Journal of Academic Research in Economics

Volume 10 Number 3 December 2018

ISSN 2066-0855

PROOFREADERS

MIHAELA BEBESELEA, Spiru Haret University
ONORINA BOTEZAT, Spiru Haret University
CLAUDIU CHIRU, Spiru Haret University
MIHAELA CIOBANICA, Spiru Haret University
DANIEL DANECI, Spiru Haret University
MIHNEA DRUMEA, Spiru Haret University
DRAGOȘ IPATE, Spiru Haret University
PAULA MITRAN, Spiru Haret University
LAVINIA NADRAG, Ovidius University Constanta
OCTAV NEGURITA, Spiru Haret University
IULIANA PARVU, Spiru Haret University
LAURA PATACHE, Spiru Haret University
MEVLUDIYE SIMSEK, Bilecik University
ADINA TRANDAFIR, Spiru Haret University

CONTENTS

ASSESSING THE ASYMMETRIC RELATIONSHIP AMONGST THE IMPLIED VOLATILITIES OF BITCOIN, PRECIOUS METALS AND CRUDE OIL: EVIDENCE FROM LINEAR AND NONLINEAR ARDL MODELS

HAZGUI SAMAH
High Business School, Tunis
hazguisamah066219@hotmail.fr

Abstract

This work aims to analyze the cointegration and causality relationship among BTC, GOLD, SILVER, BRENT and WTI prices using the linear and nonlinear ARDL for the period from 17/07/2010 to 27/07/2018 with daily data. First of all, we apply a linear ARDL model to explore the long-run dynamics of relative prices and BTC price changes. Secondly, we employ an innovative nonlinear ARDL model proposed by Shin and al 2014 to estimate the asymmetric long and short run impacts of BTC prices. We find that Bitcoin, oil and precious metal volatilities interact in a nonlinear manner. The results of this paper have relevant implications for investors and market participants, by managing their investments and minimize their risks.

Keywords: Bitcoin, Crude oil, Precious metal, Cointegration, Nonlinearity, Bounds Testing Approach.

JEL Classification codes: C39, F39, G11, G15, Q40, Q30.

