ECONOMIC POLICY UNCERTAINTY, GLOBAL OIL PRICE, INTEREST RATE, AND STOCK MARKET RETURNS - A COINTEGRATION AND CAUSALITY ANALYSIS[1]

Abdurahman Jemal YESUF[*]

Emin AVCI[**]

Abstract

This study examines the time-varying cointegration and causal relationship between stock market indices, economic policy uncertainties, changes in global oil prices, and variation in short-term interest rates in two countries such as Russia and China, the largest oil exporting and importing countries respectively. The empirical analysis is based on the Johanssen (1996) cointegration and VEC Granger and Morris's (1976) causality test with the selected variables in view of monthly data over the period from 1996:01 to 2016:12. The outcome of the Johansen tests indicated the existence of a long-run relationship among variables both in China and Russia. In the short run, the Block Exogeneity Wald Tests have indicated the presence of unidirectional Granger causality between variables in both countries. This study has taken into account the 1998 Russian crisis and the 2008/09 global financial crisis.

Keywords: Economic policy uncertainty, Oil price, Interest Rates, Stock Market, Johansen Cointegration, Block Exogeneity Wald Tests

JEL codes: E61, E43, C58, P34, G21

I. INTRODUCTION

The primary goal of this study is probing the relationship among economic policy uncertainty, the price of global crude oil, short-run lending rates, and stock market returns of

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China and Russia both in the short and long term. In this paper, economic policy uncertainty is used to refer to 'risks' that will be resulted from 'changes in the existing policies' that are related to economic activities and restrict the decision-making and actions of economic units including financial institutions, organizations, investors, and consumers. There have been many studies in the last two decades that indicated the real implications of uncertainty about the future for investors' behavior (Bloom, 2009; Bloom, Bond, & Van Reenen, 2007). The studies have established a high relationship between uncertainty and decision-making process. For instance, according to Gulko (2002), usually during stock market crashes political uncertainty is high. It increases uncertainties about future economic policies. Thus, during this time investors become reluctant to make timely investment decisions. The greater the degree of Economic Policy Uncertainty (EPU), the higher will be the probability of delaying in decision making by economic agents.

This study used the Baker, Bloom, Wang & Davis (2013)'s news-based EPU index for quantitative measurement for the degree of changes in uncertainties of government economic policies. Basically, the EPU index is developed from three sorts of underlying components. The first constituent measures policy-related economic uncertainties from 'newspaper coverage'. The next component of the index deals with government federal tax provisions. The last component of the index reflects the disagreements in forecasting of variables related to government economic policies.

A growing amount of literature has established a link between oil prices, economic uncertainty, and stock market prices. Oil is the world's number one exporting product. China and Russia are the two major actors in the global energy market as a consumer and exporter of oil.[2]China is the largest oil importer; its total oil consumption is estimated to be above 11% world's oil consumption during 2012. On the other hand, Russia is the biggest oil exporter in the world.[3]China spends billions of dollars each year to import oil from the global oil market whereas Russia earns billions of dollars as revenue from export of oils to the world. Therefore, any change in oil price or production may have a significant impact on the economies' of these countries. Any shock in oil price is expected to affect their industries as well as stock markets directly or indirectly.

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[2]In 2015 alone, out of the value of all global export products, the share of crude oil shipments was 4.8% which is amounting US$786.3 billion."http://www.worldstopexports.com/worlds-top-oil-exports-country/".
[3]Russia become the world's largest oil producer for the first time in December, 2016.
"https://www.bloomberg.com/news/articles/2017-02-20/russia-overtakes-saudi-arabia-as-world-s-largest-crude-producer."

The remaining parts of the article are classified in the following way: Section 2 summarizes literature related to the topic; Section three of the paper presents data descriptions with econometric models used. The main findings and analysis are presented in the fourth part of the paper. The last part (section 5) sums up the findings and concludes the analysis.

II.   LITERATURE REVIEW

Studies to measure uncertainties related to the economy in general and economic policies, in particular, are one of the fast-growing research areas. In spite of this, there is no general consensus regarding the definition and best approach to capture the real uncertainty in economic activities of a country. Until now a trendy strategy is to look for the fundamental factors of uncertainty, either from macro data (Jurado et al., 2013) or from newspaper coverage (Tucket et al., 2014 and Baker et al., 2013).

The EPU index is a relatively new measurement of uncertainty related to economic policies. Regarding the causal relationship among EPU, Global oil price and stock market returns, there are some recent studies which are mainly for major emerging markets. The results of such studies are also varying due to variation in models used, time of the study, or place of study. A good example is Chang et al. (2015), where the researchers have examined the correlation between EPU and the stock markets indices of seven sample OECD countries. The outcome of their study indicates that not all the stock markets were alike and that the theoretical expectation of a decrease in stock prices due to a policy change announcement was not always supported. However, Pastor & Veronesi (2012) come with a general approach predicting the fall of stock prices, average, during a policy change announcement. They have established a negative relationship between stock prices and uncertainties in government economic policies.

