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The Effects of the Political Turbulences on the Stock Exchange Indices

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Abstract. *Political turbulence is known to influence the velocity of economic development and reduce investments. Our paper aims to point up the linkage between political instability and the evolution of the Romanian capital market. We model the volatility of two of the Bucharest Stock Exchange indices BET and BET-NG using a GARCH/ARCH approach for daily data between 2010 and 2021. Results highlight the interconnections between political and economic policy uncertainty and the financial market. In both cases, for BET and BET-NG, our study shows that different types of political events have different levels of influence on the indices' volatility. Unexpected "shock" type events with negative impacts resulted in much higher volatility than positive events. When there were events that had fiscal connotations, they had a much greater power of penetration in the investment environment because it comes down to figures and calculations that had a direct, measurable impact. There is a need for political involvement, certainty, lack of ambiguity, and predictability, both from a legislative point of view and how it is applied.*
KEYWORDS: political events, volatility, stock indices, policies
JEL classification: C10, G14, G18

Introduction

In this article, we study the influence of political events and economic policies on two of the Bucharest Stock Exchange indices, BET and BET-NG. The study covers the period after Romania acceded to the European Union and after the onset of the global crisis from 2008 to 2010, namely the period 2010 to 2021.

Our study starts from other previous studies, Vancea et al. (2017) which show that political events influence the financial markets in Romania. The study runs for a period of 11 years and includes in addition to the representative index of the Bucharest Stock Exchange, the BET-NG sector index, which represents the energy sector.

In this study, we analyze political events such as presidential elections (2014 and 2019), parliamentary and local elections (2012, 2016, and 2020), European elections (2014 and 2019), the suspension of President Traian Basescu (July 2012) and the resignation of the first ministers Boc (2012), Ponta (2015), and Tudose (2018). During this period were initiated 17 censorship motions, five of which were approved and led to the fall of the Government: Ungureanu (2012), Grindeanu (2018), Dancila (2019), Orban (2020), and Citu (2021). Besides political events, we analyze legislative initiatives that had an influence on the capital market during the period under study. Among these measures, austerity measures taken by the authorities during the 2010 crisis and the Emergency Ordinance 114 of December 2018 had a significant impact, which led to high volatility in the stock market.

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Literature review

There are authors such as Bragues (2010) who believe that to get a complete view, the whole constellation of currencies, stocks, bonds, money market instruments, derivatives, and hedge funds needs to be analyzed in terms of the policy. Financial markets are always intertwined with politics, being influenced and shaped by it.

Wisniewski (2007) documented that the non-fundamental component of the stock market index appears to be significantly influenced by the political orientation of the president and his approval rating, election cycle, and military conflicts. Bialkowski et al. (2008) prove that national elections induce higher stock market volatility.

Darby et al. (2000) focus on the link between political instability due to uncertain electoral outcomes and economic growth through the effect on a government's decisions on allocating government expenditure between public consumption and investment.

Durnev (2010) shows that political uncertainty surrounding elections can affect how corporate investment responds to stock prices. According to his study, election uncertainty leads to inefficient capital allocation, reducing company performance.

Liu et al. (2016) test the causal link between political uncertainty and asset prices in an unexpected event (a political scandal) in China and document significant drops in stock prices around the scandal. Hou et al. (2020) highlight that political uncertainty also affects the commodity markets in their study. In the periods toward US presidential elections, commodity prices and inventories register essential declines.

Ahir et al. (2018) construct a World Uncertainty Index for 143 countries and find that the level of uncertainty is positively associated with economic policy uncertainty and stock market volatility and negatively with GDP growth.

The relationship between election uncertainty, economic policy uncertainty, and financial market uncertainty in seven US presidential election campaigns (from 1992 to 2016) was also examined by Goodell et al. (2019).

Researchers such as Pastor and Veronessi (2013) analyze how changes in government policy affect stock prices. They interpret political uncertainty as "uncertainty about future government actions." Studying two types of political events, national elections and global summits, Kelly et al. (2014) find that political uncertainty is priced in the options market. Also, options provide valuable protection against the risk associated with major political events.

The correspondence between the turbulences recorded in the political activity and the volatility of the exchange rate in Romania is revealed by the study of Vancea and Aivaz (2017).

Colon et al. (2020) explore the effects of political and economic uncertainty on the cryptocurrency market, suggesting that uncertainty is an essential determinant of cryptocurrency returns.