1. INTRODUCTION

Bitcoin is the first and the famous virtual currency to come into existence. In eight-years, the Bitcoin price has increased exponentially and many investors have profit from its movement. Researchs were first interested in its technical and legal aspects, then, the economics and financial papers appear. Brière and al 2015 find a low correlation of Bitcoin with traditional assets and alternative investments and indicate its significant diversification benefits, despite its high volatility. They also predicate that adding a 3% of bitcoins can enhance the risk return trade off of well diversified portfolios. Baek and Elbeck 2015 show that Bitcoin returns are not influenced by economic fundamentals, but by sellers and buyers and that Bitcoin is 26 times more volatile than the american index. Bouoiyour and Selmi 2015 show that the Bitcoin price is appositively affected by the exchange trade ratio and investors attraction in the short term. Cheung and al 2015, Fry and Cheah 2016 prove the existence of bubbles in the Bitcoin market. Dyhrberg 2016 indicates that Bitcoin is a hedge for UK currency and equities. Popper 2015, Luther and Salter 2017 point that Bitcoin is the digital gold because it is an alternative to traditional stores of value. Li and Wang 2017 indicate that Bitcoin is less sensitive to technological factors and more sensitive to economic fundamentals in long term. Bouri and al 2017a show the hedging capability of Bitcoin against global uncertainty. Bouri and al 2017c find that Bitcoin is a diversifier for major world equities, bonds, oil, gold, general commodity index, and american dollar. Ender and al 2018 reveal a negative relationship between Bitcoin returns and economic policy uncertainty, suggesting a hedging ability of Bitcoin. Several studies have focused on bitcoin price mouvement via a linear ARDL model and several findings have emerged like Bouoiyour and Selmi 2015 who failed to detect any significant relation between the Bitcoin and gold market, Ciaian and al 2016 exihibit that the Bitcoin price is not sensitive to macro financial developments in the long run, Li and Wang 2017 find a significant relationship between the Bitcoin price and changes in economic fundamentals in the short and long runs. These studies has ignored the asymmetric and non-linear effects. Nevertheless, it is unclear what relation exists between Bitcoin and commodities especially in term of non-linearity. Recently, there is some developments in econometric modelling based on the ADRL framework, which have led to the emergence of the non linear ARDL model. For example, Lee and Lin 2012 attest that macroeconomic variables are impacted by the structural breaks and oil and gold prices follow a nonlinear pattern. Naifar and Al Dohaiman 2013 indicate that ARDL fail to detect the nonlinearities between stocks, oil and gold prices. Bildirici and Turkmen 2015 prove that the power of nonlinear models is higher than the linear models. Gao and al 2015 show that previous studies should be paid more attention to the nonlinear relationship between oil and gold since the positive and negative oil shocks certainly have a different impact on the economy. An and al 2014, Ma and al 2013 and Vacha and Barunik 2012 suggest that most economic and financial variables exhibit a nonlinear behavior over time, and that they may interact with each other in a nonlinear manner. This non-linear behavior of time series can be caused by successive episodes of economic and financial crises, wars and extreme events, geopolitical tensions and sudden changes in the economic cycle as well as the complexity of financial markets induced by the heterogeneity of economic agents, globalization and the multiplicity of regulations. All of these factors can lead to unexpected changes in the behavior of economic and financial variables which induce structural breaks, asymmetric responses to news and leverage effects. Under these conditions, our variables are likely to behave nonlinearly and their common dynamics seem to be more complex than a simple and stable relationship. In this context, we examined the non-linear and asymmetric prices of the GOLD, SILVER, BRENT and WTI prices on the BTC price, using advanced autoregressive distributed lag (ARDL) model, namely the non-linear ARDL model (NARDL). This model allow us to have a clear view of the existing relationship, which is useful to investors. Understand the non-linearity and the asymmetry would help them to generate better investment strategies. The rest of the article is organized as follows. Section 2 introduces the empirical framework and describes the data. Section 3 reports the obtained results. Section 4 concludes.

2. METHODOLOGY AND DATA

The daily data series used for this paper are from 17/7/2010 to 27/07/2018. The starting date is depicted by the accessibility of Bitcoin price. The closing prices for the Bitcoin index are sourced from coindesk.com. GOLD, SILVER, BRENT and WTI prices are expressed in US dollars and collected from Federal Reserve Economic Data. To investigate the relationship between BTC, GOLD, SILVER, BRENT and WTI changes, we estimate the ARDL bounds testing developed by Pesaran and al 2001. This method is more flexible when compared to the traditional cointegration approaches, such as those of Engle and Granger 1987, Johansen and Juselius 1990 methods. The ARDL models as follows:

$$\Delta lnB\,TC_t = \beta_0 + \sum_{i-1}^{n_1}\beta_{1i}\,\Delta lnB\,TC_{t-1} + \sum_{i-1}^{n_2}\beta_{2i}\,\Delta lnGOLD_{t-1} + \sum_{i-1}^{n_3}\beta_{3i}\,\Delta lnSILVER_{t-1} + \sum_{i-1}^{n_4}\beta_{4i}\,\Delta lnBRENT_{t-1} + \sum_{i-1}^{n_5}\beta_{5i}\,\Delta lnWTI_{t-1} + \lambda_1 ln\,BTC_{t-1} + \lambda_2 ln\,GOLD_{t-1} + \lambda_3 ln\,SILVER_{t-1} + \lambda_4\,ln\,BRENT_{t-1} + \lambda_5 + ln\,WTI_{t-1} + \vartheta_t \quad (1)$$