Furthermore, volatility is also a common feature of oil price in general as is widely used as a final consumption good and a direct input in the production process (Swanepoel, 2006). The literature about the link between shocks in the global oil price and fluctuations in market returns also shows various results. Most studies indicated that fluctuations in global oil price have a direct and indirect relation to the volatility in stock prices. However, the extent of the relationship and magnitude of causality is varying from one stock market to the other and from country to country. According to some studies such as Apergis & Miller (2009), Miller & Ratti (2009), and Peersman & Van Robays (2012), the effect of global oil price shocks on returns in the stock market range from statistically significant negative to insignificant negative. Studies

by Kilian (2009), Kang &Ratti, (2013), Hamilton (2009), and Kilian & Park (2009) have also reported that stock market reactions for any changes or shocks in global oil price depend on the causes of the price changes. However, some researchers have established a stable negative relationship between changes in oil prices and stock market returns (Jones & Kaul (1996), Kling (1985), and Sadorsky (1999)).

Previous studies have also found different results regarding the influence of oil price changes on exporting country and importing countries' stock markets. J. Penm et al. (2008) has reported that oil price raises contribute to a decline in stock market returns in oil importing countries including France, UK, and the USA. Another study by Park & Ratti (2008) has found similar results for the USA and 12 'oil-importing' countries in the EU. The negative effect of global oil price shocks has also impacted emerging markets. Masih et al. (2011) reported that volatilities in oil price have a negative impact on the real returns of the stock market in South Korea.

The volatile nature of the global oil prices is usually one of the concerns of policymakers, multinational institutions, investors as well as politicians. They always fear the possibility of the detrimental impact of the change on the macroeconomy (Goodnes, 2015). There are a few studies that have analyzed linkages between changes in the oil price and EPU. Among others, Kang & Ratti (2013) have shown the combined effect of EPU and changes in the oil-price on stock markets. The combined effect of the two on the market prices is either by affecting the discount rate or the future expected cash flows. Studies have also reported that uncertainties about changes in real oil-price have substantial negative effects on the real economic activities (Elder & Serletis, 2010; Serletis & Rahman, 2011). In another study, Yoon & Ratti (2011) have linked volatility in oil prices to firm-level investment. Changes in global oil price and uncertainties about government economic policies are likewise interconnected and influence the real market returns.

Many studies have also established a relationship between interest rates and stock prices or market returns. Since the interest rate has a direct effect on the cost of production, profit, and net present values of firms' future cash flows, it is considered as the most significant variable affecting stock markets. In theory, interest rates have an inverse relation with stock market returns. Higher interest rate lowers profits and net present values of firms' future cash flows. Regarding the relationship between stock market returns and interest rates, there are longstanding academic studies that offer evidence that interest rates affect stock prices. Studies such as Fama (1981), Hogan et al. (1982), Chen et al (1986), Hardouvelis (1987), Elton &

Gruber (1987), and Choi et al. (1992) have established the existence of a relationship between interest rates and stock market returns. However, existing studies have reported mixed results regarding the direction and degree of the relationship between interest rates and stock markets. For instance, Fama (1981) has studied the relationship between stock market returns and interest rates in the US and has found that returns of the US stock markets have a strong and positive relationship with interest rates and real economic variables. On the other hand, a study by Alam & Salah (2009) has examined the existing correlation between interest rates and stock market indices for fifteen countries during the period from January 1988 to March 2003. For all cases, they have found a negative correlation among the stock market indices and the interest rates. Since this study is based on two different countries, therefore, this type of different results regarding the relationship between stock market returns and short-term interest rates is also expected in this study.

III. DATA AND EMPIRICAL METHODOLOGY

III.I. Data Sources and Descriptions

The data series used in this study is mainly secondary data which was collected from well-known data sources, such as IMF database, the OECD Stat, Datastream, National Banks of China and Russia, and Economic Policy Uncertainty (EPU) web page. The study was conducted on the Shanghai Stock Exchange (SSE) and Moscow Stock Exchange (MICEX). The independent variables were Economic Policy Uncertainty (EPU) Index both for China and Russia, monthly average Global Brent Crude Oil Price (CO), monthly interest rate (short-term lending rate - IR) both for China and Russia and the monthly average S&P 500 index (SP500). The measure of uncertainties in government economic policies was based on Baker et al. (2016, 2013) EPU Index. The empirical analysis was done based on monthly data collected for the periods ranging from January 1, 1996, to December 31st, 2016. Hence, there were 252 monthly observations per variable. Dummy variables were also used to avoid a bias statistical result. Accordingly, in this study, two dummy variables such as the Russian financial crises and the global financial crisis are employed for major world events that had substantial economic effects.