Methodology

In our study, we analyzed using ARIMA, ARCH/ GARCH models (Gherghina et al., 2021; Predescu and Stancu, 2011; Banerjee, 2021; Bora and Basistha, 2021; Curto and Serrasqueiro, 2021; Alexandru et al., 2013; Duttilo et al., 2021; Ghergut et al., 2013 Fakhfekh et al., 2021; Vancea and Aivaz, 2012; Ftiti et al., 2021; Vancea et al, 2017; Ghorbel and Jeribi, 2021) daily values for BET and BET-NG, starting from January 3rd2010 to December 31th2021 to highlight the interconnection between political shocks and the financial markets volatility.

BET is the first index developed by BSE and represents the reference index for the local capital market. BET reflects the performance of the most traded companies on BSE's regulated market, excluding financial investment companies (SIFs).

BET-NG is a sector index that reflects the evolution of all the companies listed on BSE's regulated market included in the energy and related utilities sector.

AutoRegressive Moving Average (**ARMA**) was introduced in 1970 by Box and Jenkins and its equation is as follows:

$$r_t = \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_p \varepsilon_{t-p}$$

Where, y_t −stands for the dependent variable in *t* period, β are the coefficients for the autoregressive terms, θ are the coefficients for the moving average term, ε_t residual terms in current t period.

Introduced for the first time in the literature in 1982 (Engle, 1982), the AutoRegressive Conditional Heteroscedasticity (**ARCH)** to measure the variance of inflation in the United Kingdom:

$$y_t = \theta_0 + \theta_1 y_{t-1} + \cdots + \theta_n y_{t-n} + \varepsilon_t$$

Where

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_n \varepsilon_{t-n}^2 + \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \varepsilon_t$$

y_t is the autoregressive model AR(q), σ_t^2 aresquares of the error regressed to a constant and q lagged values.

And

$\alpha_0 > 0$ and $\alpha_i > 0$: to guarantee positive variance;

$\alpha_1 > \alpha_2 > s \ldots > \alpha_n$: Recent past lags have more influence than older ones;

$0 \leq \sum_{i=1}^{i=n} \alpha_i < 1$;

An extended version of **ARCH** models was introduced by Bollerslev (1986) named Generalized Autoregressive Conditional Heteroscedasticity (GARCH). GARCH models allow us to model the variance as an ARIMA process and conditional variation depends on its precursory lags. GARCH models modulate the autoregressive (AR) process from the ARCH model into an ARMA process by adding a moving average (MA) process.>. Below we have the equation for a GARCH(p,q) model (Bollerslev, 1986):

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2$$

With ω>0, $\alpha_i > 0$, β_i>0 condition for positive variance

the $0 \leq \sum_{i=1}^{q} \alpha_i + \sum_{i=1}^{q} \beta_i < 1$ condition for decaying variance

Where: σ_t^2- stands for the variance, ω – „white noise" - the constant in the dispersion equation, α - "ARCH" coefficient; ε_{t-1} residual terms in previous period t–1; β -"GARCH" coefficient.

ARCH (1) model takes into account the volatility to predict the next values of the time series. The basic idea in an Arch model is that if volatility is high in period t-1, the volatility will be high

in time t and vice versa. In other words the value of a time series in t moment is affected by ***the random error (ε_t) and the volatility in time t (σ_t).*** Since the volatility in time t is a function of the time series in t-1, σ_t is affected by the value of tithe me series in t-1.

GARCH (1, 1) model is equivalent to Arthe CH (2) model, while GARCH (p, q) is equivalent to ARCH (q + p) (Gujarati, 2003). In our study, we will compare the results from these 2 models and select the best fitted one. **In GARCH (1, 1)** the value of a time series in t moment is affected by the ***white noise (ε_t), the values of time series in t-1, and the volatility yesterday (σ_{t-1}).*** For long time series the GARCH (1, 1) model can be generalized as the GARCH (p, q) model and when q=0 GARCH reduces to ARCH.