Where ϑ_t is the error term that must be white noise, while Δ is the first difference operator. In line with Shin et al 2014 the non-linear version of ARDL approach can be defined as:

$$\Delta lnB\,TC_{k,t} = \mu + \rho lnB\,TC_{k,t-1} + \theta_1^+ lnGOLD_{k,t-1}{}^+ + \theta_1^- lnGOLD_{k,t-1}{}^- + \theta_2^+ lnSILVER_{k,t-1}{}^+ + \theta_2^- lnSILVER_{k,t-1}{}^- + \theta_3^+ lnBRENT_{k,t-1}{}^+ + {} + \theta_3^- lnBRENT_{k,t-1}{}^- + \theta_4^+ lnWTI_{k,t-1}{}^+ + \theta_4^- lnWTI_{k,t-1}{}^- + {} + \sum_{i=1}^{\rho-1}\alpha_i\,\Delta lnB\,TC_{k,t-i} + \sum_{i=0}^{q}\pi_{1,i}^+\,\Delta\ln GOLD_{t-1}^{+} + \sum_{i=0}^{q}\pi_{1,i}^-\,\Delta\ln GOLD_{t-1}^{-} + \sum_{i=0}^{q}\pi_{2,i}^+\,\Delta\ln SILVER_{t-1}^{+} + \sum_{i=0}^{q}\pi_{2,i}^-\,\Delta\ln SILVER_{t-1}^{-} + \sum_{i=0}^{q}\pi_{3,i}^+\,\Delta\ln BRENT_{t-1}^{+} + \sum_{i=0}^{q}\pi_{3,i}^-\,\Delta\ln BRENT_{t-1}^{-} + \sum_{i=0}^{q}\pi_{4,i}^+\,\Delta WTI_{t-1}^{+} + \sum_{i=0}^{q}\pi_{4,i}^-\,\Delta WTI_{t-1}^{-} + \varepsilon_t \quad (2)$$

Where ε_t refers to the error term. $\ln GOLD^+$, $\ln GOLD^-$, $\ln SILVER^+$, $\ln SILVER^-$, $\ln BRENT^+$, $\ln BRENT^-$, $\ln WTI^+$ and $\ln WTI^-$ are the partial sums of positive and negative changes in each of explanatory variables respectiveley. Where, $\ln BTC_{k,t}$, $\ln GOLD_{k,t}$, $\ln SILVER_{k,t}$, $\ln BRENT_{k,t}$ and $\ln WTI_{k,t}$ stand for the BTC , gold , silver, brent and WTI prices spread of the kth industry in period t. In order to analyse the cointegration among selected variables, the bounds test will be applied. This test is based on the joint F-statistic or Wald test, which is used to test the null hypothesis of no cointegration $H_0\colon y_k = 0$, against $H_1\colon y_k \neq 0$ where k=1,2,3…. The F-statistic value will be compared with the upper and lower bounds critical values (i) if F-statistic lies above the upper bounds critical values, H_0 is rejected (ii) if F-statistic lies between the upper and lower bound critical values, H_0 is inconclusive. In this case and following Kremers and al 1992, Benerjee and al 1998, then the decision regarding the existence of a long run-relationship will be based on the error correlation term. If the error correlation term is negative and significant, this implies the existence of a long run relationship among the variables

(iii) if the F-statistic lies below the lower bounds critical value, this indicates evidence of no cointegration among the variables.

3. EMPIRICAL RESULTS

The results reported in table 1 shows that the mean of the gold is greater than the other series. The BTC exhibits high volatility clustering with a standard deviation of 3.00352, while gold exhibits the low volatility clustering. All the series are skewed negatively except GOLD and SILVER. The coefficient of kurtosis appears inferior to 3 for all variables indicating that the distribution is less flattened than normal distribution. The Jarque-Bera test revealed high, leading to reject the assumption of normality for all the estimated variables.