Table I. Descriptive Statistics of the Data

	SSE	CO	EPU-China	IR-China	SP500	MICEX	EPU-Russia	IR-Russia
Mean	2118.182	55.890	124.149	2.244	1304.068	896.201	117.723	22.800
Median	1985.390	47.679	99.719	1.065	1254.560	790.220	99.733	12.700
Maximum	5954.770	133.900	646.911	12.240	2238.830	2459.880	421.655	203.600
Minimum	537.350	9.800	9.067	-0.080	636.020	43.810	12.399	7.900
Std. Dev.	954.354	34.620	89.628	2.527	377.263	631.675	75.727	30.972
Skewness	1.138	0.524	2.168	0.954	0.686	0.384	1.139	4.092
Kurtosis	4.623	1.950	9.930	3.140	2.968	1.965	4.236	20.297
Jarque-Bera	82.027	23.095	701.734	38.389	19.781	17.434	70.545	3844.700
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
# Obsv.	252	252	252	252	252	252	252	252

SSE: Shanghai Stock Exchange Index (China); CO: Global Crude Oil Price; EPU-China: Economic Policy Uncertainty Index for China; SP500: Standard & Poor 500 Index; MICEX: Moscow Interbank Currency Exchange Index (Russia's Stock Market Index); EPU-Russia: Economic Policy Uncertainty Index for Russia; and IR-Russia: Short-term Interest Rate for Russia

Table I shows basic statistics for stock market indices and the independent variables such as interest rate, global oil price, and S&P 500 index. The maximum values of the stock market indexes were 5954.770 and 2459.880 for SSE and MICEX respectively. The mean values are also calculated as 2118.182 and 896.201 respectively. Standard deviation figures computed in the above Table shows that Stock market returns in both countries were not stable during the study period. During those times the standard deviations of the stock market indices were 954.354 and 631.675 for SSE and MICEX respectively. Generally, high standard deviations are considered as a sign of high variability in the time series data. Table I also gives information regarding independent variables such as the degree of uncertainties in governments' economic policies and short-term interest rates in both countries, global crude oil price and S&P 500 index.

III.II. Econometric Methods

III.II.I. Theoretical Model

Since the main goal of the study, as indicated above, is investigating the cointegration and causal relationship among the selected macroeconomic variables and stock market indices,

the theoretical model should be based on a multivariate linear model with a range of four macroeconomic explanatory variables. Therefore, the identified model seeks to hypothesize that change in stock market returns is a function of changes in these variables.

$$SP = f(EPU, CO, IR, SP500, D) + \varepsilon \tag{1}$$

Where *SP* is stock market Return, *D* is dummy variable, and ε represents variables outside the model.

Based on this, the econometric model (the multiple regression models) of the above function has formulated mathematically as follows:

$$LogSSE_{China}$$
$$= \alpha, + \beta_1 LogEPU_t + \beta_2 LogCO_t + \beta_3 LogIR_t + \beta_4 LogS\&P500_t + \beta_5 D_t + u_t \tag{2}$$

$$LogMICEX_{Russia}$$
$$= \alpha, + \beta_1 LogEPU_t + \beta_2 LogCO_t + \beta_3 IR_t + \beta_4 LogS\&P500_t + \beta_5 D_t + u_t \tag{3}$$

$$H_0 = \beta_1 + \beta_2 + \beta_3 + \ldots + \beta_n = 0$$

III.II.II. Unit Root Test

For making a meaningful inference from the data analysis, the first step should be testing the data series for stationarity. Stationarity is also vital for improving the reliability as well as the accuracy of models that will be developed. In this study, the Augmented Dickey-Fuller (ADF) test is applied to identify the stationarity of the data. The following equation is the basis for the ADF test.

$$\Delta y_t = \alpha_0 + \lambda y_{t-1} + \alpha_1 t + \sum_{i=1}^{\rho} \beta_i \Delta y_{t-1} + u_t \tag{4}$$

Where λ denotes a time trend, α_1 and β_i are coefficients, and ρ represents the lag number, u_t is an error correction term.

There are three versions of the ADF models for the data generating process of y_t. In principle, these specifications can be tried, contingent upon whether the series show a trend or not. These are:

$$\Delta y_t = \lambda y_{t-1} + \sum_{i=1}^{\rho} \beta_i \Delta y_{t-1} + u_t \tag{5}$$

$$\Delta y_t = \alpha_0 + \lambda y_{t-1} + \sum_{i=1}^{\rho} \beta_i \Delta y_{t-1} + u_t \tag{6}$$

$$\Delta y_t = \alpha_0 + \lambda y_{t-1} + \sum_{i=1}^{\rho} \beta_i \Delta y_{t-1} + \alpha_1 t + u_t \tag{7}$$

Where $\alpha_1 t$ is a linear time trend;

Based on the above question, the null (H_0) and alternative hypotheses for the unit root test in y_{t-1} are:

The null (H_0): $\lambda = (0)$, *Series has unit root (non-stationary)*; and $(H_1): \lambda(0)$, *Stationary*. The rule of thumb is that the data series is non-stationary if the calculated or statistical value is greater than the "critical value"; if not, the (H_0) of $\lambda = 0$ will be rejected.

III.II.III. Optimal Lag Length

One of the major concerns under ADF, Johansen cointegration, and VECM tests is determining the optimum lag-length of the model. Therefore, to determine the maximum lag-order of the model, the study applied the Akaike Information Criterion (AIC).

$$[\text{AIC} = -2\ln(\text{L}) + 2\text{p}] \tag{8}$$

Where "L" refers to the maximized value of the likelihood function of the model; p refers to number parameters estimated in the model.