In our study, the variable that we used is the BET and BET-NG daily values from 03.01.2010 to 31.12.2021. The time series was logarithmically transformed in order to attenuate the monostatic nature. The formula for daily rate is in line with Vancea et al, (2017); Bora and Basistha (2021); Predescu and Stancu, (2011); Curto and Serrasqueiro (2021); Gherghina et al., (2021); Fakhfekh et al. (2021);

$$R_t = ln\left(\frac{I_t}{I_{t-1}}\right)$$

Where R_t stands for the BET and BET-NG rate in period t, I_t stands for the BET or BET-NG values at time t and I_{t-1} are the value from previous period (t-1).

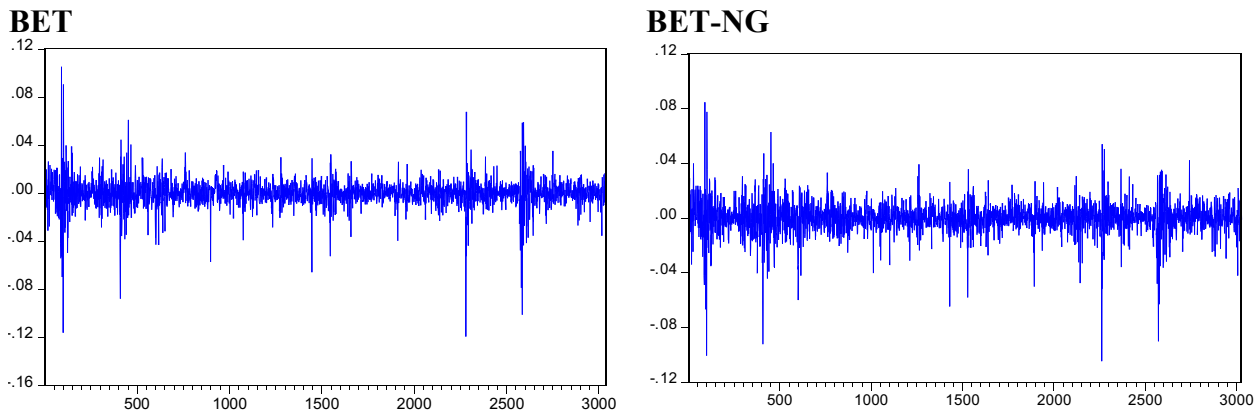


Figure 1. The evolution of the daily rate fluctuation of BET and BET-NG 2010-2021

Source*:* Authors' computation, Stata.

We can notice in Fig. 1, the high volatility of the BET and BET-NG index. In the first period, we can identify volatility clusters (significant fluctuations are succeeded by the same volatile periods, but also they seem to be correlated with political turbulence) followed by high volatility at the beginning of the Covid-19 crisis (March 2020). BET-NG seems to face periods of higher volatility than BET.

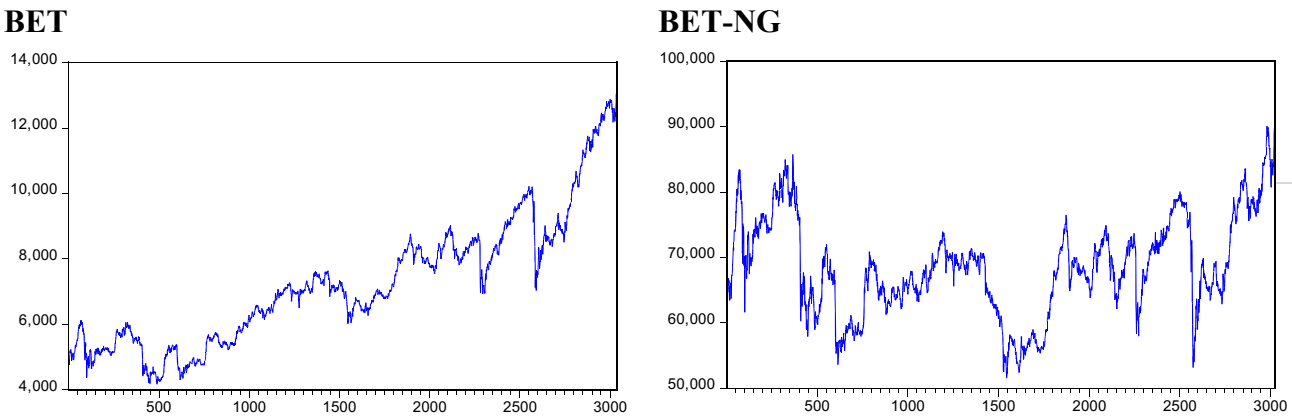


Figure 2. The evolution of BET and BET-NG 2010-2021

Source*:* Authors' computation, Stata.