Table 1. *Descriptive statistics of the variables (log)*

	LBTC	LGOLD	LSILVER	LBRENT	LWTI
MEAN	4.734947	7.206880	3.056458	4.347097	4.256325
ST.DEV	3.00352	0.131760	0.302962	0.373202	0.345240
MIN	-2.995732	6.957307	2.614911	3.327910	3.266141
MAX	9.850114	7.543644	3.883294	4.853123	4.730833
S.K	-0.674220	0.649611	0.660020	-0.426084	-0.462323
K.R	2.813171	2.458365	2.129780	1.825612	1.888556
J.B	161.5371	172.9549	218.2107	183.6944	182.3768
OB	2095	2095	2095	2095	2095

Note: ST.DEV: Standard Deviation, S.K: Skewness, K.R: Kurtosis, J.B: Jarque- Berra, O.B: observations. L are natural log operators.

Two different unit root tests have been implemented to assess the integration order of the series as well as to add a robust testing of their statistical characteristics : (i) the Dickey and Fuller 1979 (ADF) test; (ii) the Phillips and Perron 1988 (PP) unit root test. The results are reported in table 2. ADF and PP unit root tests conclude that the variables are stationary in the first differences, thus, we can use both the bounds test and the Johansen method to test the cointegration relationship.

Table 2. *Unit root tests results (log)*

Variables	ADF test		PP test	
	Level	First difference	Level	First difference
LBTC	-2.430369	-44.60427***	-2.106567	-45.65179***
LGOLD	-1.819979	-47.54343***	-1.802130	-47.52053***
LSILVER	-1.291517	-47.68772***	-1.289777	-47.64897***
LBRENT	-1.129148	-46.26383***	-1.150591	-46.27137***
LWTI	-1.346631	-48.65775***	-1.311177	-48.59539***

Notes: *** imply significance at the 1% level. The lag lengths for the ADF test was selected using Shwarz info criterion (SIC).

The correlations between the variables are reported in table 3. The highest correlation is observed between the implied volatility indices of BRENT and WTI markets. Furthermore, gold has the highest positive correlation with silver, suggesting their importance in industrial uses. Bitcoin has a negative linear association with all other variables under investigation, making it a good diversification hedge in the short run.

Table 3. *Correlation matrix*

	LBTC	LGOLD	LSILVER	LBRENT	LWTI
LBTC	1				
LGOLD	-0.514841	1			
LSILVER	-0.705234	0.903948	1		
LBRENT	-0.504784	0.699057	0.777332	1	
LWTI	-0.498414	0.623485	0.719846	0.983341	1

Note : all correlations are significant at the 1 % level.

The Johansen results are reported in table 4 and they confirm the evidence of cointegration detected by the maximum Eigenvalue and Trace test.

Table 4. *Johansen cointegration test results*

H_0	λ_{trace}	5%C.V	λ_{max}	5%C.V
r=0	101.0110	69.81889	45.45748	33.87687
r≤1	55.55352	47.85613	27.63872	27.58434
r≤2	27.91480	29.79707	18.20228	21.13162
r≤3	9.712521	15.49471	7.703404	14.26460
r≤4	2.009117	3.841466	2.009117	3.84146

Note : C.V denotes critical values. λ_{trace} and λ_{max} are the test statistics used to determine the existence of cointegration and specifically the number of cointegration vectors.

As the lag order of the variables is an important step for the model specification within ARDL bounds testing framework, we determine the lag optimization based on lag-order selection among various information criteria. We show that the optimum lag is 8 (see table 5).