III.II.IV. Cointegration Test (Johansen Cointegration Test)

In this study, the Johansen's (Johansen & Juselius, 1990) methodology is used for checking cointegration in a multivariate system. The test starts by considering a general Vector Autoregressive Models (VAR (p)) which is given by:

$$Y_t = \mu + A_1 Y_{t-1} + A_2 Y_{t-2} + A_3 Y_{t-3} \dots\dots\dots\dots + A_\rho Y_{t-\rho} + u_t \tag{9}$$

Where Y_t is an "n-vector" (n≥2) of non-stationary I(1) variables, A_i is an (n × n) matrix of coefficient for each lag; ρ refers to the optimum lag-length; u_t is a vector of error terms.

In order to run (or to use) the Johansen cointegration test, the above VAR (Equ. 9) should be changed into a vector error correlation model (VECM) form:

$$\Delta Y_t = \mu + \Pi Y_{t-p} + \Gamma_1 \Delta Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + \cdots\dots\dots + \Gamma_{\rho-1} \Delta Y_{t-\rho+1} + u_t \tag{10}$$

$$\Delta Y_t = \mu + \Pi Y_{t-p} + \sum \Gamma_1 \Delta Y_{t-1} + u_t; \qquad t = 1, 2, 3, \dots \tag{11}$$

Π represents the coefficient matrix of the first lag and Γ_i are the matrices for each differenced lag,

$$i.e.\ \Gamma_i = -\left(-I + A_1 + A_2 + \cdots + A_p\right)\ and\ \Pi = \left(-I + A_1 + A_2 + \cdots + A_p\right)$$

$$\Gamma_i = -\left(\sum_{j=1}^{i} A_j\right) + I_n\ and\ \Pi = \left(\sum_{i=1}^{\rho} A_i\right) - I_n$$

$\boldsymbol{\Pi}$ stands to represent the existing number of cointegrated vectors. Thus, determining the rank of the matrix ($\boldsymbol{\Pi}$) is the primary goal of the Johansen model. The "Trace test" and the "Maximum Eigen value test" are used to determine the number of cointegration vectors.

$$\Omega_{trace}(m) = -K \sum_{i=m+1}^{s} \ln(1 - \hat{\Omega}_i) \tag{12}$$

$$\Omega_{max}(m, m+1) = -Kln(1 - \hat{\Omega}_{m+1}) \tag{13}$$

Where $\hat{\Omega}$ denotes the estimated values for the ith ordered Eigen values, m refers to number of co-integrating vectors, s represents number of variables, and K indicates number of usable observations (0,1,2,..K).

Therefore, the hypotheses for Ω_{trace} and Ω_{max} tests are:

(Ω_{trace}) Test: H_0: $m = i$, H_1: $m \geq 1$; and

(Ω_{max}) Test: H_0: $m = i$. H_1: $m = i+1$.

III.II.V. Granger Causality Test

The results of the ADF stationarity test and the Johansen's cointegration test determines the model to be applied for causality tests. If all the data series are stationary at first difference and co-integrated of order 1, then, the causality test will be based on the VEC Granger causality test. If not, the normal Granger (1969) causality test will be used. The regression equation for VEC Granger Causality tests can be formulated as follows:

$$\Delta Y_t = \lambda_i + \sum_{i=1}^{p_1} \omega_i \Delta Y_{t-i} + \sum_{i=1}^{p_2} \Phi_i \Delta X_{t-i} + \gamma_1 \hat{\varepsilon}_{t-1} + \varepsilon_t \tag{14}$$

$$\Delta X_t = \delta_i + \sum_{i=1}^{p_3} \psi_i \Delta X_{t-i} + \sum_{i=1}^{p_4} \beta_i \Delta Y_{t-i} + \gamma_2 \hat{u}_{t-1} + \epsilon_t \tag{15}$$

Where $\hat{\varepsilon}_{t-1}$ and $\hat{u}_{t-1}$ are the error corrections, γ_i is the rate at which previous period long-run disequilibrium is corrected. In general, the testable hypothesis can be rewrite as:

H_0: $\psi_j = 0$ (there is no causal relationship between variables)

H_1: $\psi_j \neq 0$ (causality exists between variables)

IV. EMPIRICAL RESULTS

IV.I. ADF Unit Root Test Results

One of the required conditions for the causality analysis was the stationarity of all variables. Unit root test increases reliability and accuracy in the development of the models. Table II presents the outputs of the ADF unit root test for China and Russia.