We used the three stages method (Box and Jenkins, 1970) to predict a time series using ARMA models: identification, estimation and diagnostic and forecasting. in the first stage, identification we analyze the proprieties of our variable BET and BET-NG. At this point in our study, we are going to test the stationarity using the ADF (Augmented Dickey-Fuller) test. Were tested the following hypotheses:

H0: BET and BET-NG rate series have a root unit and are non-stationary.

H1: BET and BET-NG rate series are stationary.

Table 1. Results for unit root test (Augmented Dickey-Fuller Test)

BET				**BET-NG**			
		t-Statistic	Prob.*			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-36.42139	0.0000	Augmented Dickey-Fuller test statistic		-36.02696	0.0000
Test critical values:	1% level	-3.432315		Test critical values:	1% level	-3.432323	
	5% level	-2.862294			5% level	-2.862297	
	10% level	-2.567215			10% level	-2.567217	

Source*:* Authors' computation, Stata.

Table 1 from above suggests that we can reject the null hypotheses; the time series is stationary for a significance level of 5% for both indexes BET and BET-NG. Results indicate that the test values are much higher than the theoretical critical values, and the ARMA (p, q) model is going to be used in our investigation, instead of the ARIMA (p, i, q) model which is preferred if BET and BET-NG rate series have a root unit and the series are non-stationary.

To determine the p and q and the presence of the ARCH effects we can check the correlograms graph in Appendix 1. and Appendix 2. which represents the correlogram of the BET and BET-NG rate variance.

Table 2. ARMA results

BET				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000346	0.000251	1.382879	0.1668
AR(1)	0.602776	0.186619	3.229985	0.0013
MA(1)	-0.577917	0.191179	-3.022916	0.0025
SIGMASQ	0.000125	1.00E-06	124.6307	0.0000
Akaike info criterion	-6.149096	Hannan-Quinn criter.		-6.146246
Schwarz criterion	-6.141169	Log likelihood		9341.402
BET-NG				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000144	0.000249	0.576148	0.5646
AR(1)	0.456521	0.142323	3.207639	0.0014
MA(1)	-0.404820	0.147039	-2.753140	0.0059
SIGMASQ	0.000130	1.30E-06	99.51296	0.0000
Akaike info criterion	-6.108894	Schwarz criterion		-6.100943
Log likelihood	9246.757	Hannan-Quinn criter.		-6.106036

Source*:* Authors' computation, Stata.

The coefficients of the AR (1) and MA (1) terms are highly significant, meaning that there is significant predictability in the variance term. According to the information criteria from Table 2, the ARMA (1, 1) is robust and the equation is expressed below:

$$r_{BET_t} = 0.000346 + 0.602776y_{t-1} - 0.577917\varepsilon_{t-1} + \varepsilon_t$$

$$r_{BET-NG_t} = 0.000144 + 0.456521y_{t-1} - 0.404820\varepsilon_{t-1} + \varepsilon_t$$

The second step in estimating ARCH and GARCH models is to test the existence of ARCH effects. If the test confirms the existence of ARCH/GARCH effects, we will re-estimate the ARMA model including the ARCH/ GARCH components.

Now if we have the mean equation we will conduct the Heteroscedasticity test and select the ARCH option. We are going to test for the next hypothesis:

H0: There are no ARCH effects up the specified lag

H1: there are ARCH effects up to the specified lag

Table 3. Test for ARCH effects

BET				
Heteroscedasticity Test: ARCH LAG 1				
F-statistic	299.6954	Prob. F(1,3034)		0.0000
Obs*R-squared	272.9329	Prob. Chi-Square(1)		0.0000
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	8.69E-05	1.04E-05	8.381730	0.0000
RESID^2(-1)	0.299639	0.017308	17.31171	0.0000
Heteroscedasticity Test: ARCH LAG 2				
F-statistic	154.6157	Prob. F(2,3032)		0.0000
Obs*R-squared	280.8897	Prob. Chi-Square(2)		0.0000
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	8.16E-05	1.05E-05	7.793441	0.0000
RESID^2(-1)	0.281121	0.018124	15.51109	0.0000
RESID^2(-2)	0.058920	0.018112	3.253080	0.0012
BET-NG				
Heteroscedasticity Test: ARCH LAG 1				
F-statistic	222.3622	Prob. F(1,3023)		0.0000
Obs*R-squared	207.2637	Prob. Chi-Square(1)		0.0000
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	9.55E-05	8.79E-06	10.86858	0.0000
RESID^2(-1)	0.261599	0.017543	14.91181	0.0000
Heteroscedasticity Test: ARCH LAG 2				
F-statistic	128.5885	Prob. F(2,3021)		0.0000
Obs*R-squared	237.2365	Prob. Chi-Square(2)		0.0000
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	8.53E-05	8.91E-06	9.575140	0.0000
RESID^2(-1)	0.233250	0.018088	12.89530	0.0000
RESID^2(-2)	0.105313	0.018077	5.825811	0.0000

