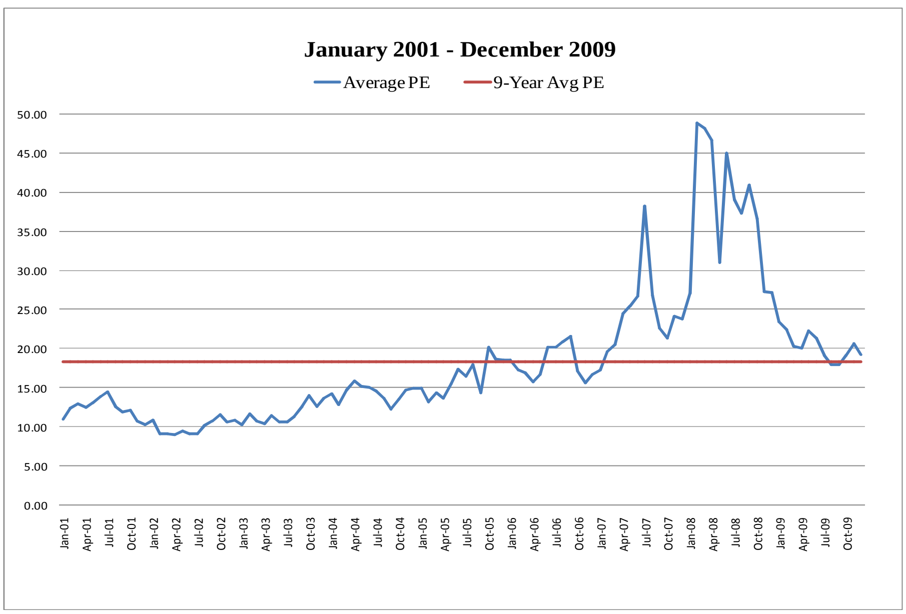


Figure 2 – Nigerian Stock Exchange Price-Earnings Ratios

The "acid test" of a leading indicator is its ability to improve the performance of forecasts of GDP or other macroeconomic variables of interest. Tests conducted with short to medium term forecast horizons show that the information in stock prices can reduce forecast errors by up to 92 percent compared to an AR(1) model and up to 68 percent compared to an ARIMA model. Deflating the All-Share Index using the CPI did not improve the performance of the models. Also, VECMs performed poorly in comparison to models based on an ARIMA framework.

The evidence presented in this paper suggests that the All Share Index should be added, in nominal form, to a composite index of leading economic indicators (CILEI) for Nigeria, with a two-quarter lag[14]. This is likely to improve the accuracy of the composite index of leading economic indicators. Other financial variables should also be evaluated for inclusion in the CILEI since they embody expectations of economic agents in the same manner that the ASI does. A leading candidate among financial variables is the Treasury bond yield curve, as operationalized by the spread between a benchmark long maturity bond (e.g., the 10-year federal government bond) and a short maturity security (e.g., the three month government bill). Estrella and Mishkin (1996) show that

[14] Most financial variables in composite indices of leading indicators are incorporated in nominal form.

the yield spread outperforms most other macroeconomic variables in predicting U.S. recessions two to six quarters ahead. The Federal Reserve Bank of New York has documented the reliability of the slope of the yield curve as a leading indicator of economic activity in the U.S.[15]

The methodology utilized in this paper could be replicated in order to investigate the information content of the yield curve in Nigeria. The addition of the stock index and yield curve to the CILEI is in keeping with international best practice, as several nations, including the U.S., UK, Japan and South Africa have both financial variables in their composite indices of leading economic indicators.

In addition to leading indices, other approaches could be explored in order to improve GDP forecasts. Further research could investigate the efficacy of using monetary aggregates, credit to the private sector, oil revenues, rainfall statistics and surveys of economists to improve predictions of the future path of economic activity. More accurate forecasts of economic activity will enhance our ability to manage the economy via monetary and fiscal policies.

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[15] See http://www.newyorkfed.org/research/capital_markets/ycfaq.html

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