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International oil prices and sectoral stock prices: An asymmetric kernel and nonlinear autoregressive distributed lag analysis

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***Abstract*---**In this work, we test the price sensitivity of sector indices to changes in the oil prices over the period 2001 to 2021 using the asymmetric kernel method and the non-linear autoregressive method with distributed lags (NARDL) proposed by Shin et al., (2014). We capture both short-term and long-term non-linearities, through positive and negative partial sum decompositions of the explanatory variables and show a non-linear relationship between the prices of oil and sector indices. Furthermore, the results show that fluctuations in oil prices do not have a statistically significant impact on West African sectoral stock prices except for the financial and agricultural sectors. Finally, we observe only a short-term asymmetry and a cointegration relationship between the price of oil and the agricultural sector. These results are robust and further enrich the decision support tools for financial market participants in their investment strategy.

***Keywords*---**Oil price, Share prices, Associated kernel, NARDL.
JEL Classification: E31; C32; Q43

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1. Introduction

Oil and its derivatives are essential in the production chain of industries in net oil-importing countries (Lescaroux and Mignon, 2008). In the real sphere, a positive and sustained change in the price of oil translates into an increase in production costs and a change in business behaviour. For example, companies facing high production costs due to increased oil prices have a higher propensity to invest in research and development or turn to alternative production methods that are less intensive in oil.

In the financial sphere, the predictability of the behaviour of investors seems less obvious. Financial theory explains response of stock prices to changing oil prices through direct and indirect channels. The price of oil can directly impact stock prices by affecting future cash flows through their effects on the global economy or indirectly impact stock prices by affecting the interest rate used to discount future cash flows (Basher et al., 2012; Ciner, 2013).

Regarding this indirect channel, an increase in oil prices is supposed to cause an increase in production costs and is likely to generate an inflationary shock in oil-importing economies. The decline in purchasing power suffered by households leads them to slow down their consumption expenditure. At the level of investment, the fall in the level of consumption and the induced increase in production costs of companies have negative effects on the price of securities of non-oil-producing companies. On the other hand, companies operating in the oil sector are faced with an increase in the price of their securities. Thus, although the oil price significantly affects financial markets in general and stock markets (Cong et al., 2008; Creti et al., 2014), it seems that the nature and intensity of these effects varies depending on the sector in which the company is located; or potentially, depending on its size.

Moreover, traditional economics and finance are insufficient to explain the investment decisions of economic actors (Kahneman and Tversky, 1979). One possible reason is the linearity assumption. Analyses using a linear model very often led to misleading results. The nonlinear characteristics of a significant majority of macroeconomic risk factors should not be overlooked in econometric research (Shin et al, 2014). In addition, following Mork's (1989) observation, many studies reveal that oil prices have an asymmetrical influence on economic activities. On the one hand, the negative impact of higher oil prices on economic activity would be significantly stronger than the positive impact of lower oil prices on the economy. On the other hand, the main macroeconomic variables would show an asymmetric behaviour during the different periods of economic activity (Kocaarslan et al, 2019). The asymmetrical effects in the relationship linking the price of oil to stock market prices would play a central role in world markets (Ang and Bekaert, 2002).

Thus, with all these findings, it appears that the answers relating to the relationship between oil prices and stock market prices are not definitive, particularly sector stock prices, which are the subject of little attention. In the case of the countries of the West African Monetary Union (WAMU) - Benin, Burkina Faso, Ivory Coast, Guinea Bissau, Mali, Niger, Senegal, Togo - the problem of this link is acute. These countries are net importers of oil with a strong predominance of the primary sector in their economies. One is led to wonder if the case of the regional stock exchange (BRVM) can constitute a relaxation in the theoretical conceptions. Indeed, between 2010 and 2020, the price of crude oil has increased by approximately 1.23% per annum on average. As for inflation in the WAMU zone, it nevertheless remained relatively low over the same period. It is estimated to increase at 1.4% per annum on average. Stock market prices, for their part, varied very little in the zone. On an annual average, the progression of the main index of the regional stock exchange entitled BRVM 10 is estimated at 0.16% over the same period. We are therefore led to believe that inflation and stock prices in the WAMU zone are not very sensitive to variations in the price of oil.

Therefore, when analysing the context specific to WAMU, it is therefore appropriate to ask whether the evolution of oil prices significantly influences West African stock markets, mainly West African sectoral stock markets. Three questions arise from here. First, what is the nature of this relationship? Then, what is the intensity of this relationship and, finally, how would the behaviour of BRVM investors translate vis-à-vis the evolution of oil prices?

The objective of this work is to explain the relationship between oil prices and the West African sectoral stock market indices from November 2001 to January 2020 using the kernel method and the nonlinear version of the scaled delay autoregressive method (NARDL). In addition to the goal of the paper, our decision to do a bivariate analysis is also motivated by several empirical high ranking research on the kernel method (Renault and Scaillet, 2004; Calabrese and Zenga; 2010; Gospodinov and Hirukawa; 2012; Fall et al, 2021) and on the NARDL method (Saliou and Isah, 2017; Rafiq and Bloch, 2016; Jiang and Liu, 2021) which analyze the variables taken two by two. The kernel method and the NARDL method are particularly suitable for this type of analysis involving cointegrated variables. Indeed, upon examination of the statistical tests, it appears that the variables of interest in this paper are non-stationary and integrated of order one (oil and indices of sectoral stock markets). Moreover, the additional tests carried out prove the robustness of the results of the present work and thus confirm the hypothesis of the existence of a long-term stable non-linear relationship which links the explanatory variable. As an extension of this bivariate analysis, we plan to carry out a multivariate analysis. Firstly, the results of the asymmetric kernel method show that this relationship is rather non-linear; thus, supporting the hypothesis that the relationship between inflation and stock market indices varies across different inflationary economies. The corollary of these results is that investors could modify the structure of their portfolio depending on the evolution of oil prices. Secondly, the NARDL regressions show that variations in oil prices have no impact on West African sector stock prices, except for the financial and agricultural sectors. Thirdly, there is only a short-term asymmetry between the price of oil and the price of the stock market index linked to the agriculture sector. Finally, a cointegration relationship is established between the price of oil and the agricultural sector.

The rest of the article is presented as follows: Section 2 presents the literature review. In section 3, we explain our methodology and the data used. Section 4 describes the empirical results and verifies the robustness of our results. Section 5 comments on the implications of the results. Section 6 is the conclusion.

2. Literature review

Our literature review is divided into three parts. The first part refers to the effects of the price of oil on the financial markets while taking caution to differentiate between exporting and importing countries. The second part references work that examines the relationship between the price of oil and the financial markets while considering asymmetry. The third part highlights the effects of oil prices on the sector indices.

2.1 The effects of oil prices on the financial markets of importing vs exporting countries

Several studies find that the price of oil has no effect on stock prices (Apergis and Miller, 2009; Huang et al., 2017) and when it has, the effects are ambiguous (Miller and Ratti, 2009). Other works find that oil price variations are likely to affect the economies of these oil-exporting and oil-importing countries (Bashar, 2006; Mohanty et al. 2011; Wang et al., 2013; Arouri et al., 2011; Kayalar et al., 2017). For example, Bashar (2006) points out that the relationship between oil and stock markets is positive for oil-exporting countries and negative for oil-importing countries. Mohanty et al. (2011) examine the relationship between oil prices and stock market returns of six Gulf Cooperation Council (GCC) countries, namely Bahrain, Kuwait, Oman, Qatar, United Arab Emirates and Saudi Arabia. They find a significant positive relationship between changes in oil prices and stock market returns in GCC countries, except for Kuwait.

Wang et al. (2013) evaluate the dynamic response to oil price shocks on a set of stock markets from oil-exporting countries. By decoupling demand and supply shocks on a monthly basis for data acquired between 1999-2018, their results show a time-varying response of all stock market returns to different oil shocks. Stock market returns react more to demand shocks than to supply shocks. Furthermore, the effect of supply shocks on stock returns is generally small and negative, while aggregate demand shocks exert a positive effect on almost all stock returns. Similarly, demand shocks specific to oil have a positive effect on the returns of oil-exporting stocks and negative effects in the case of oil-importing countries, except for the Chinese market.