Table 5. *Lag-order selection*

Lag	Log L	LR	FPE	AIC	SI	HQ
0	1521.310	/	1.56 e-07	-1.482219	-1.468479	-1.477179
1	25715.68	48246.83	8.58 e-18	-25.10819	-25.02573	-25.07795
2	25812.26	192.1270	8.00 e-18	-25.17816	-25.02699*	-25.12272*
3	25828.99	33.20546	8.06 e-18	-25.17008	-24.95019	-25.08944
4	25862.89	67.09905	7.99 e-18	-25.17878	-24.89018	-25.07293
5	25904.40	81.96120	7.86 e-18	-25.19492	-24.83760	-25.06387
6	25934.29	58.87974	1.83 e-18	-25.19970	-24.77367	-25.04345
7	25957.51	45.61289	7.84 e-18	-25.19795	-24.70321	-25.01650
8	25990.24	64.15025*	7.78 e-18*	-25.20551*	-24.64205	-24.99886
9	26006.98	32.72172	7.84 e-18	-25.19743	-24.56526	-24.96558

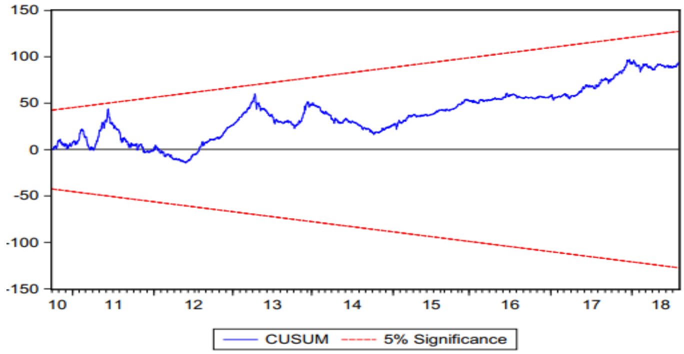
Notes: * indicates lag order selected by the criterion; LR: sequential modified LR test statistic (each test at 5% level); FPE: Final prediction error; AIC: Akaike criterion; SC: Schwarz information criterion; HQ: Hannan-Quinn information criterion ; (/) indicates it could not be estimated.

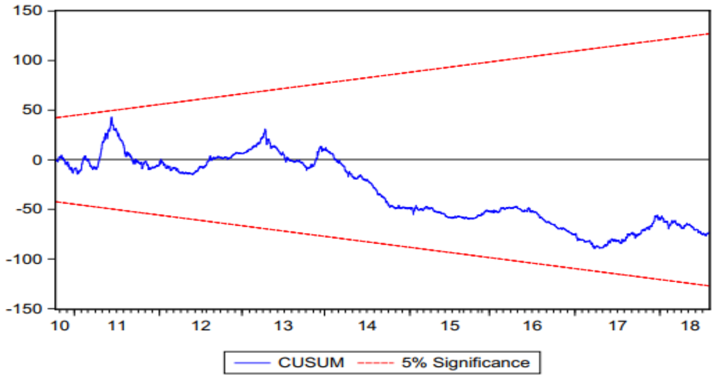
As it is seen in the table 6, in the linear model there is an evidence in favor of non-rejection of the null hypothesis of no cointegration. This result may be due to the nonlinear structure of the variables. Conditionally, the results of the non linear model should be investigated. The same table shows that the results obtained determine statistically significant evidence in favor of the existence of long run cointegrating relationship since the F-statistic exceed the critical upper bound. The coefficients of the estimated lagged error correction term were negative and significant in NARDL, thus, confirms the existence of a long-run relation among the variables. In addition, the coefficient suggests that a deviation from the long-run equilibrium following a shock was corrected by approximately 0.7%.

Table 6. *Bounds tests for cointegration in the ardl and nardl models*

Estimated model	FLBTC (LBTC/LGOLD, LSILVER, LBRENT, LWTI)							
ARDL MODEL	**LINEAR ARDL MODEL**				**NON LINEAIR**			
F-statistics (bound test)	2.755777***				4.529977***			
EC_{t-1}	-0.000166				-0.007070***			
Critical values	***1%***	***2.5 %***	***5%***	***10%***	***1%***	***2.5 %***	***5%***	***10%***
Lower bounds I(0)	3.74	3.25	2.86	2.45	3.41	2.96	2.62	2.26
Upper bounds I(1)	5.06	4.49	4.01	3.52	4.68	4.18	3.79	3.35
R^2	0.050095				0.062622			
ADJ. R^2	0.029259				0.037732			
Durbon-Watson stat	1.998662				1.998079			
Outcome	no-cointegration				cointegration			