Table II. Unit Root test results

Variable	ADF Test Results		Phillips Perron-Test Results		Order of Stationarity
	Level	1st Difference	Level	1st Difference	
LogSSE	-2.718265 [7] (0.0724) {0}	-6.277726 [3] (0.0000) {1}	-2.832220 [7] (0.0552) {0}	-14.70150 [7] (0.0000) {1}	I(1)
LogEPU	-2.429445 [3] (0.1347) {0}	-11.70347 [2] (0.0000) {1}	-0.497965 [7] (-0.497965){0}	-25.43099 [21] (0.0000) {1}	I(1)
LogIR	-1.857551 [2] (0.3521) {0}	-12.54699 [1] (0.0001) {1}	-1.988179 [7] (0.2920) {0}	-22.69506 [12] (0.0001) {1}	I(1)
LogCO	-1.629717[1] (0.4659) {0}	-12.65157[0] (0.0000) {1}	-1.586777[3] (0.4879) {0}	-12.64962 [2] (0.0000) {1}	I(1)
LogS&P 500	-1.535447 [0] (0.5141) {0}	-14.56199 [0] (0.0000) {1}	-1.653301 [6] (0.4538) {0}	-14.61226 [5] (0.0000) {1}	I(1)
LogMICEX	-1.967443 [3] (0.3012) {0}	-7.830735 [2] (0.0000) {1}	-2.104234 [6] (0.2433) {0}	-12.81371 [6] (0.0000) {1}	I(1)
LogEPU	-2.360248 [7] (0.1543) {0}	-9.603115[6] (0.0000) {1}	-0.683832 [8] (0.4200) {0}	-57.51781[6] (0.0000) {1}	I(1)
LogIR	-1.967443 [3] (0.3012) {0}	-10.10476 [8] (0.0000) {1}	-3.514171 [6] (0.0400) {0}	-16.92992 [7] (0.0000) {1}	I(1)

N.B.: ( ) denotes the p-values (MacKinnon (1996)); [ ] are number of lags; {} are level of integration; Critical values: 1% = −3.46, 5% = −2.88, 10% = −2.57. Lag-length has determined based on AIC, maxlag = (12).

Based on equation 5, 6, and 7, the null (H_0) and alternative hypotheses for the unit root test in y_{t-1} were that (H_0) : $\lambda = (0)$, series has unit root (non-stationary); and (H_1): $\lambda <$ (0), stationary. The rule of thumb is that the data series is non-stationary if the calculated or statistical value is greater than the "critical value"; if not, the (H₀) of λ =0 will be rejected. Accordingly, it has clearly indicated in the table that the time series data was not stationary at

level for all variables. The ADF test results indicated that the null hypothesis was accepted for all variables. Hence, unable to reject the null hypothesis implied that the time series data was non-stationarity or has a unit root and integrated at the level, I (0). Therefore, this result enabled to apply the Johansson long-run cointegration test.

The Phillips and Perron (1988) unit root test has also given similar results (Table II). The Phillips-Perron (PP) test is almost similar to Augmented Dickey-Fuller tests. The only difference is mainly in how they deal with serial correlation and heteroskedasticity in the errors. The PP test indicated the same conclusion with that of the ADF tests.

IV.II. Lag-Length Selection

Wrong selection of lag-length generally changes the true result of cointegration test as the lag length determination is very sensitive to the result. Therefore, based on AIC, the optimum VAR lag order (p) was determined to be 2 for China and 4 for Russia. At these points, the value of AIC was the smallest. Hence, further tests were based on these lag lengths.

Table III. Optimum VAR Lag Lengths

Country	VAR Lag-Order(p)	AIC (Smallest Value)
China	2	-4.642681*
Russia	4	-1.676758*

*NB. * indicates the AIC value at the selected lag-order*

IV.III. Johansen Cointegration Test Results

Cointegration tests entail testing the error correction term's integration order in the relationship. Johansen's (Johansen and Juselius, 1990 & Johansen, 1991) approach derives two likelihood estimators for the Cointegration rank: the trace test (λ_{trace}) and the maximum Eigenvalue (λ_{max}) tests. Therefore, these two statistics were formally used for testing the rank of cointegration (r). Since the Johannes test is sensitive to the existence of a deterministic trend (Johansen, 1991, 1995), tests for cointegration was performed based on the assumption of a linear deterministic trend and the best lag-length of two (2-lags) for China and 4 for Russia.

Table IV. The Trace Statistics Test Results– CHINA (SSE Index)

Model	H_0	H_1	Eigenvalue	Trace Statistics	Critical Value (5%)	Prob.**
λ_{trace}	$r = 0*$	$r = 1$	0.166383	70.98640	69.81889	0.0402
	$r \leq 1$	$r = 2$	0.061076	28.03891	47.85613	0.8120
	$r \leq 2$	$r = 3$	0.034397	13.16592	29.79707	0.8839
	$r \leq 3$	$r = 4$	0.017798	4.905435	15.49471	0.8188
	$r \leq 4$	$r = 5$	0.002824	0.667355	3.841466	0.4140

H_0 rejected at 5 percent level of confidence
***p-values (MacKinnon-Haug-Michelis (1999))*

Table V. The Maximum Eigenvalue Test Results – CHINA (SSE Index)