Arouri et al. (2011) point out that oil prices affect stock markets through various channels. According to them, in oil-importing countries where oil is relied on as the main factor of production, an increase in oil prices negatively affects company revenues. Therefore, low cash flow, which directly influences the value of company shares, leads to a depreciation of the stock market. However, in oil-exporting countries, an increase in the price of oil leads to high earnings expectations and stock market appreciation.

Additionally, Kayalar et al. (2017) studied the dependence between oil prices, exchange rates and stock markets from January 2005 to April 2016, using the copula approach. They found that stock markets and exchange rates of oil exporters show a higher dependence on the price of oil, but a lesser sensitivity to fluctuations in oil prices in emerging oil importers.

Finally, Chkir et al. (2020) argue that given the dependence on oil prices by both oil exporting and importing countries leaves them vulnerable to changes in oil prices especially in the second half of this decade as well as influence stock returns.

2.2 The effect of price on financial markets while considering an asymmetry

Most of the literature focuses on the effects of oil price changes on stock market returns. Current data suggests that changes in oil prices are associated with fluctuations in stock prices, although the results are mixed. Some previous studies argue that there is a negative and asymmetric impact of oil shocks on financial markets (Jones and Kaul, 1996; Gjerde and Sættem, 1999; Driesprong et al., 2008; Chen, 2009; Miller and Ratti, 2009; Filis, 2010). Jiang and Liu (2021) explore the potential asymmetric impacts of positive and negative crude oil price shocks on stock prices in six major international financial markets, including China, Hong Kong, US, Japan, UK and Germany between January 2007 and March 2020. They use the NARDL model proposed by Shin et al. (2014) and find that oil price fluctuations have asymmetric effects on the stock price index but with varying performance four financial markets. For example, they find that the impacts of oil price volatility on two Chinese stock price indices are different, and the asymmetric effects of the volatility on stock indices in China and other financial markets are significantly different. Also, their research highlights a long-term stable co-integration link between stock indices and the price of oil, except for the Japanese and German stock markets.

Finally, Rafiq and Bloch (2016) examine the links between oil prices and 25 other commodities. Using annual data from 1900 to 2011, ARDL and NARDL models they capture the causalities in the short term thanks to asymmetric Granger causality tests due to Hatemi-J (2012). Their work shows that nonlinearity cannot be rejected for the relationship between the price of oil and most other commodities. The NARDL results revealed that a positive shock to oil prices raises the prices of at least 20 commodities while a decline in oil prices lowers the long-term prices of grain and aluminium only. In the immediate term, the price of oil lessens the impact of the fall in the prices of many basic products. The results of long-run asymmetry tests indicate that a positive shock to oil prices raises the prices of at least 20 commodities, with positive elasticities ranging from 0.23 percent for wool prices to a maximum of 0.88 percent for silver prices. In contrast, a decline in the price of oil lowers long-term prices to the five percent significance level for wheat, corn, and aluminium only, with magnitudes ranging from 0.37 to 0.68 percent. In the short term. their results show that declines in oil prices have significant impacts on lower prices for many commodities. Moreover, the results of the asymmetric Granger causality test indicate that a negative shock to oil prices causes a decline in the prices of at least 13 commodities, while a positive shock to oil prices causes a price increase for only three raw materials. Their results also reveal that there are substantial differences in the impact of oil prices between commodity groups. For example, while oil prices do not appear to have much impact on the market prices of beverages and grains, especially once endogeneity is considered, they do have a substantial impact on non-food crops and metal prices, even after controlling for potential endogeneity. This suggests a link using commodities as raw materials in industrial production.

2.3 The effect of price on sector indices

Like the works that have illustrated the link between the price of oil and those of global financial markets (Jones and Kaul, 1996; Sadorsky, 1999; Basher and Shdorsky, 2006; Nandha and Faff, 2008; Masih et al., 2011; Tchatoka et al., 2019), some studies have focused on the relationship between oil and sector indices. This work can be divided into two main axes. The first one describes the link between the price of oil and the prices of sector indices (Gogineni, 2010; Lee and Ni, 2002; Narayan and Sharma, 2011, 2014; Brails-Ford and Faff, 1999; Cong et al., 2008; Gogineni 2010; Broadstock et al., 2012; Zhang and Cao, 2013; Wen et al., 2014; Zhu et al., 2016; Paris, 2018; Degiannakis et al., 2018). And the second axis, highlights the effect of oil price volatility on sector indices (Malik and Ewing, 2009; Antonakakis et al., 2018; Hamdi et al., 2019).

In regard to the first axis, several studies show that oil shocks have a significant impact on oil-intensive industries (Gogineni, 2010; Lee and Ni, 2002; Narayan and Sharma, 2011, 2014), in particular on oil sectors and companies (Chang et al., 2009; Kang et al., 2017). Some of this work focuses on the relationship between oil price shocks and stock market returns of oil sectors or companies (Brails-Ford and Faff, 1999; Cong et al., 2008; Gogineni 2010; Broadstock et al., 2012; Zhang and Cao, 2013; Wen et al., 2014; Zhu et al., 2016). Cong et al. (2008) illustrate the interactive relationships between oil shocks and the Chinese stock market using multivariate vector auto-regression between January 1996 and December 2007. Their work shows that oil price shocks do not show any statistically significant impact on the actual equity returns of most Chinese equity indices, except for the manufacturing index and some oil companies. They suggest that certain "significant" oil shocks drive down the stock prices of oil companies.

Nandha and Faff (2008) analysed WTI oil price data and indices of 35 different industrial sectors between April 1983 and September 2005. They show that the increase in the price of oil has a negative impact on all economic sectors except for the oil and gas industry and the mining sector on the one hand. On the other hand, they do not detect any asymmetric effect from WTI variations. These results support the work of Brails-Ford and Faff (1999) on oil price changes and prices in the banking sector and the oil and gas sector Gogineni (2010) used the approach of ordinary least squares and quantile regression and with daily data from 1998 to 2006, to examine the effect of changes in oil prices on index sectors in the United States. These results show that the relationship between industry returns, and oil price change depends on both the cost and demand side dependence of oil and that the influence of these factors changes from industry to industry. Broadstock et al. (2012) demonstrate that energy-related stocks are more sensitive to shocks in the international crude oil market. Zhang and Cao (2013) explore the relationship between international oil price shocks and sectoral dynamics of the Chinese stock market. Their work shows that the behaviour and response of the Chinese stock market to international oil shocks differs significantly from the behaviour and responses of the European stock markets as documented in the literature. Firstly, in China, only the mining industry has a strong and consistent link to international oil shocks when systematic risk factors are controlled. Secondly, they find no clear evidence of asymmetries in China's sectoral stock-oil relationship. Wen et al. (2014) show evidence of significant and asymmetric spill overs between Chinese new energy and fossil fuel prices is found based on daily samples taken from August, 2006 to September, 2012. Zhu et al. (2016) use quantile regression methodology to assess the effects of changes in crude oil prices on real stock returns of Chinese industry from 1994 to 2014. They note that the interdependence between crude oil and market returns is positive and that the structure and the degree of interdependence vary according to the sectors. Based on the quantile regression model and monthly data over the period 1994 to 2013.

