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The Relationship Between Oil Prices and the Nigerian Stock Market, an Analysis Based on Fractional Integration and Cointegration

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ABSTRACT

This paper deals with the analysis of the relationship between oil prices and the stock market in Nigeria. We focus on measuring the degree of persistence of the series using long range dependence techniques, and based on the similarities observed between the two series, a fractionally cointegrated modeling framework is proposed. The results first indicate that the two series display a similar order of integration, which is close to, although above 1. Testing the hypothesis of cointegration, this is decisively rejected since the order of integration in the potential equilibrium relationship was similar to that of the parent individual series. However, testing a long memory model with oil prices acting as a weakly exogenous regressor, we obtained significant evidence of a positive relationship between the two variables though with a very short memory effect, this relation being significant only during the following three months.

Keywords: Oil prices; Nigeria; Fractional cointegration

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1. Introduction

In this paper we examine the dynamic structure of stock market prices in Nigeria, testing first their degree of persistence to determine whether the market is efficient. Moreover, due to the inefficiencies found in the market, and based on the fact that stock market returns display long memory behaviour, we also examine if oil prices may have had an influence on the behaviour of the stock prices. For this purpose we first use a fractionally cointegrated model, testing if there exists a long run equilibrium relationship between the two variables. Then, an I(d) regression model with oil prices being taken as a weakly exogenous regressor is also considered. Our results indicate that previous behaviour of oil prices determines the behaviour of the Nigerian stock market in the short run.

Modelling stock market prices in Africa is an issue that has not been investigated very much. Using simple techniques based on correlation analysis, Olowe (1998; 1999) showed that the Nigerian stock market appears to be efficient in the weak form. This was also confirmed in other studies by Samuel and Yacout (1981), Ayadi (1984), Omole (1997) and Oludoyi (1999). Further work by Adelegan (2004) showed that share prices do not respond freely to forces of demand and supply, while Nwokoma (2002) found that share prices respond more to their past prices than to changes in the macroeconomic variables. In a more general context, Magnusson and Wydick (2002) examined the efficiency of African emerging stock markets, using data from eight African countries: **(**Botswana, Côte d'Ivoire, Ghana, Kenya, Mauritius, Nigeria, South Africa, Zimbabwe)**:** six of the eight stock markets pass the basic hurdles of weak-form efficiency, that is, past movements in stock prices cannot be used to predict future movements in prices. In a related paper, Appiah-Kusi and Menyah (2003) also examined African stock markets. They used EGARCH-M models and tested the weak-form efficiency in eleven African markets; their results showed that the majority of the markets do not exhibit weak-form efficiency. Mlambo and Biekpe (2005) tested the efficient market hypothesis of ten African stock markets using the runs test methodology for serial dependency. It was concluded in this study that for Kenya and Zimbabwe, the weak form efficiency hypothesis could not be rejected since a significant number of stocks conformed to the random walk hypothesis. Vitali and Mollah (2010) investigated the weak-form of market efficiency in Africa by testing the random walk hypothesis through multiple approaches, specifically unit root, autocorrelation, run tests and variance ratio tests on daily price indices of seven countries for the time period 1999 - 2009. The major results in the paper rejected the random walk hypothesis for all of the countries except for South Africa.

From the above literature, it seems clear that though several papers have investigated the efficient market hypothesis in various sub-Saharan countries, most of them have focused exclusively on testing for random walks by means of unit root tests and none of them have used fractional integration as an alternative and richer approach. Moreover, these widely employed (unit root) tests, in small samples, have very low power against alternatives such as trend-stationary models (DeJong et al., 1992), structural breaks (Campbell and Perron, 1991), regime-switching (Nelson et al., 2001), or fractionally integration (Diebold and Rudebusch, 1991; Hassler and Wolters, 1994; Lee and Schmidt, 1996). As already mentioned, in this paper we focus on the latter type of alternatives, noting that fractional integration includes the classic unit root models as particular cases of interest.