To confirm the stability of the estimated ARDL and NARDL models, we use the cumulative sum (CUSUM) test method of Brown and al 1975 to verify the recursive residuals in figure 1. The straight lines represent the critical bounds at 5% significance level. When the CUSUM is outside of these two straight lines, the null hypothesis of instability is accepted. However, the CUSUM remain within the area restricted by the lines, thus, our models are with stable recursive residuals and confirm that the long and short-run coefficients in the error correction model were stable. Therfore, there is no statistical evidence of parameter instability.





Notes: The straight lines represent the critical bounds at 5% significance level.

The results of the variance decomposition are reported in table 7. We find that 99.39% percent of Bitcoin price is explained by its own innovative shocks. The contribution of gold prices affects the dynamic of BTC (0.46%). Likewise, SILVER, BRENT and WTI do not have a great effect on this new crypto-currency, with respective percentages equal to 0.03%, 0.05% and 0.06%.

Figure 1. *Cumulative sum (cusum) test on ardl and nardl models*

Table 7. *Variance decompostion of btc price*

Period	S.E	LBTC	LGOLD	LSILVER	LBRENT	LWTI
1	0.061776	100.000	0.000000	0.000000	0.000000	0.00000
2	0.089172	99.48527	0.487190	0.000576	0.024021	0.00295
3	0.111162	99.29030	0.686231	0.001001	0.019708	0.00339
4	0.131327	99.45266	0.529020	0.002128	0.013688	0.00251
5	0.150263	99.55879	0.404286	0.004366	0.022109	0.01045
6	0.166107	99.58637	0.363062	0.022009	0.011936	0.00920
7	0.181264	99.54286	0.381379	0.043436	0.024508	0.00782
8	0.195788	99.48788	0.415367	0.039116	0.038244	0.01939
9	0.209408	99.44100	0.439186	0.034879	0.045500	0.39434
10	0.222305	99.38864	0.464524	0.031007	0.051821	0.06401

4. CONCLUSION

Scholars and practitioners have started to examine the relationship between Bitcoin and several economic and financial variables. However, very little has been written about Bitcoin, precious metals and crude oil in particular. In this study, we investigate the links between Bitcoin price and gold, silver, brent, WTI prices using daily data for the period July 2010 to July 2018. In particular, we focus on the linkages between variables under both the linear and nonlinear frameworks. We find the presence of non-linear relationship between selected variables. We conclude that the imposition of a linear symmetric model could be misleading in explaining the relationship between series. The long run effect did not appear in the symmetric model. However, the asymmetric model reveal the presence of such relationship. Therefore, the use of the asymmetric ARDL model contributes to the understanding the nonlinear dynamics between BTC, GOLD, SILVER, BRENT and WTI changes. Our results show that the estimated variables are rather interactive in a nonlinear manner. This finding leads to a more efficient investment decision for investors and other market participants, such as financial managers, analysts and firms in managing their investments and minimizing their portfolio risks. Investors should respond asymmetrically to the increase and decrease of GOLD, SILVER, BRENTa nd WTI prices when investing BTC.

REFERENCES

Baek, C., & Elbeck, M. (2015). Bitcoin as an investment or speculative vehicle? A first look. *Applied Economics Letters*, *22*(1), 30-34.

Balcilar, M., Bouri, E., Gupta, R., Roubaud, D. (2017). Can volume predict Bitcoin returns and volatility? A quantiles-based approach. *Economic Modelling*, *64*, 74–81.

Bildirici, M. E., & Turkmen, C. (2015). Nonlinear causality between oil and precious metals. *Resources Policy*, *46*, 202–211.