From the analysis of the literature, several conclusions can be drawn. First, there is a scarcity of research on the asymmetric relationship between oil prices and the sectoral indices of the West African Monetary Union (UMOA). Second, most of the work available focuses on the developed or emerging countries or on some African countries with a focus on the link between oil prices and global indices (Arrouri and Raoult , 2010; Gourene et al., 2019; Lv et al., 2020; Tiwari et al., 2021). Third, the stock market in WAMU includes countries with frontier markets which are characterized by low per capita income, indebtedness while displaying a high growth rate, young population, economic stability and acceptable geopolitics on the one hand. On the other hand, frontier markets are poorly correlated with each other (Gourene et al. 2019) and offer a higher return and lower volatility than emerging and more advanced markets because valuations, economic cycles and development of each country is at a different level and stage. Evidently these are riskier and restrictive markets with low liquidity or access by foreign investors, as well as wide gaps in valuations and corporate governance. These markets are still poorly correlated to developed and emerging markets. Their interest is to offer greater growth potential than developed markets. In addition to the recent discovery of oil and gas in Senegal (between 2014 and 2017) and Ivory Coast (in 2021) will make this economic zone a net oil exporting zone with gigantic benefits. Indeed, Senegal has the potential to produce between 2.5 to 4 billion barrels of crude oil and Cote d’Ivoire between 1.5 and 2 billion barrels. All these add to the factors we will examine in the relationship between oil prices and those of sector indices. Hence the formulation of the following hypotheses:

- H1: The fall in oil prices has a negative effect on the price of assets on the sectoral markets
- H2: The rise in oil prices has a positive effect on the price of assets on the sectoral markets
- H3: Changes in oil prices do not affect the prices of sector indices that are weakly dependent on oil

Thus, in the following, we will see the data and the methodologies used in our work.

3. Data and Methodologies

In this section, we discuss the data and the different methodologies used in our work.

3.1 Data

The data sets we use are weekly BRENT oil price data and BRVM sector index prices from October 26 to August 20, 2021. We opted for weekly data for better robustness of the results due to the difference in working days between the different exchanges (Sugimoto et al., 2014; Gourène et al., 2019) to the detriment of monthly (Joo and Park, 2021), intraday (Jawadi et al. 2015; 2016) and daily data (Diaz and Jareno, 2009).

Also, we chose BRENT oil price and sector indices prices for the following reasons: First, following Fasanya et al. (2021) BRENT oil futures price is the indicator of world oil price accounting for more than 30% of its world market. Most market analysts and decision makers in the world consider BRENT oil price trends when evaluating world oil prices. Prices for other crude oils are also calculated based on BRENT crude oil which remains the benchmark for other crude oil prices in Europe, Middle East and Africa hence their prices are at par with global oil price trends. . . BRENT is traded on international markets, notably in Rotterdam or on the US stock exchanges Intercontinental Exchange (ICE) and New York Mercantile Exchange (NYMEX). Second, we note that most of the other works examining the link between the price of oil and the financial markets focus on the global indices of these financial markets (Bachmeier, 2008; Arrouri and Raoult, 2010, Arrouri et al., 2011). This analysis has a major drawback, it fails to consider the heterogeneities that may exist within the global index insofar as the global index is an average of the intrinsic indices that compose it. Focusing on sector indices helps to overcome this problem. Our intuition is reinforced by the assertions of Arouri et al. (2012) who argue that the use of sectoral indices is advantageous because aggregate indices can mask the characteristics of different sectors.

Furthermore, it is interesting to note that the market in the WAMU zone is made up of several indices, including the BRVM 10 index, the BRVM Composite index and sector indices. The BRVM 10 index is the index that includes the activity of the ten companies with the largest market capitalization on the stock market on the Regional Stock Exchange (BRVM). Among these companies, we have: Total Côte d'Ivoire, Sonatel SN, or Ecobank Transnational Incorporated TG. In addition to the BRVM 10 index, the Regional Stock Exchange (BRVM) also includes the BRVM composite index (BRVMC) which brings together all the companies listed on this stock exchange. Alongside the BRVM 10 and the BRVM Composite are the sector indices that are the subject of our work. These sector indices (variables) are made up of companies according to the different sectors of activity. There are seven (07) sectors; industry (12 companies), public services (4 companies), finance (15 companies), transport (2 companies), agriculture (5 companies), distribution (7 companies) and other sectors (1 company). Thus, Table 1 summarizes the acronym, definition and sources of the variables used in our work.

Table 1: Choice of variables

Acronym	Definition	Sources
BRENT	BRENT Oil Price	Eikon Reuters DataStream
FINANCE	Stock market index relating to the financial sector	Eikon Reuters DataStream
INDUSTRIAL	Stock market index relating to the industries sector	Eikon Reuters DataStream
UTILITIES	Stock market index relating to the utilities sector	Eikon Reuters DataStream
TRANSPORTATION	Stock market index relating to the transport sector	Eikon Reuters DataStream
OTHERS	Stock market index relative to other sectors	Eikon Reuters DataStream
DISTRIBUTION	Stock market index relating to the distribution sector	Eikon Reuters DataStream
AGRICULTURAL	Stock market index relating to the agriculture sector	Eikon Reuters DataStream

3.2 Methodologies

To carry out our work, we first use the associated kernel method (Wansouwé et al., 2016; Doho et al., 2022) followed by the nonlinear autoregressive method with distributed delays (NARDL) proposed by Shin et al. (2014).

3.2.1 Asymmetric kernel Method

In this data-driven method, we use the log-normal (LN), gamma (G) and reciprocal inverse Gaussian (RIG) kernels because our data are continuous, non-negative and not normally distributed. These associated (asymmetric) kernels are already available in the *Ake* package for the smoothing of density and regression functions with continuous (nonnegative) and dicrete (count, categorical) supports of data and are are summarized in Table 1. Considering the relation between a response variable Y and an explanatory variable x given by:

$$Y = m(x) + \varepsilon \qquad (1)$$

where m is the unknown regression function from $\mathbb{T} \subseteq \mathbb{R}$ *to* $\mathbb{R}$ and ε the disturbance term with null mean and finite variance. Let $(X_1, Y_1), \dots, (X_n, Y_n)$ be a sequence of independent and identically distributed (iid) random variables on $\mathbb{T}$ X $\mathbb{R}\,(\subseteq \mathbb{R}^2)$ with $m(x) = \mathbb{E}(Y|X = x)$ of (1). The regression estimator $\widehat{m}_n$ of m from Nadaraya (1964) and Watson (1964) using associated kernels is:

$$\widetilde{m}_n(x;h) = \sum_{i=1}^{n} \frac{Y_i K_{x,h}(X_i)}{\sum_{i=1}^{n} K_{x,h}(X_i)} = \widetilde{m}_n(x), \qquad \forall x \in \mathbb{T}_1 \subseteq \mathbb{R} \qquad (2)$$

where $h \equiv h_n$ is the bandwidth parameter such that $h_n \longrightarrow 0$ as $n \longrightarrow \infty$. The reader can refer, for example, to Kokonendji and Somé (2018, 2021) and recently Essatafa et al. (2023) for density smoothing studies in continuous and discrete cases, respectively Let us extend the definition by Esstafa et al. (2023) including both continuous and discrete cases.

Definition 1. Let $\mathbb{T} \subseteq \mathbb{R}$ be the support of the regression function, to be estimated; $x \in \mathbb{T}$ a target and h a bandwidth. A parametrized probability density or mass function (pdmf) $K_{x,h}(.)$ of support $\mathbb{S}_{x,h}(\subseteq \mathbb{R})$ is called "associated kernel" if the following conditions are satisfied:

$$x \in \mathbb{S}_{x,h}, \lim_{h\to 0} \mathbb{E}(z_{x,h}) = x, and \lim_{h\to 0} Var(z_{x,h}) = \mu \in [0,1),$$

where $z_{x,h}$ denotes the random variable with pdmf $K_{x,h}$. In practice, the Ake package of Wansouwé et al. (2016) is used with the three continuous associated kernels; gamma (G), lognormal (LN) and reciprocal inverse Gaussian (RIG). See Doho et al. 2022 for a review and an application of these associated kernels to inflation and sectoral stock price indices and also Kokonendji and Somé (2021), for a review of the main univariate kernels is continuous in the literature. These three asymmetric kernels also satisfy Definition 1; see Table 1.

Table 1. Semicontinuous univariate associated kernels on $\mathbb{S}_{x,h} \subseteq [0,\infty)$ available in *Ake* package

Name	$K_{x,h}(u)$	$\mathbb{E}(z_{x,h})$	$Var(z_{x,h})$
LN	$(uh\sqrt{2\pi})^{-1}\exp(\[\log\{x\exp(h^2)\} - \log u]/2h^2)$	$x[\exp(3h^2/2)]$	$x^2\exp(3h^2)[\exp(h^2) - 1]$
G	$h^{-1-x/h}u^{x/h}\exp(-u/h)/\Gamma(1+x/h)$	$x+h$	$(x+h)h$
RIG	$(\sqrt{2\pi uh})^{-1}\exp\{[x-h][2-(x-h)/u-u/(x-h)]/2h\}$	$\sqrt{x^2+xh} - x + h$	$h\left\{\sqrt{x^2+xh}+2h\right\}$

$\Gamma(v) := \int_0^\infty s^{v-1}\exp(-s)ds$ is the usual gamma function with $v > 0$.