On the other hand, and regarding the long run behaviour of oil prices, there is no consensus whatsoever about the order of integration of this variable. For instance, Bentzen (2007), Cunado and Pérez de Gracia (2005), and Jalali-Naini and Asali (2004), find that several series corresponding to crude oil prices contain unit roots, whereas Postali and Picchetti (2005) and Moshiri and Foroutan (2006) find that this variable is stationary with structural changes. In addition, Gil-Alana (2001, 2003) finds that this variable (ROP) might be fractionally integrated, and Cuestas and Regis (2010) found a non-linear trend stationarity model for the S&P daily spot oil prices series.

The relationship between oil prices and other macroeconomic variables have promoted many lines of research. The first account of a long run relationship between GDP and oil prices appears in Hamilton (1983). He found a negative relationship between the two variables. Other authors have also examined the relationship between oil prices and other variables. Thus, for example, several papers have studied the long run co-movements of oil prices and inflation (Cunado and Perez de Gracia, 2005), a few of which have estimated the Phillips curve augmented with the price of oil (Hooker, 2002, and LeBlanc and Chinn, 2004). A number of authors have acknowledged the effects of oil prices on the dynamics of unemployment (see Gil-Alana, 2003, among others) and international terms of trade (Backus and Crusini, 2000).

The price of oil has been known to be an important factor which predicts significantly the fluctuations in stock prices (Jones and Kaul, 1996). More recently, Eryigit (2009) found a positive significant relationship between oil price change and stock indices of tourism, food, beverages, chemical and leather in Turkey. Filis, Degiannakis and Floros (2011) and Antonakakis and Filis (2013) investigated the dynamic correlation between stock markets prices and oil prices for oil importing and oil exporting countries using volatility models, and found that time varying correlations are the same in both oil importing and oil exporting countries. Their results further showed that the correlation increases negatively in response to aggregate demand of oil prices shocks except during the 2008 global financial crisis when the oil prices lags started exhibiting positive correlation with stock markets.

In Nigeria, there are fewer empirical articles that have considered the possible relationship between oil prices and stocks in Nigeria. Adaramola (2011) considered the relationships of some macroeconomic variables with stocks using a panel model and found that oil price among other variables is significantly correlated with the behaviour of the stock market. Layade and Okoruwa (2012) also applied panel data estimation approach on agro-allied stocks in Nigeria with oil prices and obtained a significant positive relationship between oil prices and stock prices. None of these papers, neither in Nigeria nor on an international level dealt with the issue of a possible relationship between stocks and oil prices using fractional integration and cointegration techniques.

In this paper, we examine the link in the long run relationship between oil prices and activity in the stock market, using the All Share Index (ASI) of the Nigerian Stock Exchange. The remainder of the paper is structured as follows: Section 2 is devoted to the methodology employed in the paper. Section 3 presents the data and the univariate empirical results. Section 4 focuses on the multivariate model incorporating oil prices in the stock market equation. Section 5 contains some concluding comments and extensions.

2. Methodology

The methodology used in the paper to examine the stochastic properties of the series is based on the concepts of unit roots and long range dependence or long memory. We initially consider testing unit roots and other nonstationarities by means of standard methods, after which we proceed to checking for long range dependence. This is due to the fact that a series may display a degree of association between the observations much higher than the one usually considered in the literature and based on autoregressions and integer degrees of differentiation.

2.1 Testing for unit roots

A difference stationary series is said to be unit integrated if the order of the integration of the series, denoted by *d*, is a unit value. For any general *d*, these processes are denoted as I(d). In the standard case of I(d) models,

$$(1 - L)^d x_t = u_t, \qquad t = 0, \pm 1, \ldots, \tag{1}$$

with $x_t = 0$ for $t \leq 0$, and d = 1 or 2, where L is the lag-operator ($Lx_t = x_{t-1}$), and the resulting covariance stationary process u_t, which is I(0) process is then obtained by taking the first or second differences. As part of the methodology in time series analysis, there is a need to check whether a series is stationary or not before using it in a regression model. Unit root tests are usually conducted by means of the classical Augmented Dickey Fuller (ADF) test of Dickey and Fuller (1979). This test has gained popularity in testing for unit roots but it has very low power if the series under investigation is, for example, non-linear. Macroeconomic variables often display non-linear dynamics and ADF-type tests may not be sensitive enough to judge well the level of stationarity of the series. A recent test proposed by Kapetanios, Shin and Snell (KSS, 2003) will be applied in the paper along with the ADF test to determine the level stationarity/nonstationary of the series.