Source*:* Authors' computation, Stata.

We reject the null hypothesis; the test results suggest that there are arch effects up to the second lag for both of our indexes BET and BET_NG, p-value is smaller than 0.05.

We are going to add a second layer to our estimation for an optimal forecast and will analyze volatility in BET and BET-NG series using ARCH type models that look at the volatility variance of the error term as an additional variable to be forecast. Based on the correlogram graph and heteroscedasticity test results, we are going to estimate an ARCH (2) model that is similar to the GARCH (1, 1) model, compare the results and chose the best-fitted model. These models incorporate the autoregressive and moving average in the heteroskedastic variance.

Table 4. ARIMA and ARCH (2) results

BET

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000643	0.000129	4.980543	0.0000
AR(1)	0.364212	0.149915	2.429463	0.0151
MA(1)	-0.312918	0.155562	-2.011536	0.0443
	Variance Equation			
C	4.65E-05	1.29E-06	36.07902	0.0000
RESID(-1)^2	0.500906	0.018514	27.05505	0.0000
RESID(-2)^2	0.226146	0.018832	12.00838	0.0000
Akaike info criterion	-6.497551	Schwarz criterion		-6.485657
Log likelihood	9869.282	Hannan-Quinn criter.		-6.493275

BET-NG

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000376	0.000162	2.317203	0.0205
AR(1)	0.399012	0.156449	2.550426	0.0108
MA(1)	-0.347467	0.163483	-2.125402	0.0336
Variance Equation				
C	6.05E-05	1.51E-06	40.14585	0.0000
RESID(-1)^2	0.319080	0.018365	17.37435	0.0000
RESID(-2)^2	0.273490	0.019261	14.19945	0.0000
Akaike info criterion	-6.339088	Schwarz criterion		-6.327158
Log likelihood	9593.871	Hannan-Quinn criter.		-6.334799

Source*:* Authors' computation, Stata.

The coefficients of the ARCH (2) are highly significant, meaning that there is significant predictability in the variance term. The AR (1) and MA (1) coefficients are also significant at 5 % and 10%. According to the information criteria from Table 4, the ARCH (2) model is robust and the variance equation is expressed below:

$$h_{BET_t} = 4.65E-05 + 0.500906\varepsilon_{t-1}^2 + 0.226146\varepsilon_{t-2}^2 + \varepsilon_t$$

$$h_{BET-NG_t} = 6.05E-05 + 0.319080\varepsilon_{t-1}^2 + 0.27349\varepsilon_{t-2}^2 + \varepsilon_t$$

The coefficients $\alpha_0 > 0, \alpha_1 > 0$ and $\alpha_2 > 0$ suggesting that the positive variance is guaranteed. In addition, we can observe that for both indexes BET and BET-NG recent past lags have more influence than older ones.

Table 5. Test for arch effects

BET				
Heteroscedasticity Test: ARCH LAG 2				
F-statistic	0.881737	Prob. F(2,3031)		0.4142
Obs*R-squared	1.764194	Prob. Chi-Square(2)		0.4139
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.030443	0.062327	16.53285	0.0000
WGT_RESID^2(-1)	-0.007504	0.018159	-0.413220	0.6795
WGT_RESID^2(-2)	-0.022972	0.018159	-1.265056	0.2059
BET-NG				
Heteroscedasticity Test: ARCH LAG 2				
F-statistic	1.127176	Prob. F(2,3020)		0.3241
Obs*R-squared	2.254908	Prob. Chi-Square(2)		0.3239
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.038508	0.057401	18.09220	0.0000
WGT_RESID^2(-1)	-0.016584	0.018193	-0.911564	0.3621
WGT_RESID^2(-2)	-0.021972	0.018193	-1.207733	0.2272

Source*:* Authors' computation, Stata.