In kernel regression, the bandwidth (tuning) parameter selection, which controls the degree (accuracy) of smoothing, is obtained here by unbiased cross-validation (UCV) and implemented in the *Ake* package; see, for instance, Somé (2022) for a Bayesian approach. Thus, for a given associated kernel, the optimal bandwidth (smoothing) parameter $\hat{h}_{ucv} = \arg min_{h>0}\, UCV(h)$ with

$$UCV(h) = \frac{1}{n}\sum_{i=1}^{n}\{Y_i - \widetilde{m}_{-i}(X_i)\}^2$$

where $\widetilde{m}_{-i}(X_i)$ is computed as $\widetilde{m}_n$ of (2) excluding X_i. We check the accuracy of the regression model using the practical coefficient of determination R^2 with the response variable Y_i and the non-intercept regressor x_i:

$$R^2 = \frac{\sum_{i=1}^{n}\{\widetilde{m}_n(x_i) - \bar{y}\}^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}, \qquad (4)$$

with $\bar{y} = n^{-1}(y_1 + \cdots + y_n)$. All numerical and graphical computations are performed using the Ake package on the R software; see R Development Core Team (2022).

3.2.2 NARDL Method

The NARDL model is a non-linear version of the ARDL model. In this model proposed by Shin et al. (2014), we take the autoregressive representation of Pesaran et al. (2001) and incorporate asymmetric effects in the short and long-run to account for the asymmetry in the relationship between oil price (BRENT) and sectoral stock price. Because of these advantages, the NARDL method has recently been used to perform rigorous nonlinear analysis in various studies in the energy literature (Tugcu and Topcu, 2018). The nonlinear cointegration regression (Shin et al., 2014) is specified as:

$$stock\_price_t = \beta^+ brent_t^+ + \beta^- brent_t^- + \mu_t, \qquad (5)$$

where β^+ and β^- are the long-term parameters of $k{\times}1$ vector of $brent_t$ regressors decomposed as:

$$brent_t = brent_0 + brent_t^+ + brent_t^-, \qquad (6)$$

with $brent_t^+$ $(resp. brent_t^-)$ being the decomposition of the variables oil price (brent) into its positive (resp. negative) partial sums

$$brent_t^+ = \sum_{j=1}^{t} \Delta brent_t^+ = \sum_{j=1}^{t} \max(\Delta brent_j, 0), \quad (7)$$

$$brent_t^- = \sum_{j=1}^{t} \Delta brent_t^- = \sum_{j=1}^{t} \min(\Delta brent_j, 0), \quad (8)$$

Where $\Delta brent_t^+$ (resp. $\Delta brent_t^-$) reflect increases (resp. decreases) of oil price (brent). The *NARDL (p, q)* form of the Eq. (6), in the form of asymmetric error correction model can be specified as:

$$\Delta stock\_price_t = \tau \; stock\_price_{t-1} + \phi^+ brent_{t-1}^+ + \phi^- brent_{t-1}^- + \sum_{j=1}^{p-1} \lambda_j \Delta stock\_price_{t-j} + \sum_{j=0}^{q} \gamma_j^+ \Delta brent_{t-j}^+ + \sum_{j=0}^{q} \gamma_j^- \Delta brent_{t-j}^- + \varepsilon_t \quad (9)$$

With $\phi^+ = -\tau \; \beta^+$ and $\phi^- = -\tau \; \beta^-$. According to Raza et al. (2016) in nonlinear framework, the first two steps, to ascertain cointegration between the variables, are same as in linear ARDL bound testing procedure *i.e.,* estimating Eq. (9) using ordinary least-squared (OLS) and conducting the joint null $(\tau = \phi^+ = \phi^- = 0)$ hypothesis test. However, in NARDL, the Wald test is used to examine the long-run $(\phi^+ = \phi^-)$ and short-run $(\gamma_j^+ = \gamma_j^-)$ asymmetries in the relationship. Finally, the asymmetric cumulative dynamic multiplier effect of any unit changes in $brent^+$and $brent^-$ on $stock\_price_t$ is examined respectively as follows:

$$m_b^+ = \sum_{j=0}^{h} \frac{\partial stock\_price_{t+j}}{\partial brent_t^+}, m_b^- = \sum_{j=0}^{h} \frac{\partial stock\_price_{t+j}}{\partial brent_t^-}, b = 1, 2, 3, \ldots$$

With $b \to \infty$, $m_b^+ \to \beta^+$ and $m_h^- \to \beta^-$. The asymmetric long-term coefficients for $brent_t^+$ and $brent_t^-$ are respectively β^+ and β^- and can be calculate as $\beta^+ = -\frac{\phi^+}{\tau}$ et $\beta^- = -\frac{\phi^-}{\tau}$.

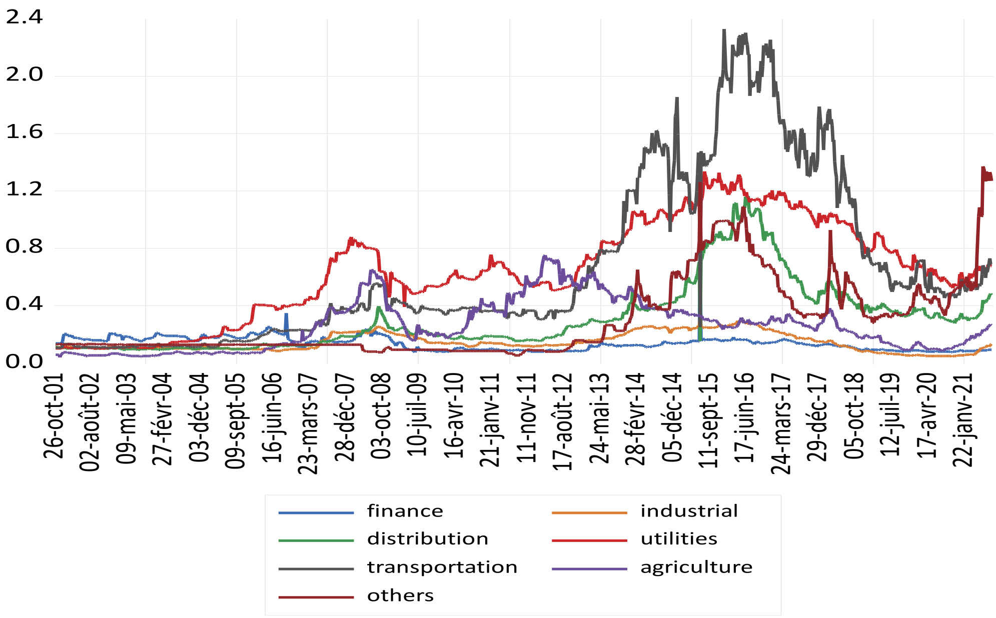
4. Empirical results

In this section, we present the empirical results from the kernel method and the NARDL method.

4.1 Descriptive statistics

The evolutions of the BRENT oil price and the sector indices are represented respectively by figures 1 and 2 below. According to these figures, BRENT oil prices and those of the sector indices are generally unstable. These chronicles seem non-stationary in mean and in variance. Specifically, BRENT oil prices and those of sector indices follow a general upward multiplicative trend from October 2001 to October 2008 before suffering drastic drops, mainly due to the subprime crisis (Enwereuzoh et al., 2021). This is followed by a second multiplicative price increase which peak in 2012 and 2016 for BRENT oil and sector indices respectively. We also observe that BRENT oil prices suffered two sharp drops in 2015 and in 2020 on the one hand and on the other hand a similar occurrence to the prices of sector indices which suffered a severe drop in 2020. This latest decline could be explained to be due to the recent coronavirus health crisis which began in December 2019 in China and then spread across the world, inflicting a free fall on world stock markets. These intuitions can be reinforced by the application of unit root tests. But before performing the unit root tests, we will first discuss the results of the descriptive statistics (Table 2).