The starting point in the KSS test is the same specification as in the Dickey Fuller (DF) regression model with correction for possible serial correlation defined as,

$$\Delta x_t = \sum_{j=1}^{p} \rho_j \Delta x_{t-j} + \delta_{ADF} x_{t-1} + u_t, \qquad t = 1, 2, \ldots \tag{2}$$

where p indicates the AR order. In this model, δ is the OLS estimate from the above regression, the ρ's are the autoregressive values, and u_t is the error term assumed to be white noise. In practice, implementation of KSS often ignores the augmented component, and we then have,

$$\Delta x_t = \delta_{KSS} x_{t-1}^3 + u_t, \qquad t = 1, 2, \ldots, \tag{3}$$

derived by approximating the truncated non-linear regression model,

$$\Delta x_t = \gamma x_{t-1} \left[1 - \exp(-\theta x_{t-1}^2)\right] + \varepsilon_t, \qquad t = 1, 2, \ldots \tag{4}$$

where γ and θ are parameters in the model and ε_t is a white noise process. Both the ADF and KSS are tested using the test statistic,

$$t = \frac{\hat{\delta}}{se(\hat{\delta})}, \tag{5}$$

where $se(\hat{\delta})$ is the standard error of $\hat{\delta}$ estimated in (2) and (3) above. We test the null hypothesis H_o: $\delta = 0$ for unit roots against the alternative H_1: $\delta < 0$ for stationarity. Just as the ADF test, the KSS can be conducted on the three classical cases of i) no intercept in the regression model; ii) with an intercept only and iii) in the presence of both, an intercept and a linear time trend. The details of the test statistic and asymptotic critical points for the ADF test are given in Dickey and Fuller (1979), Davidson and Mackinnon (1993), Hamilton (1994) and Hayashi (2000). That of the KSS test can be found in Kapetanios, Shin and Snell (2003).

2.2 The Fractional I(d) process

We can provide two definitions of long memory, one in the frequency domain and the other in the time domain. Let us consider a zero-mean covariance stationary process, $\{x_t, t = 0, \pm 1, \ldots\}$ with autocovariance function $\gamma_u = E(x_t\ x_{t+u})$. The time domain definition of long memory states that:

$$\sum_{u=-\infty}^{\infty} |\gamma_u| = \infty .$$

Assume that x_t has an absolutely continuous spectral distribution, so that it has a spectral density function, $f(\lambda)$; according to the frequency domain definition of long memory, the spectral density function is unbounded at some frequency λ in the interval $[0, \pi)$, i.e.,

$$f(\lambda) \rightarrow \infty \quad \text{as} \quad \lambda \rightarrow \lambda^*, \qquad \lambda^* \in [0, \pi].$$

Most of the existing empirical literature considers the case when the singularity or pole in the spectrum occurs at the zero frequency. This is the standard case of the I(d) models as in equation (1). In that model, u_t has a spectral density function that is positive and finite at any frequency. This includes a wide range of stationary model specifications such as white noise, autoregressive (AR), moving average (MA), autoregressive moving average (ARMA) etc.[1]

Note that the parameter *d* plays a crucial role in describing the degree of dependence of the series. Specifically, if $d = 0$ in (1), $x_t = u_t$, and the series is I(0), potentially including ARMA structures with the autocorrelations decaying at an exponential rate. If *d* belongs to the interval (0, 0.5), the series is still covariance stationary but the autocorrelations take longer to disappear than in the I(0) case. If d is in the interval [0.5, 1), the series is no longer covariance stationary; however, it is still mean-reverting with shocks affecting its disappearance in the long run. Finally, if $d \geq 1$ the series is nonstationary and non-mean-reverting.