	H_0	H_1	Eigenvalue	Max-Eigen Statistic	Critical Value (5%)	Prob.**
λ_{max}	$r = 0 *$	$r = 1$	0.166383	42.94749	33.87687	0.0032
	$r \leq 1$	$r = 2$	0.061076	14.87299	27.58434	0.7582
	$r \leq 2$	$r = 3$	0.034397	8.260486	21.13162	0.8871
	$r \leq 3$	$r = 4$	0.017798	4.238080	14.26460	0.8334
	$r \leq 4$	$r = 5$	0.002824	0.667355	3.841466	0.4140

H_0 rejected at 5 percent level of confidence
***p-values (MacKinnon-Haug-Michelis (1999))*

The trace test (λ_{trace}), Table IV and VI, is based on Equation 12. The test evaluates the null hypothesis that the number of distinct co-integrating vectors is less than or equal to r against a general alternative hypothesis that there are more than r (the number of distinct co-integrating vectors is more than r). It starts with p eigenvalues, and then successively the largest is removed. $\lambda_{trace} = 0$ when all the $\lambda_i = 0$, for i = 1, 2, . . . n. Therefore, in this test, H_0: rank (Π) $\leq$ r; and H_1: r < rank (Π) $\leq$ n. For the succeeding test, if this null hypothesis is rejected, the next null hypothesis is that rank (Π) $\leq$ r +1 and the alternative hypothesis is that r + 1 < rank (Π) $\leq$ n.

The maximum eigenvalue test (λ_{max}), Table IV and VI, is conducted based on Equation 13. The test examines the null hypothesis of the number of co-integrating vectors r (rank (Π) = r) against the alternative hypothesis of r+1 (rank (Π) = r + 1) cointegrating vectors. If the variables in y_t are not co-integrated, the rank of Π is zero and all the characteristic roots are

zero. For both statistical tests, critical values for testing the rank of the Π matrix have derived from Johansen's (1988) and Johansen & Juselius's (1990) critical value table. If the test statistic is greater than the critical value from Johansen's tables, the null hypothesis will be rejected.

Table IV and V present part of the cointegration test results for China. As it is clearly shown in Table III, the trace statistics (70.98640) is above the critical value (69.81889) with the p-value of 0.0402 (4.02%) which indicates that the hypothesis of zero cointegration vector (H_0: r = 0) has been rejected. However, the test results were inadequate to accept the alternative hypothesis that claims the existence of two or more cointegration vector (H_1: r =2) as the trace statistics (28.03891) was much less than the critical value (47.85613). It means that there was only one cointegration relation between the variables, H1: r=1. Hence, the optimum number of cointegration relation among the variables with two lags was, then, equal to one, i.e. rank ($\boldsymbol{\Pi}$) =1. The Max-Eigenvalue test has also supported the existence of only one cointegration relation at 5% significance level. In this case, since the critical value (33.87687) was less than the trace statistics of 42.94749 with the p-value of 0.0032, the null hypothesis was not acceptable at 5% significance level.

Table VI. The Trace Statistics Test Results- RUSSIA (MICEX Index)

Model	H_0	H_1	Eigenvalue	Trace Statistics	Critical Value (5%)	Prob.**
λ_{trace}	$r = 0*$	$r = 1$	0.161630	85.55284	69.81889	0.0017
	$r \leq 1$	$r = 2$	0.100788	42.00773	47.85613	0.1585
	$r \leq 2$	$r = 3$	0.044723	15.76719	29.79707	0.7285
	$r \leq 3$	$r = 4$	0.014582	4.465971	15.49471	0.8626
	$r \leq 4$	$r = 5$	0.003386	0.837790	3.841466	0.3600

*H_0 rejected at 5 percent level of confidence
**p-values (MacKinnon-Haug-Michelis (1999))

On the other hand, the Johansen cointegration test results for Russian (Table VI and VII) indicated that at least two variables in the system have cointegrated in the long-run. The null hypothesis (r = 0) has rejected in both tests with significant p-values of 0.0017 and 0.0026. The test, however, has failed to reject the H_0: $r \leq 1$ hypothesis as the trace statistics value of 42.00773 was below the critical value of 47.85613. Hence, the final number of co-integrated vectors with four lags was equal to one, i.e. rank ($\boldsymbol{\Pi}$) =1.

Table VII. The Maximum Eigenvalue Test Results - RUSSIA (MICEX Index)

Model	H_0	H_1	Eigenvalue	Max-Eigen Statistic	Critical Value (5%)	Prob.**
λ_{max}	$r = 0^*$	$r = 1$	0.161630	43.54511	33.87687	0.0026
	$r \leq 1$	$r = 2$	0.100788	26.24053	27.58434	0.0735
	$r \leq 2$	$r = 3$	0.044723	11.30122	21.13162	0.6173
	$r \leq 3$	$r = 4$	0.014582	3.628181	14.26460	0.8964
	$r \leq 4$	$r = 5$	0.003386	0.837790	3.841466	0.3600

H_0 rejected at 5 percent level of confidence
**p-values (MacKinnon-Haug-Michelis (1999))*

From the above results of the Johannes cointegration test at least two implications can be derived. The first major implication is that the variables used in the model have cointegration in the long run. It means that, in order to recover short-run, divergence from their long-run equilibrium, at least one variable tends to adjust proportionally in the short-run. The second major implication is also that as expected by the Granger representation theorem, in the system, there was a minimum of one Granger causality between the variables. In general, since the rank ($\boldsymbol{\Pi}$) was different from zero in both countries, the series was co-integrating among the variables. Therefore, the causality test should be performed by using the VEC Granger Causality model.