1. Evolution of the price of oil (BRENT)



2. Evolution of sector index prices

Table 2: Descriptive statistics

	Obs.	Mean	Maximum	Minimum	St-dev	Skewness	Kurtosis	Jacque-Bera
BRENT	1031	53.50	96.07	19.81	18.77	0.21	2.17	37.16***
FINANCES	1031	0.13	0.79	0.79	0.04	2.82	36.94	508889***
INDUSTRIAL	1031	0.14	0.32	0.32	0.06	0.55	2.22	79.43***
UTILITIES	1031	0.63	1.33	1.33	0.33	0.003	2.06	37.66***
TRANSPORTATION	1031	0.65	2.32	2.32	0.58	1.18	3.25	243.88***
OTHERS	1031	0.29	1.37	1.37	0.26	1.56	4.96	583.56***
DISTRIBUTION	1031	0.30	1.16	1.16	0.23	1.62	5.24	668.49***
AGRICULTURAL	1031	0.26	0.75	0.75	0.17	0.67	2.61	83.99***

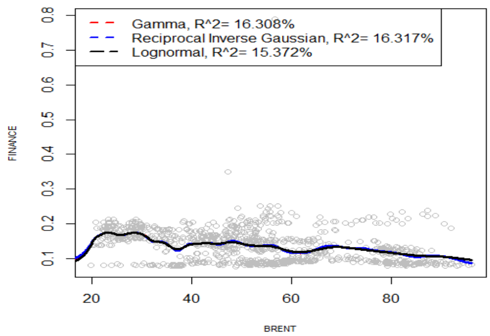
Source : Auteurs, à partir du logiciel Eviews 12
BRENT : inflation, DISTRIBUTION : sector of distribution, FINANCES : financial sector, INDUSTRIAL : industrial sector, UTILITIES : utilities sector, AGRICULTURAL : agricultural sector, TRANSPORTATION : transportation sector, OTHERS : others secteurs.
**** significatif à 1%*

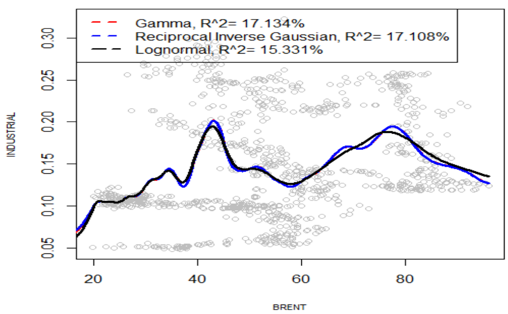
According to Table 2, the average BRENT oil price is €53.50 with an estimated standard deviation of 18.77 (greater than 5), an indicator of oil price volatility. Then, we observe that the standard deviations of the sector indices are all low (less than 5) varying between 0.04 and 0.58 for the financial and transport sectors respectively. These results show a stability of the prices of the sectoral indices of the WAMU zone and even a low volatility of the financial market of the WAMU zone (Gourene and Mendy, 2018). This suggests that the WAMU financial market (BRVM) is small offering very few and fairly negotiable securities. In addition, the average prices of the sector indices vary from lows of 0.13 and 0.14 to 0.63 and 0.68 as the highest. The financial and industrial sectors dominate the lower spectrum while public service and transport sector are on the higher end.

The asymmetry coefficients (skewness) of all the series differ from zero (theoretical value of the skewness coefficient for a normal distribution) to positive, illustrating the presence of asymmetry. The existing asymmetry can be an indicator of non-linearity insofar as we know that linear Gaussian models are essentially symmetric (Lardic and Mignon, 2002). This also shows that the distributions of our series are spread to the right. Therefore, the series reacts more to a positive shock than to a negative shock. Then, the kurtosis coefficients of BRENT, industry, utilities, and agriculture are found to be less than 3 (value of the kurtosis coefficient for a normal distribution). Whereas the kurtosis coefficients of the financial sector, distribution, public services, transport, and other sectors, are higher than 3. The excess of kurtosis attests to a strong probability of occurrence of extreme points (Lardic and Mignon 2002) largely for the financial sector whose kurtosis coefficient is equal to 36.94. Finally, Jarque-Bera tests reject the null hypothesis that all series are normally distributed. This last result is a common characteristic of financial series (Dutta et al., 2017) confirming our choice of a non-linear model.

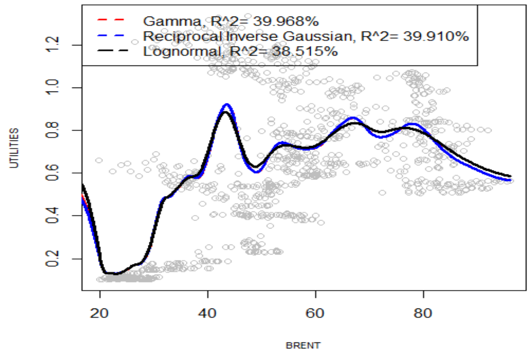
4.2 Results of the kernel method

The results of the kernel method are contained in graphs A.1 to A.7 below.

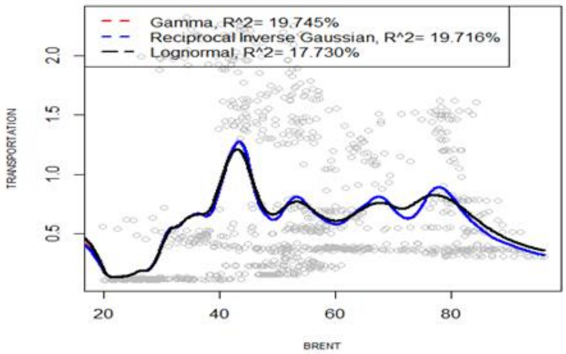




Graph A.1: Link between the price of BRENT oil and stock prices in the FINANCIAL sector
Graph A.2: Link between the price of BRENT oil and stock prices in the

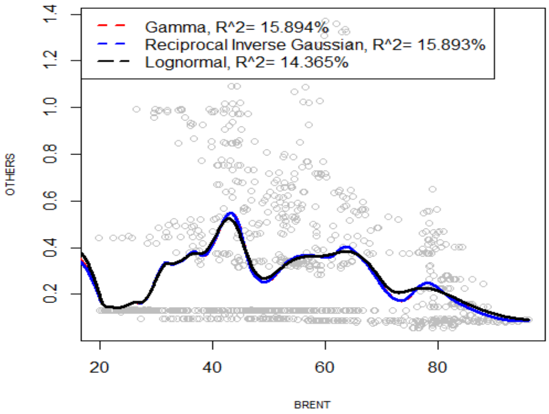


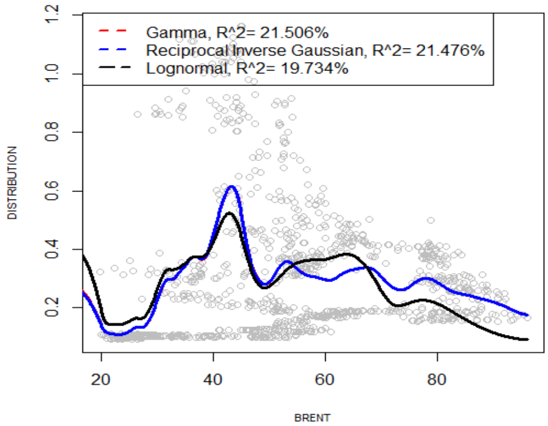
INDUSTRIAL sector



Graph A.3: Link between the price of BRENT oil and prices of stocks in the utilities sector