The methodology employed here to estimate the fractional differencing parameter is based on the Whittle function in the frequency domain (Dahlhaus, 1989). We also employ a testing procedure developed by Robinson (1994) allowing to test for any real value of *d* in I(d) models. This method is based on the Lagrange Multiplier (LM) procedure and is the most efficient one in the context of fractional integration. We consider the following model:

$$y_t \;=\; \beta^T z_t \;+\; x_t\,, \qquad t \;=\; 1, 2, \ldots, \tag{6}$$

where y_t is the observed time series, z_t is a (kx1) vector of deterministic terms or weakly exogenous regressors, and thus it may include an intercept ($z_t = 1$) or an intercept with a linear trend (i.e., $z_t = (1,t)^T$), and x_t are the regression errors, which follow an I(d) model of the same form as in equation (1). This methods tests the null hypothesis H_o: $d = d_o$ for any real value d_o in (1) and (6), and based on its parametric nature, we need to include a a specific model for the I(0) disturbances.

[1] If u_t in (1) is an ARMA(p, q) process, x_t is then said to follow a Fractionally Integrated ARMA or ARFIMA(p, d, q) model.

Robinson (1994) showed that, under certain very mild regularity conditions, the LM-based statistic[2] ($\hat{r}$):

$$\hat{r} \rightarrow_d N(0,1) \quad \text{as} \quad T \rightarrow \infty, \tag{7}$$

where " $\rightarrow_d$ " stands for convergence in distribution, and this limit behaviour holds independently of the regressors z_t used in (6) and the specific model for the I(0) disturbances u_t in (1).

Alternatively to the methods presented, we could have employed Wald and LR test statistics against fractional alternatives with the same null and limit theory as the LM test of Robinson (1994). Lobato and Velasco (2007) essentially employed such a Wald testing procedure, although this method requires a consistent estimate of *d*, and therefore the LM test of Robinson (1994) seems computationally more attractive. Other methods, such as the one developed by Demetrescu, Kuzin and Hassler (2008), which have been shown to be robust with respect to unconditional heteroscedasticity, were also implemented leading to practically the same results as those reported in the paper.

3. Empirical results

3.1 The Data

The data used in this study are the monthly Nigerian stocks (All Share Index) and Crude Oil Prices in dollars per barrel. Both series span from January 2000 to December 2011 giving a total of 144 data points. The Nigerian All Share Index (ASI) data were obtained from the Nigerian Stock Exchange (NSE) database, while that of oil prices were retrieved from the website http://www.indexmundi.com, and correspond to the monthly Brent crude oil price in dollars per barrel at the international market.

[2] The specific form of the test statistic can be found in any of the numerous empirical applications using this method (e.g., Gil-Alana and Robinson, 1997; Gil-Alana, 2000; Gil-Alana and Henry, 2003, etc.).

Figures 1 and 2 display the plots of the ASI and oil prices over the sample period. Both series increased gradually from 2000, assuming almost the same swinging pattern to reach the peak at around 2008. After that, they start decreasing sharply and reach a common trough at the first quarter of 2009. Since then, there has not been a significant increase in the values of the Nigerian stocks. After 2009, oil prices have increased astronomically again reaching $120 dollars per barrel in the international market. The fact that the two series display similar swinging behavior is an indication of a possible long run equilibrium relationship between the two variables.

[Insert Figures 1 and 2 about here]

We first tested for the presence of unit roots in the two series. The null hypotheses of unit roots in both ASI and oil prices cannot be rejected at the 5% level as shown in the results of the ADF and KSS tests in Table 1(i) and (ii) respectively. However, as earlier mentioned, these results should be taken with caution noting the low power of these tests in the context of fractional integration.

[Insert Table 1 about here]

We next estimate the parameters of the model given by the equations (6) and (1) with $z_t = (1,t)^T$, $t \geq 1$, $(0, 0)^T$ otherwise, i.e.,

$$y_t = \beta_0 + \beta_1 t + x_t, \qquad t = 1, 2, . \tag{8}$$

$$(1 - L)^d x_t = u_t, \qquad t = 1, 2, \ldots, \tag{9}$$

assuming first that the disturbance term u_t is a white noise process, and then considering the possibility of weak autocorrelation, first with the model of Bloomfield (1973)[3] and then using a seasonal AR(1) process of form:

$$u_t = \rho u_{t-4} + \varepsilon_t, \qquad t = 1, 2, \tag{10}$$

[3]This is a non-parametric approach that produces autocorrelations decaying exponentially as in the AR(MA) case.