After testing for ARCH effects in the residuals we can accept the null hypothesis – there are no arch effects in our time series with a probability higher than 95%. We can conclude that there is no more heteroscedasticity in our ARCH (2) model, two ARCH terms are sufficient to mitigate the heteroscedasticity and our specification is robust.

Table 6. ARIMA and GARCH (1, 1) results

BET				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000646	0.000129	5.007001	0.0000
AR(1)	0.486001	0.211194	2.301201	0.0214
MA(1)	-0.454048	0.218067	-2.082152	0.0373

BET				
	Variance Equation			
C	7.58E-06	6.06E-07	12.50763	0.0000
RESID(-1)^2	0.234844	0.012105	19.40078	0.0000
GARCH(-1)	0.720969	0.012554	57.43108	0.0000
Akaike info criterion	-6.564498	Schwarz criterion		-6.552604
Log likelihood	9970.907	Hannan-Quinn criter.		-6.560222
BET-NG				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000443	0.000160	2.763400	0.0057
AR(1)	0.456672	0.246058	1.855953	0.0635
MA(1)	-0.427899	0.250878	-1.705604	0.0881
	Variance Equation			
C	6.34E-06	5.52E-07	11.50267	0.0000
RESID(-1)^2	0.154472	0.008706	17.74219	0.0000
GARCH(-1)	0.801670	0.011004	72.85561	0.0000
Akaike info criterion	-6.414182	Schwarz criterion		-6.402252
Log likelihood	9707.451	Hannan-Quinn criter.		-6.409893

Source*:* Authors' computation, Stata.

Results suggest that the coefficients for both indexes BET and BET-NG of the GARCH (1, 1) model are highly significant, meaning that there is significant predictability in the variance term. When comes to the AR(1) and MA(1) results, the coefficients are less significant; for BET are significant at 10% and for BET-NG the coefficients were less high than the critical value and we cannot be 95% confident that a relationship exists. According to the information criteria from Table 6, the GARCH (1,1) model is robust and the variance equation is expressed below:

$$\sigma^2_{BET_t} = 7.58\text{E} - 06 + 0.234844\ \varepsilon^2_{t-1} + 0.720969\ \sigma^2_{t-1} + \varepsilon_t$$

$$\sigma^2_{BET-NG_t} = 6.34\text{E} - 06 + 0.154472\ \varepsilon^2_{t-1} + 0.801670\ \sigma^2_{t-1} + \varepsilon_t$$

All the coefficients are higher than 0 indicating positive variance The sum between the ARCH and the GARCH terms is <1 which ensures the stationarity and the non-negativity of the variance process; the sum is very close to 1, indicating the persistence in volatility.

Table 7. Test for arch effects (heteroscedasticity)

BET				
Heteroscedasticity Test: ARCH LAG 2				
F-statistic	0.135067	Prob. F(2,3031)		0.8737
Obs*R-squared	0.270378	Prob. Chi-Square(2)		0.8736
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.010343	0.075166	13.44147	0.0000
WGT_RESID^2(-1)	-0.000777	0.018163	-0.042755	0.9659
WGT_RESID^2(-2)	-0.009409	0.018163	-0.518017	0.6045
BET-NG				
Heteroscedasticity Test: ARCH LAG 2				
F-statistic	0.329253	Prob. F(2,3020)		0.7195
Obs*R-squared	0.659017	Prob. Chi-Square(2)		0.7193
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.994616	0.062979	15.79291	0.0000
WGT_RESID^2(-1)	-0.007126	0.018196	-0.391650	0.6953
WGT_RESID^2(-2)	0.012880	0.018196	0.707863	0.4791

Source*:* Authors computation, Stata.

When testing for ARCH effects in the residuals we can accept the null hypothesis – there are no arch effects in our time series with a probability higher than 95%. We can conclude that there is no more heteroscedasticity in our GARCH (1, 1) model and our specification are robust.