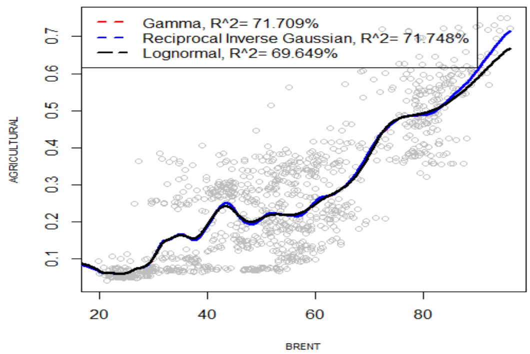
Graph A.4: Link between the price of oil BRENT and prices of stocks in the TRANSPORT sector





Graph A.5: Link between the price of BRENT oil and the prices of shares in the other sectors

Graph A.6: Link between the price of BRENT oil and the prices of shares in the distribution sector



Graph A.7: Link between the price of BRENT oil and the prices of agricultural stocks

All the graphs clearly show that the link between the prices of oil and sector indices is not linear. Hence, influencing the use of nonlinear modelling as highlighted in several works (Anoruo, 2011; Lee and Lin, 2012; Naifar and Al Dohaiman, 2013; Bildirici and Turkmen, 2015). For example, Anoruo (2011) reviews the procedure for testing linear and nonlinear models and states that a fundamental limitation of linear modelling is that it fails to capture asymmetry in the behaviour of variables over time. Lee and Lin (2012) further explain that macroeconomic variables are affected by structural breaks and that oil and gold prices follow a nonlinear pattern. Naifar and Al Dohaiman (2013) go on to document that linear models fail to detect existing non-linearities in the relationship between stocks, oil and gold prices. Bildirici and Turkmen (2015) also find that the explanatory power of nonlinear models is greater than that of linear models. Finally, Rafiq and Bloch (2016) argue that the linearity or symmetry assumption is too restrictive, as in many cases there is potentially an asymmetric (non-linear) structure subject to the magnitude and direction of impacts. Asymmetries may reflect institutional arrangements, such as price cap regulation, and market structure (such as marketing cartels) or how production capacity reacts differently to positive and negative changes in current market conditions.

Over the past two decades, new methods have been developed in econometric literature to deal with nonlinearity (Pesaran et al., 2001; Hansen and Seo, 2002; Psaradakis et al., 2004; Kapetanios et al., 2006; Shin et al., 2014). We use one of these methods to deal with the impact of oil prices on those of sector indices in the WAMU space. In the following, the results of the NARDL model are presented and in following with the recommendations of Eggoh (2008) all variables were transformed into logarithms. We then proceeded to the evaluation[1] of the stationarity properties of our variables applying two-unit root tests which are the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. The results of the ADF and PP test show that all our variables are stationary in first difference (in appendix 1). Therefore, they are integrated of order 1.

[1] Also, Preliminary tests (stationarity tests, Pearson correlation matrix) were carried out by integrating the positive and negative partial sums of oil (increase/decrease) and showed that these variables were integrated of order 1 firstly and are also weakly correlated with the variables of the model secondly. The results of these tests are available on request from the authors.

4.3 Results of the NARDL method

In this part, we present the results of the cointegration test at the terminals (see table 3) while in table 4 the results of the estimates of the NARDL modelling are reported. The FPSS test refers to the F statistic proposed by Pesaran et al. (2001) to test the null hypothesis of no cointegration, while the tBDM test is the t-statistic proposed by Banerjee et al. (1998) to test the null hypothesis of no long-term relationship.

4.3.1 Results of bounds testing cointegration

In Table 3, we notice that the two tests do not confirm the presence of a long-term non-linear relationship between oil prices and the indices of some sectors - industry, public service, transport, distribution and other - because, for example, the calculated F-statistics are below the critical limit of less than 10%. However, we find evidence of a cointegration relationship between the oil price and the finance sector on the one hand and on the other hand between the oil price and the agriculture sector because the calculated F-statistics are above the critical limit of less than 10%.

Table 3: Bounds testing cointegration tests

	t_{BDM} statistics	F_{PSS} statistics	Results
Brent and **Finance**	**-2.9210****	**2.8719***	**Cointegration**
Brent and Industrial	-1.5264	0.8213	No cointegration
Brent and Public service	-1.4194	2.3449	No cointegration
Brent and Transport	-1.6134	1.8016	No cointegration
Brent and Others	-1.5237	1.3176	No cointegration
Brent and Distribution	-1.1817	1.4305	No cointegration
Brent and **Agriculture**	**-2.6709***	**2.5965***	**Cointegration**

*Note: * indicate significance at 10% level, ** indicate significance at 5% level, *** indicate significance at 1% level. For tBDM test the critical values are -2.57 and -4.04, -2.86 and -4.38, -3.43 and -4.99 for 10%, 5% and 1%, respectively. For FPSS the critical values are 1.99 and 2.94, 2.27, and 3.28, 2.88 and 3.99 for 10%, 5%, and 1%, respectively. See Pesaran, M. H., Shin, Y., and Smith, R. J. (2001).*