with white noise ε_t.[4]

[Insert Table 2 about here]

Table 2 displays the estimates of *d* and the corresponding 95% confidence intervals of the non-rejection values of d using Robinson (1994), for the three standard cases of no deterministic terms ($\beta_0 = \beta_1 = 0$ a priori in equation (8)), an intercept (β_0 unknown and $\beta_1 = 0$), and an intercept with a linear trend (β_0 and β_1 unknown). The test results presented above suggest that the series are I(d) with d slightly above 1. In fact, the confidence intervals exclude the unit root (i.e. d = 1) in the majority of the cases. The only case where the unit root null hypothesis cannot be rejected corresponds to the oil prices series with Bloomfield disturbances. Focusing on the deterministic terms, the time trend coefficient was found to be statistically insignificant in all cases, while the intercept was significant. The estimated fractional differencing parameter was found to be about 1.20 for the stock market index, and between 1.01 and 1.34 for the oil prices depending on the specification of the disturbance term. Moreover, the fact that the confidence intervals overlap suggest that the two series may display the same degree of integration. In fact, we tested the equality of the order of integration of the two variables using an adaptation of Robinson and Yajima's (2002) statistic with log-periodogram estimation and different trimming and bandwidth numbers, and evidence of an equal order of integration was obtained in all cases. This will enable us to study the possibility of fractional cointegration in the following section.

4. The influence of oil prices

Two approaches were examined in the multivariate framework. On the one hand, the possibility of fractional cointegration was taken into account. On the other hand, a long

[4]Higher seasonal AR orders produces virtually the same results in all cases.

memory regression model including (present and past values of) oil prices as a weakly exogenous regressor was examined.

We started with the fractional cointegration framework. Based on the assumption that the two series displays the same degree of integration,[3] we conducted first the Hausman test for no cointegration of Marinucci and Robinson (2001) comparing estimates of d based on the log-periodogram with a more efficient bivariate method based on the Whittle function and which makes uses of the information of equal orders of integration. Using this approach the test rejected the hypothesis of cointegration at the 5% level, and the same evidence was obtained when using the methodology devised in Gil-Alana and Hualde (2008) and using Robinson and Hualde's (2003) approach. To summarize, we noticed that the order of integration of the two parent series was very similar to the one obtained in the hypothesized cointegrated relationship, being the latter slightly above 1 though smaller than the one achieved in the individual series. Due to this lack of cointegration, we consider the second approach based on an I(d) model with the oil prices acting as weakly exogenous regressors.

We consider here the following model:

$$SMP_t \;=\; \alpha + \beta\, OP_{t-k} \;+\; x_{t,} \qquad (1-L)^d\, x_t \;=\; u_t, \qquad t \;=\; 1, 2, \ldots, \tag{11}$$

where SMP_t refers to the Stock Market Prices and OP_t is Oil prices, and we consider different types of I(0) disturbances (white noise, Bloomfield autocorrelated and seasonal AR), and k = 0, 1, 2, 3, 4, 5 and 6. In this set-up, *d* indicates the degree of persistence, and β is an indicator of the effect on present (and past) oil prices on the stock market prices.

[Insert Tables 3 – 5 about here]

The results are reported in Tables 3 – 5 respectively for the cases of white noise, Bloomfield and seasonal AR disturbances. They are very similar across the three tables and

[3] In a bivariate model, as is the case in the present work, a necessary condition for cointegration is that the two series must display the same degree of integration.

consistent with the above comment on the lack of cointegration, the orders of integration in (11) is equal to or above 1 in the three models. We also observe a significant positive coefficient for the first three periods. This indicates an instantaneous significant positive effect (k = 0) that remains significant albeit with a smaller magnitude during the following two periods. After three periods (months) the effect becomes statistically insignificant in the three models.