Bildirici, M. E., & Turkmen, C. (2015). The chaotic relationship between oil return, gold, silver and copper returns in TURKEY: Non-Linear ARDL and Augmented Nonlinear Granger. *Procedia-Social and Behavioral Sciences*, *210*, 397-407.

Bouoiyour, J., & Selmi, R. (2015). What does bitcoin look like? *Annals of Economics and Finance*, *16*(2), 449–492.

Bouri, E., Gupta, R., Tiwari, A K., & Roubaud, D. (2017a). Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Finance Research Letters*, *23*, 87–95.

Bouri, E., Jalkh, N., Molnár, P., & Roubaud, D. (2017b). Bitcoin for energy commodities before and after the December 2013 crash: Diversifier, hedge or safe haven? *Applied Economics*, *40* (50), 5063–5073.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L.I. (2017c.) On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? *Finance Research Letters*, *20*, 192–198.

Brière, M., Oosterlinck, K., & Szafarz, A. (2015). Virtual currency, tangible return: Portfolio diversification with bitcoin. *Journal Asset Management*, *16* (6), 365–373.

Cheung, A., Roca, E., & Su, J J. (2015). Crypto-currency bubbles: An application of the Phillips–Shi–Yu (2013) methodology on Mt. Gox bitcoin prices. *Applied Economics*, *47* (23), 2348–2358.

Ciaian, P., Rajcaniova, M., & Kancs, A. (2016). The economics of BitCoin price formation. *Applied Economics*, *48* (19), 1799–1815.

Dyhrberg, A.H. (2016a). Bitcoin, gold and the dollar–A GARCH volatility analysis. *Finance Research Letters 16*, 85–92.

Dyhrberg, A.H.(2016b.) Hedging capabilities of bitcoin. Is. it Virtual Gold.?. *Finance Research Letters 16*, 139–144.

Ender, D., Gozgor, G., Lau, C. M., Vigne, S. (2018). Does economic policy uncertainty predict the Bitcoin returns? An empirical investigation. *Finance Research Letters*.

Fousekis, P., Katrakilidis, C., & Trachanas, E. (2016). Vertical price transmission in the US beef sector: Evidence from the nonlinear ARDL model. *Economic Modelling, 52*, 499–506.

Fry, J., & Eng, T. 2016. Negative bubbles and shocks in cryptocurrency markets. *International Review of Financial Analysis, 47*, 343–352.

Ibrahim, M.H. (2015). Oil and food prices in Malaysia: A nonlinear ARDL analysis. *Agricultural and Food Economics, 3*(1), 1-14.

Johansen, S. (1988). Statistical Analysis of Cointegration Vectors. *Journal of Economic Dynamics and Control, 12*, 231–254.

Kumar, S. 2017. On the nonlinear relation between crude oil and gold. *Resources Policy, 51*, 219–224.

Luther, W. J., Salter, A. (2017). Bitcoin and the Bailout. *The Quarterly review of economics and finance, 66*, 50-56.

Naifar, N., Dohaiman, M. S. (2013). Nonlinear analysis among crude oil prices, stock markets' return and macroeconomic variables. *International. Review of Economic and Finance, 27*, 416–431

Reboredo, J. C., Rivera, C. (2014). Wavelet-based evidence of the impact of oil prices on stock returns. *International Review of Economics and Finance, 29*, 145-176.

Pesaran, M. H., Shin, Y., Smith, R. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics, 16*, 289-326.

Popper, N. (2015). *Digital gold: The untold story of Bitcoin*. London: Penguin.

Shin, Y., Yu, B., Greenwood-Nimmo, M., (2014). Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. In: William, C., Horrace, R., Sickles, C. (Eds.), Festschrift in Honor of Peter Schmidt: *Econometric Methods and Applications*. Springer Science & Business Media, New York (NY), pp 281–314.

Wang, L., X. Chong, A. (2017). The technology and economic determinants of cryptocurrency exchange rates: The case of Bitcoin. *Decision Support Systems, 95*, 49–60.