In Table 4, the empirical model validation tests, namely the Portmanteau tests, confirm the absence of any correlation existing between the residuals for all the estimates except for columns 1.2 and 1.3. The Jacque-Bera (JB) tests validate the absence of normality of the residuals for all our estimates. However, we accept this hypothesis of normality of the residuals by applying the law of large numbers. Then, the Breusch/Pagan tests and the Ramsey functional form tests (RESET) respectively show the presence of homoscedasticity and confirm that the functional forms of our specifications are not correct for all our estimates except that of column 1.7. Thus, the estimate in column 1.7 is empirically valid insofar as it is supported by almost all empirical validation tests. Moreover, there is no cointegration relationship between oil prices and those of the indices of the industry sector, public service, transport, distribution, and other sectors. Apart from the estimates associated with these models not being empirically valid, our analyses and interpretations will focus on the possible asymmetric impact of variations in crude oil prices on agricultural sector prices. Nevertheless, we included all the results of our estimates in Table 4. Evidently, the variations in the price of oil have a negative but statistically insignificant effect on the financial sector prices (see table 4, column 1.1) in the short term. The long-term coefficients of variations in oil prices are statistically insignificant on the finance sector. These results indicate that variations in the finance sector are not affected by variations in oil prices, thus confirming arguments made elsewhere that the price of oil has had no effect or that its effects are ambiguous on stock prices (Apergis and Miller, 2009; Huang et al., 2017). This result can be explained in several ways, mainly the level of use of oil in the activity of the companies concerned. First, it is worth noting that most companies listed on the BRVM are from Ivory Coast, which represents 40% of GDP and owns the only oil refinery in the West African Monetary Union (UMOA) and the other companies listed are from countries that import energy from Ivory Coast. Secondly, oil is not a main resource in the production or goods and services by these companies, their main source of energy is thermoelectric power produced from natural gas and compressed air from the OCEAN Energy, CNR (Canadian Natural Resources) and FOXTROT platforms (Kouakou, 2011). Consequently, any oil price variations can only have a lesser or even insignificant impact on the production costs and the energy bill of these companies, hence an insignificant effect on the sector indices prices linked to these companies. We also observe that variations in the price of oil have statistically positive and significant effects on prices in the agricultural sector (see Table 4, column 1.7) in the short term. Our estimates show that negative variations have a greater impact than positive variations because the coefficient of negative variations is higher (+0.01424) in terms of magnitude than that of positive variations (+0.01421). Also, the Wald test (in Table 4) highlights an asymmetry between oil prices and those of the agricultural sector only in the short term (see Table 4, column 1.7). These results corroborate others who have highlighted that an asymmetric relationship exists between oil prices and financial market variations (Jones and Kaul, 1996; Gjerde and Sættem, 1999; Driesprong et al., 2008; Chen, 2009; Miller and Ratti, 2009; Filis, 2010, Jiang and Liu 2021) . Thus, we can argue that agricultural sector prices react positively and asymmetrically to the rise or fall of oil prices in the short term. We observe significant long-term coefficients of variations in oil prices on the agricultural sector. Our estimates reveal that in the long-term negative variations in oil prices have a negative and statistically significant impact estimated at -1.458. Any positive variations in oil prices have a positive and statistically significant effect on agricultural sector prices, estimated at +1.456. Similar to the short term, we observe that the negative impact is of oil prices higher than its positive impact on agriculture sector prices. Next, Figure B.1 plots the cumulative dynamic response of agricultural sector prices following an oil price shock. Firstly, the cumulative response from the agriculture sector prices following a positive and negative oil price shock is asymmetric in the short-run and symmetric in the long run. Specifically, the cumulative dynamic price response of the agriculture sector following a positive oil price shock is negative and instantaneously declined to reach a threshold after a two-week period but then gradually attained a positive after a ten-week period. As for the cumulative dynamic price response of the agriculture sector following a negative oil price shock, it declines sharply (similar to the positive oil price shock) and remains negative throughout the shock. These results suggest a delayed effect of the real impact of positive and negative oil price shocks on agricultural sector prices and could be explained through the under-response theory or the gradual diffusion hypothesis and empirically through the work of Rafiq and Bloch (2016) (Driesprong et al., 2008; Phan et al., 2015). Indeed, the gradual diffusion hypothesis argues that changes in oil prices should impact financial markets with a lag and supported by the under-reaction theory (Jones and Kaul, 1996; Driesprong et al., 2008; Narayan and Sharma, 2011; Narayan and Sharma, 2014). Empirically this shows evidence of a lagged effect of oil price changes on stock market returns. These studies argue that this type of relationship between changes in oil prices and stock market returns is rooted in the progressive information diffusion hypothesis proposed by Hong and Stein (1999) and Hong et al. (2007). This hypothesis states that investors underreaction to the price of crude oil occurs when: (a) changes in oil prices have a substantial effect on economic activity and investors find it difficult to assess the impact of information on the value of shares; and (b) when investors react to information at different times, which, as Narayan and Sharma (2011) argue, may be the result of some investors being relatively more cautious about the information than others. Overall, with (a) and (b), it's clear that because investors don't react strongly enough to new information and investor reaction takes time, they underreact when they receive information on oil prices. In addition to the gradual diffusion hypothesis, the cumulative dynamic responses of agricultural sector prices following positive and negative oil price shocks find their answers in the empirical work of Rafiq and Bloch (2016). According to them, in the immediate term, the price of oil lessens the impact of the fall in the prices of many basic products. Their long-run asymmetry test results also indicate that a positive oil price shock raises the prices of at least 20 commodities. In contrast, a decline in the price of oil lowers long-term prices to the five percent significance level for wheat, corn, and aluminium only. Moreover, their results of the asymmetric Granger causality test indicate that a negative shock to oil prices causes a decline in the prices of at least 13 commodities, while a positive shock to oil prices causes an increase in prices of only three raw materials. Their results reveal that oil prices have a substantial impact on non-food agricultural commodities and metal prices, even after controlling for potential endogeneity suggesting a link through the use of commodities as raw materials, first in industrial production. Moreover, our results confirm the work of Paris (2018) who investigate the long-term effect of the price of oil on agricultural commodity prices by accounting for the influence of biofuel production. Relying on the estimation of nonlinear, cointegration regime-switching processes, he show that biofuel development has led to an increase in the oil-price effect on agricultural commodity prices. indeed, the growing production of biofuels is contributing to the price rise of agricultural commodities. Thus, the increase (decrease) in the prices of agricultural products will affect the profits of the companies that market these raw materials and impact (increase / decrease) the price indices linked to the agricultural sector. Hence, agricultural commodities can be considered as transmission channels through which oil prices affect agricultural sector indices. The consequence of this conclusion is that the cointegration relationship found previously between oil prices and those of the agricultural index is in fact explained by the cointegration relationship between oil prices and agricultural commodities such as rubber, palm oil, sugar cane, coconut. These results also confirm several empirical studies (Nazlioglu, 2011; Nazlioglu and Soytas, 2012; Gupta et al., 2014; Gozgor and Kablamaci, 2014) which have highlighted a cointegration relationship between oil prices and commodity prices of agricultural raw materials.

4.3.2 Results of the NARDL method estimates

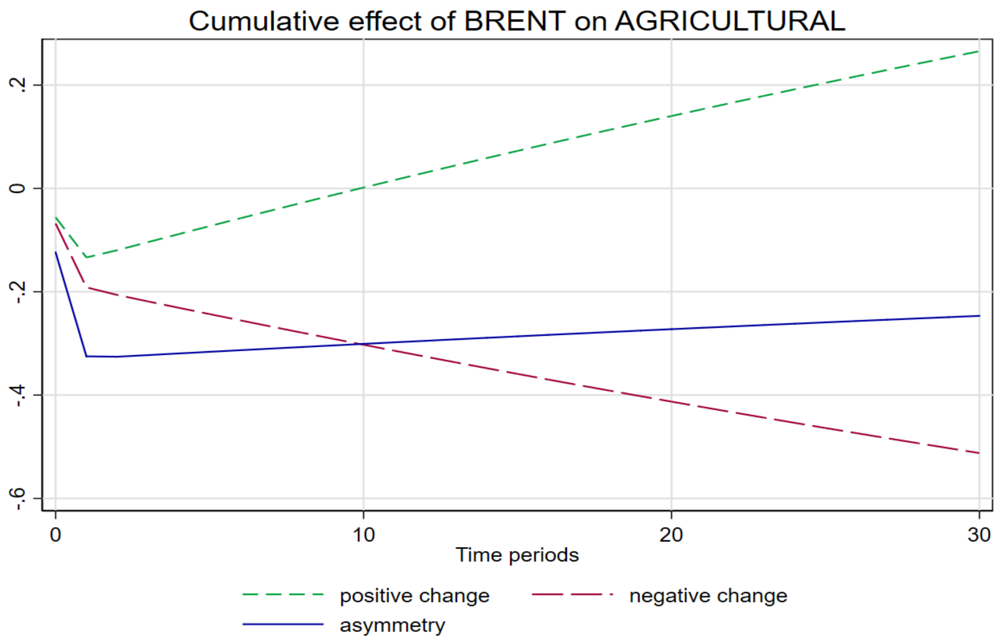
Table 4 presents the results of the NARDL estimates examining the link between oil prices and those of sector indices.

Table 4: Relationship between BRENT and sector indices

	(1.1) Financial	(1.2) Industrial	(1.3) Utilities	(1.4) Transportation	(1.5) Others	(1.6) Distribution	(1.7) Agricultural
Short term coefficients							
y_{t-1}	-0.029*** (-2.921)	-0.003 (-1.526)	-0.004 (-1.419)	-0.008 (-1.613)	-0.005 (-1.524)	-0.006 (-1.182)	-0.010*** (-2.671)
$brent^{+}_{t-1}$	-0.007 (-0.850)	0.002 (0.772)	0.005 (1.162)	0.014* (1.648)	-0.002 (-0.403)	0.011* (1.659)	0.01421* (1.791)
$brent^{-}_{t-1}$	-0.006 (-0.696)	0.002 (0.781)	0.005 (1.219)	0.014 (1.598)	-0.003 (-0.555)	0.011 (1.552)	0.01424* (1.779)
Δy_{t-1}	-0.421*** (-13.206)	0.062** (1.992)	-0.132*** (-4.274)	-0.418*** (-13.499)	0.152*** (4.895)	-0.493*** (-15.915)	0.019 (0.621)
Δy_{t-2}	-0.205*** (-6.082)	0.117*** (3.748)		-0.175*** (-5.663)		-0.194*** (-6.313)	
Δy_{t-3}	-0.085*** (-2.705)						
$\Delta brent^{+}$	-0.019 (-0.194)	-0.018 (-0.519)	0.040 (0.883)	0.040 (0.372)	-0.007 (-0.101)	-0.023 (-0.265)	-0.056 (-0.837)
$\Delta brent^{+}_{t-1}$	-0.117 (-1.201)	0.008 (0.250)	0.022 (0.508)	0.026 (0.247)	-0.092 (-1.447)	0.028 (0.336)	-0.091 (-1.438)
$\Delta brent^{+}_{t-2}$	-0.059 (-0.621)	-0.025 (-0.771)		-0.146 (-1.426)		0.016 (0.198)	
$\Delta brent^{+}_{t-3}$	0.000 (0.005)						
$\Delta brent^{-}$	0.053 (0.617)	0.067** (2.256)	-0.041 (-1.061)	-0.066 (-0.710)	0.043 (0.771)	0.015 (0.199)	0.068 (1.195)
$\Delta brent^{-}_{t-1}$	0.092	0.017	0.071*	0.062	0.003	0.088	0.109*