5. Concluding comments

This paper deals with the analysis of stock market prices in Nigeria and its relation with the oil prices. We first investigated the order of integration of the series by using long range dependence techniques and fractional integration. The results showed that the ASI series displays long memory returns with orders of integration for the logged prices above 1 in the majority of the cases. Performing the same type of analysis on the crude oil prices, the results were fairly similar and in fact, we could not reject the null hypothesis of an equal order of integration in the two series. Testing the null of cointegration, this hypothesis was decisively rejected, showing no evidence of a smaller order of integration in a potential long run equilibrium relationship between the variables. However, performing a model where oil prices acted as a weakly exogenous regressor, we showed that the estimated coefficient was significantly positive, not only instantaneously, but also if lagged periods were considered. In fact, the value remains significant during the first three periods, implying a relationship between the two variables in the short run. This result is in agreement with Adaramola (2011) and Layade and Okoruwa (2012). A marginal monthly change in the price of barrel of crude oil is expected to cause a greater effect on the market and the market re-adjusts a few days later. The higher the crude oil prices, the more the revenue that is generated in the country, and this is translated to more income for the citizens. Consequently they invest more in stocks.

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Figures and Tables

Figure 1: All Share Indices series

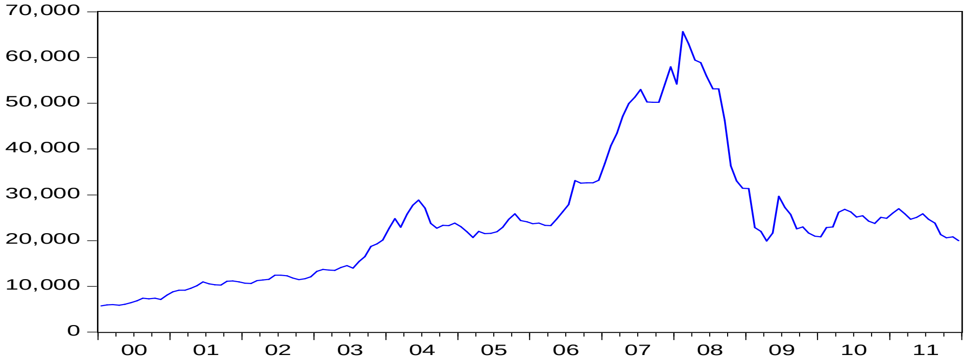

Figure 2: Brent Crude Oil Prices (US Dollars/barrel)

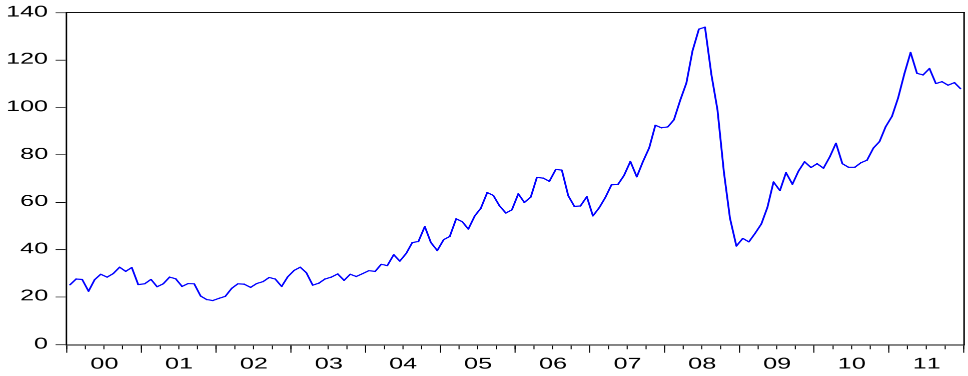

Table 1: Unit root tests results

i) Stock market prices series			
	No intercept	Intercept	An intercept and trend
ADF	-0.409145 (0.5345)	-1.563745 (0.4985)	-1.047947 (0.9330)
KSS	-1.168936 (0.2444)	-1.651364 (0.1009)	-1.247063 (0.2145)
ii) Crude oil prices series			
	No intercept	Intercept	An intercept and trend
ADF	-0.021317 (0.6740)	-1.478931 (0.5415)	-4.114917 (0.0076)
KSS	0.742697 (0.4589)	-0.739013 (0.4411)	-2.248676 (0.0261)