IV.IV. Vector Error Correction (VEC) Granger Causality

When there is cointegration among variables, the causal interactions between the dependent and independent variables should be carried out in a VEC form. It enables to determine the causal relationship in the χ^2-test of the first-differenced terms.

Table VIII. VEC Granger Causality Results for China

Variables	Independent				
	χ^2-statistics of Lagged Terms				
Dependent	ΔLogSSE	ΔLogEPU	ΔLogCO	ΔLogIR	ΔLogSP500
ΔLogSSE	--	0.004983 [0.9437]	1.011779 [0.3145]	4.068349** [0.0437]	1.437904 [0.2305]
ΔLogEPU	1.275218 [0.2588]	--	0.994462 [0.3187]	1.922417 [0.1656]	6.354061** [0.0117]
ΔLogCO	0.610239 [0.4347]	0.718059 [0.3968]	--	3.817011 [0.0507]	3.317415 [0.0685]
ΔLogIR	2.699404 [0.1004]	0.309854 [0.5778]	0.440091 [0.5071]	--	0.055110 [0.8144]
ΔLogSP500	0.543053 [0.4612]	0.453956 [0.5005]	0.006118 [0.9377]	3.350579 [0.0672]	--

*Note: ** is significant at 5%; Numbers in the squared brackets [...] are p-values. Δ is the first difference; Log is the natural logarithm, SSE is Shanghai Stock Exchange Index (China); EPU is Economic Policy Uncertainty Index for China; CO is Global Crude Oil Price; IR is Short-term Interest Rate for China, and SP500 is Standard & Poor 500 Index*

The first row in Table VII shows the short-run causality between LSSE index as the dependent variable and the rest of the variables as independent variables. The short-run causalities have determined with the χ^2-test. As shown in Table VII, the short-term interest (or lending) rates in China Granger cause to the Shanghai Stock Exchange index with χ^2-statistics of 4.068349 and the probability value of 0.0437 which is below the 5% significant level. It means the change in short-run interest rates can predict the changes in the Shanghai stock market returns. But there was no reverse causality from LogSSE to LogIR. One possible conclusion can be given from this result is that the Shanghai Stock Exchange was not efficient with respect to information about the short-term interest rate. The result indicates that the Shanghai stock market returns could be predicted using available information about short-term lending rates. This result has similarity with the reported findings of Teker & Alp (2014). Table VIII also shows that the S&P 500 index, which is a proxy for the global stock market, is the only variable that Granger causes the Chinese EPU index in the short-run. Such finding may be due to the existing strong trade relationship between China and the USA. Therefore, it was expected that when there was a decrease in demand for Chinese products in the US markets the

impact could be shown on the stock prices traded in the US market and it effects on the Chinese economy indirectly.

Table IX. VEC Granger Causality Results for Russia

Variables	Independent				
Dependent	χ^2-statistics of Lagged Terms				
	ΔLogMICEX	ΔLogEPU	ΔLogCO	ΔLogIR	ΔLogSP500
ΔLogMICEX	--	11.88490*** [0.0078]	5.830509 [0.1202]	3.720929 [0.2902]	5.265221 [0.1534]
ΔLogEPU	2.203087 [0.5313]	--	10.44795** [0.0151]	5.222456 [0.1562]	1.525007 [0.6765]
ΔLogCO	4.564970 [0.2066]	2.886585 [0.4094]	--	3.268904 [0.3520]	1.084491 [0.7808]
ΔLogIR	6.443588 [0.0919]	11.68331 [0.0086]	5.578147 [0.1340]	--	1.737282 [0.6287]
ΔLogSP500	4.136339 [0.2471]	12.78766*** [0.0051]	5.841804 [0.1196]	0.673282 [0.8795]	--

Note: *** refers to 1% significant level, ** is significant at 5%; Δ is the first difference; Log is the natural logarithm, MICEX is Moscow Interbank Currency Exchange Index (Russia's Stock Market Index); EPU is Economic Policy Uncertainty Index for Russia, CO is Global Crude Oil Price; IR is Short-term Interest Rate for Russia, and SP500 is Standard & Poor 500 Index