	(1.1) Financial	(1.2) Industrial	(1.3) Utilities	(1.4) Transportation	(1.5) Others	(1.6) Distribution	(1.7) Agricultural
	(1.042)	(0.570)	(1.764)	(0.649)	(0.044)	(1.155)	(1.830)
$\Delta brent^-_{t-2}$	0.106	-0.023		-0.008		0.038	
	(1.191)	(-0.730)		(-0.079)		(0.492)	
$\Delta brent^-_{t-3}$	-0.046						
	(-0.511)						
Constant	-0.016**	-0.002	-0.002	-0.006	-0.005	-0.007	-0.008
	(-2.191)	(-0.985)	(-0.529)	(-1.032)	(-1.305)	(-1.074)	(-1.536)
Long term coefficients							
Long run effect +	-0.237	0.721	1.212	1.791	-0.458	1.786	1.456***
	[0.7818]	[0.6139]	[2.109]	[1.717]	[0.2021]	[0.9028]	[7.741]
Long run effect -	0.198	-0.753	-1.248	-1.766	0.675	-1.736	-1.458***
	[0.5107]	[0.6279]	[1.983]	[1.506]	[0.4204]	[0.7951]	[7.315]
Asymmetrics tests (Wald tests)							
Long term	4.11**	0.245	0.106	0.0547	6.397**	0.2573	0.002867
Short term	2.804*	1.613	0.1306	0.08069	1.218	0.3939	5.983**
Observations	1027	1028	1029	1028	1029	1028	1029
Adjusted R^2	0.163	0.019	0.022	0.154	0.021	0.200	0.012
P	0.000	0.001	0.000	0.000	0.000	0.000	0.009
Diagnostics tests							
Portmanteau test up to lag 40 (chi2)	16.267	53.812	36.370	54.766	51.390	22.095	27.982
p-value	1.000	0.071	0.634	0.060	0.107	0.990	0.924
Breusch/Pagan heteroskedasticity test (chi2)	4108.837	81.270	788.972	2895.438	1154.240	1115.340	0.835
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.361
Ramsey RESET test (F)	134.690	2.755	88.149	118.418	1.629	130.031	0.688
p-value	0.000	0.041	0.000	0.000	0.181	0.000	0.559
Jarque-Bera test on normality (chi2)	2480497	13523	67365	1846915	22974	3157842	9506.351
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000

*Note: * indicate significance at 10% level, ** indicate significance at 5% level, *** indicate significance at 1% level.*



Graph B.1: Cumulative effect of BRENT oil prices on agricultural sector price

1. Implications of our results

Our work leads to the revelation of economic and investment implications in WAMU economies. We observe that WAMU economies are vulnerable to variations in oil prices. For instance, the agricultural sector, which is highly sensitive to variations in oil prices, represents more than 20% of the GDP of the leading economies in the WAMU zone. The majority of WAMU economies are dependent on this sector. Thus, WAMU economies risk weakening their stability where the agricultural sector is exposed to variations in oil prices. The results of our work refine Abdullahi and Rui's (2020) findings that there is no cointegrate relationship between oil and the West African financial market (BRVM). According to them, economic activity in the WAMU zone seems sheltered from variations in oil prices. Observing from a sectoral point of view, the authors' conclusions can be nuanced by ours. It is very likely that any links between oil and the BRVM may not be detected when monitoring the global index. However, the results on the sector indices indicate the impacts, influences or sheltering of the different sectors due to oil price variations. Our results also reveal some strategies and behaviour of investors in response to fluctuations in oil prices. Investors are either risk averse or risk tolerant; their portfolios should include company shares from industrial, distribution, transport, public services, and other sectors or company shares from the agricultural sector respectively. Subsequently an increase in oil prices translates to high gains for the risk tolerant investors. Otherwise, they face huge losses in the event of a continued decline in the price of oil. However, they can strategically protect their investments through researching information from OPEC meetings, central banks, climatic conditions, geopolitical situation or the global supply and demand (Cheema and Scrimgeour, 2019; Chkir et al. 2020, Fasanya et al., 2021) or they can hedge by buying risk hedging instruments. Investors neutral to fluctuations in oil prices will rather opt diversified portfolios by include shares from companies in the agricultural sector as well as shares from sectors that are weakly impacted by fluctuations in oil prices.

2. Conclusion

In this work, we test the price sensitivity of sector indices to changes in the oil price over the period 2001 to 2021 using the kernel method and the nonlinear autoregressive method with distributed lags (NARDL) as proposed by Shin et al. (2014), which captures both short- and long-term nonlinearities through positive and negative partial sum decompositions of the explanatory variables. The kernel method estimates show that there is a non-linear relationship between the price of BRENT oil and the prices of the sector indices. As for the NARDL regressions, they show that variations in oil prices do not have a statistically significant impact on West African sectoral stock prices, with the exception of the financial and agriculture sectors. These results are explained by the policies in terms of energy mix undertaken by the public authorities of this economic zone, which is strongly dominated by natural gas on the one hand, and on the other hand by the low dependence of oil in the production costs of companies in these industries. Finally, we find only a short-term asymmetry and a cointegration relationship between the price of oil and the agricultural sector. This cointegration relationship between oil prices and prices in the agricultural sector finds its explanation in the cointegration relationship between oil prices and the prices of raw materials used by companies in this sector of activity. These results are robust and can serve as decision support tools for financial market players in their investment strategy. Finally, it would be interesting to deepen our work by focusing on the relationship between oil prices and the prices of the companies that make up each sector index.

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Appendix

Appendix 1: Stationarity test

	Dickey-Fuller's test			Phillip-Perron's test		
	No intercept and no trend	With intercept and no trend	With intercept and trend	No intercept and no trend	With intercept and no trend	With intercept and trend
Brent *D.brent*	0.3709 -22.393***	-2.64 -22.396***	-2.56 -22.395***	0.29 -31.843***	-2.66 -31.8402***	-2.65 -31.841***
Finance *D.Finance*	-0.22 -31.61***	-2.77 -31.60***	-3.63 -31.59***	-0.03 -47.19***	-2.76 -47.17****	-3.87 -47.15****
Industrial *D.industrial*	-0.43 -19.34***	-1.06 -19.33***	-1.07 -19.32***	-0.42 -29.77****	-1.02 -29.76***	-1.03 -29.75***
Utilities D.utilities	-2.96 -24.06***	-2.31 -24.16***	-0.82 -24.32***	-2.84 -36.49***	-2.24 -36.48***	-0.90 -36.73***
Transport D.transport	-1.82 -31.45***	-1.61 -31.48***	-1.58 -31.49***	-1.82 -47.20***	-1.72 -29.76***	-1.97 -47.22***
Others D.others	-1.15 -20.49***	-0.24 -20.52***	-1.66 -20.56***	-1.15 -27.51***	-0.05 -27.54***	-1.47 -27.57***
Distribution D.Distribution	-1.37 -32.65***	-1.19 -32.67***	-1.98 -32.66***	-1.32 -50.54***	-1.39 -50.56***	-2.40 -50.53***
Agricultural D. Agricultural	-1.48 -21.67***	-1.62 -21.68***	-1.35 -21.70***	-1.48 -31.241***	-1.61 -31.249***	-1.33 -31.26***

*Note: * indicate significance at 10% level, ** indicate significance at 5% level, *** indicate significance at 1% level.*

Appendix 2: Pearson Correlation

	BRENT	FINANCE	INDUSTRIAL	UTILITIES	TRANSPORTATION	OTHERS	DISTRIBUTION	AGRICULTURE
BRENT	1.0000	0.4061*	0.2579*	0.6600*	0.4396*	0.0354	0.2907*	0.8002*

*Note: * indicate significance at 10% level, ** indicate significance at 5% level, *** indicate significance at 1% level.*