Table 2: Estimates of d in the I(d) setting

i) Stock market prices series			
	No regressors	An intercept	A linear time trend
White noise	1.171 (1.077, 1.293)	**1.182 (1.088, 1.303)**	1.182 (1.087, 1.305)
Bloomfield	1.227 (1.024, 1.475)	**1.231 (1.043, 1.485)**	1.232 (1.047, 1.486)
Seasonal AR	1.189 (1.091, 1.312)	**1.203 (1.101, 1.305)**	1.202 (1.108, 1.325)
i) Crude oil prices series			
	No regressors	An intercept	A linear time trend
White noise	1.281 (1.144, 1.463)	**1.339 (1.188, 1.526)**	1.339 (1.187, 1.527)
Bloomfield	0.953 (0.697, 1.458)	**1.010 (0.713, 1.525)**	1.010 (0.657, 1.532)
Seasonal AR	1.284 (1.131, 1.466)	**1.342 (1.187, 1.525)**	1.344 (1.184, 1.520)

In bold, the most significant models according to the deterministic terms. In parenthesis the 95% confidence intervals.

Table 3: Parameter estimates in the model given by equation (11) with white noise u_t

White noise	d (95% conf. Interval)	Intercept (t-value)	Slope coefficient (t-value)
k = 0	1.123 (1.031, 1.247)	2996.046 (1.931)	**107.741 (3.254)**
k = 1	1.116 (1.021, 1.242)	3939.956 (1.702)	**78.685 (2.346)**
k = 2	1.126 (1.033, 1.246)	4179.905 (1.807)	**69.192 (2.057)**
k = 3	1.122 (1.029, 1.239)	4940.753 (2.133)	34.314 (1.020)
k = 4	1.093 (1.003, 1.208)	5779.379 (2.521)	8.821 (0.267)
k = 5	1.083 (0.998, 1.193)	6847.437 (2.998)	-18.741 (-0.570)
k = 6	1.063 (0.984, 1.166)	8576.256 (3.830)	-69.481 (-1.107)

t-values in parenthesis in the third and fourth columns. In bold significant slope coefficients.

Table 4: Estimates in the model given by equation (11) with Bloomfield disturbances

Bloomfield	d (95% conf. Interval)	Intercept (t-value)	Slope coefficient (t-value)
k = 0	1.172 (0.983, 1.407)	3144.463 (1.389)	**101.765** **(3.044)**
k = 1	1.178 (1.003, 1.429)	4193.190 (1.829)	**68.653** **(2.022)**
k = 2	1.141 (0.959, 1.390)	4223.33 (1.830)	**67.460** **(1.992)**
k = 3	1.129 (0.943, 1.360)	4954.663 (2.141)	33.667 (0.999)
k = 4	1.071 (0.899, 1.278)	5767.924 (2.512)	9.906 (0.302)
k = 5	1.068 (0.907, 1.273)	6862.437 (3.002)	-18.851 (-0.576)
k = 6	1.077 (0.928, 1.258)	8566.046 (3.828)	-69.559 (-1.167)

t-values in parenthesis in the third and fourth columns. In bold significant slope coefficients.

Table 5: Estimates in the model given by equation (11) with seasonal AR disturbances

Seasonal AR	d (95% conf. Interval)	Intercept (t-value)	Slope coefficient (t-value)
k = 0	1.148 (1.056, 1.272)	3072.897 (1.307)	**104.628** **(3.039)**
k = 1	1.133 (1.037, 1.260)	4009.650 (1.700)	**75.872** **(2.206)**
k = 2	1.148 (1.053, 1.271)	4243.440 (1.804)	**66.664** **(1.934)**
k = 3	1.136 (1.043, 1.257)	4968.527 (2.108)	33.028 (0.959)
k = 4	1.113 (1.021, 1.230)	5789.938 (2.444)	7.922 (0.230)
k = 5	1.102 (1.016, 1.215)	6828.379 (2.873)	-18.519 (-0.537)
k = 6	1.093 (1.012, 1.198)	8554.411 (3.592)	-69.589 (-1.021)

t-values in parenthesis in the third and fourth columns. In bold significant slope coefficients.