The first column of Table IX indicates the short run contribution of LogMICEX as an independent variable to other variables in the system. As clearly shown in the Table, the p-values reported in the first row suggests the existence of unidirectional short-run causality from the Russian EPU index to the MICEX index, with significant -statistics of 11.88490 and p-value of 0.0078. It means that in the short-run, the economic policy uncertainty index predicts the MICEX index. However, the MICEX index doesn't Granger-cause the LogEPU index. So that it can be possible to make a conclusion from this result that the Moscow Stock Exchange was not efficient market as for Economic policy uncertainty index. It implies that Moscow stock market returns could be predicted during the study period using available information about Russian's economic uncertainty index in the short-run. These outcomes are in one another agreeing with the established results of Brogaard & Detzel (2012) and Vichet (2012). However, no significant causality is detected from the rest of independent variables to the LogMICEX index. It can be interpreted that the Moscow stock market prices already incorporate all available information about changes in these variables. These results can be

considered as empirical proof that, in the short run, the Moscow Stock Exchange is informationally efficient in relation to LogCO, LogIR, and LogS&P 500 index. One justification to claim that a shock in the Russian EPU affects the US stock market (S&P 500) will be through its impact on global oil supply. Since Russia is one of the largest oil suppliers to the international market, any uncertainty in the country's economy creates uncertainty about the supply of oil and it affects oil price directly and cost of production. This outcome is similar to the results reported by Subarna & Zadeh, (2012).

In the first column of Table VIII, the p-values show the Moscow stock market index as a leading indicator only for the short-term lending rates. On the other hand, the Russian EPU index can be predicted using the information for the Global crude oil price movements. There was also a VEC Granger causality running from LogCO to LogEPU with χ^2-statistics of 10.44795 and p-value of 0.0151 which is significant at 5 percent level. Since Russia is one of the world's largest oil producer and exporting countries, the causal relationship between global oil price and Russia's EPU was expected. According to Nadia & Chulpan (2015), 31.77% of the Russian consolidated budget revenues and over 51.28% of the federal revenues fall to the share of oil and gas revenues. Therefore, changes in global oil price expected to have a direct effect on Russia's economy. When oil prices drop, the country's revenue suffers greatly. This result is in line with studies by Shibanova Roenko and Guznova (2012), Ito (2012), and Rasoulinezhad (2014) who have established a relationship between Russia's economic and oil price shocks. The unidirectional Granger causality was also found between LogEPU and short-term lending rates with the p-value of 0.0086 which is significant at 1% level of confidence.

V. CONCLUSIONS

As it has been mentioned in the first part of the paper, the main goal of the study was to examine the cointegration and causality among the Global oil prices, uncertainties in economic policies, interest rates, and stock market returns in Russia and China. The analyses have done by using 252 monthly observations during the period from January 1996 to December 2016. The study investigated the existence of co-movements and causality among variables using the Johansen & Juselius (1990) cointegration test and VEC Granger Causality Tests. The uncertainty in government economic policies has measured based on the news based measure of EPU index which is developed by Baker et al. (2013, 2016). The study has also

used the USA stock market (S&P 500) index as a proxy for the "Global Stock Market Index". Financial crisis and stock market fails were also considered in this study as 'dummy variables'.

The outcomes of the analysis indicated that there was a long-run cointegration relation among variables both in China and Russia. But the Granger causality test for China has also indicated only existence of a unidirectional causality from overnight interest-rates to the Shanghai Stock Exchange index. It means the movements in interest rate enables to predict the possible variation in the SSE index. This relationship was expected as the interest based securities are alternatives for stock market investments. However, the Granger causality test carried out to test the relationship between the Shanghai stock market returns and the international crude oil price has not indicated a significant relationship. It means Global crude oil price is not the causal variable for changes in China's stock market index. This result may be due to China's unique pricing mechanism of oil products and less volatility of oil prices in China as compared to other countries. According to Haoyuan et al. (2017), the refined oil price in China does not automatically adjust in response to international oil prices. It is less frequently adjusted by National Development and Reform Committee in Central government. This result has similarities with studies done by Cong et al. (2008) and Fang and You (2014) that both claims that the impact of oil price changes on Chinese stock market is insignificant. The result also indicated an insignificant causal relationship between EPU and stock market returns in China.

In Russia, the outcomes of causality tests have shown the existence of a one direction Granger causality running from the Russian EPU index to MICEX index and from global oil price to the Russian EPU index. There was also Granger causality running from the Russian's EPU index to Banks' overnight lending rates. It means in Russia, the EPU index was an indicator for the MICEX index and the lending rate in the short-run. The direct impact of global oil price on Russia's stock market is very week. However, fluctuations in global oil price directly affect Russia's economic policy uncertainty which in turn has a direct impact on the stock market. Such that it can be concluded that global oil price shocks indirectly affect the Russian stock market through its effect on the country's economy.

Finally, the findings of the study indicate that the stock markets are inefficient in both countries. For the Shanghai Stock Exchange, the inefficiency was with respect to overnight interest rate since the Shanghai stock market returns can be predicted using available information about short-term lending rates. In Russia, the MICEX index could be also predicted using available information about Russian's economic uncertainty index in the short-run during the study periods. The remaining variables appear to have an insignificant relationship with the

MICEX index in the short-run. It indicates that all information available on changes in these variables is already incorporated in these stock market prices. Thus, this result may be seen as empirical evidence that both stock markets meet the efficient-market hypothesis (EMH) with respect to EPU index, Global oil price, and S&P 500 in China and short-term interest rates, Global oil price, and S&P 500 in Russia in the short run.

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