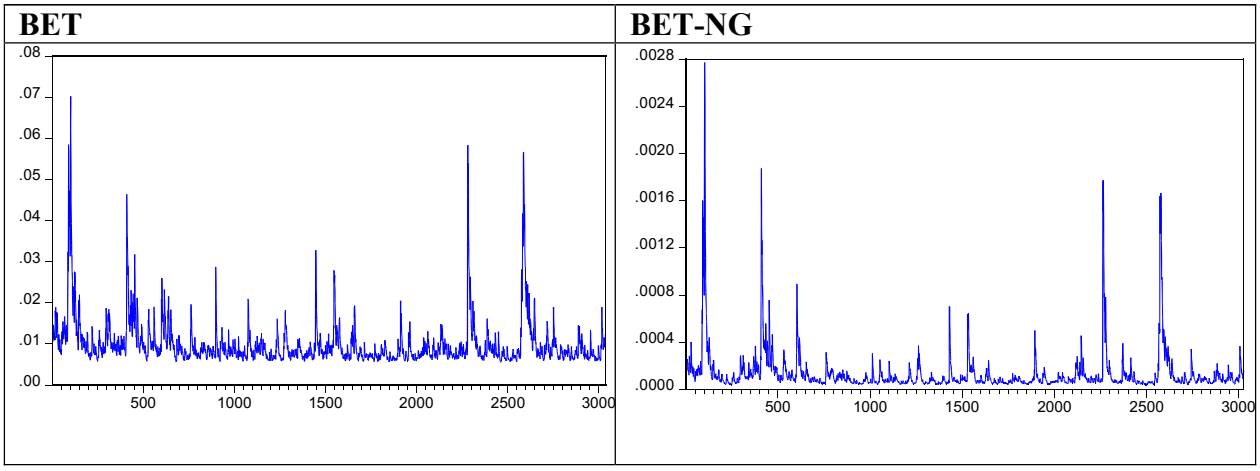


Figure 3. The volatility of the BET and BET-NG rate based on the GARCH(1,1) model

Source*:* Authors' processing, Stata.

The volatility charts help us to visualize, what our model is picking up – an extended period of high volatility followed by the extended periods of low volatility which is analyzed is directly linked to political events.

Table 8. Comparing Arch(2) vs Garch (1,1) results

Criteria	BET		BET-NG	
	ARCH(2)	GARCH(1, 1)	ARCH(2)	GARCH(1, 1)
Log likelihood	9869.282	9970.907	9593.871	9707.451
Akaike info	-6.497551	-6.564498	-6.339088	-6.414182
Schwarz	-6.485657	-6.552604	-6.327158	-6.402252
Hannan-Quinn	-6.493275	-6.560222	-6.334799	-6.409893

Source*:* Authors' computation, Stata.

In Table 8, we compare the estimation results between ARCH (2) and GARCH (1, 1) results, for BET and BET-NG index. Based on Bayesian comparison we are looking for the higher value of the long likelihood criteria and the smaller values of the Akaike, Schwarz and Hannan-Quinn criterion. Comparing the results, we conclude that GARCH (1, 1) model best fits our data based on the Bayesian approach.

Results and discussions

Using a database of daily quotations of BET and BET-NG indices for 2010-2021, this study analyses the effects of political events on the capital market evolution. By applying econometric models such as ARIMA, ARCH / GARCH, to emphasize volatility, our findings show that political uncertainty influences the indices evolution.

In this study, we analyze political events such as presidential elections (2014 and 2019), parliamentary and local elections (2012, 2016, and 2020), European elections (2014 and 2019), the suspension of President Traian Basescu (July 2012) and the resignation of the prime ministers Boc (2012), Ponta (2015), and Tudose (2018). During this period were initiated 17 censorship motions, five of which were approved and led to the fall of the Government: Ungureanu (2012), Grindeanu (2018), Dancila (2019), Orban (2020), and Citu (2021). Besides political events, we analyze legislative initiatives that had an influence on the capital market during the period under study. Among these measures, austerity measures taken by the authorities during the 2010 crisis, reducing the salaries of public servants, pensions, and subsidies had a significant impact and led to high volatility in the stock market, as the volatility charts show.

High volatility was determined after the issuance of one of the most controversial ordinances, GEO 114, in December 2018. The end of the year brings panic among investors on the stock market, and large declines in stock market indices. Issued out of nowhere, without prior consultation with businesses, economists, the NBR, the ordinance had a huge impact on financial markets. There was panic among investors, they sold the shares interpreting that following this ordinance the financial results of the companies in the banking and energy sector will decrease. Stock market indices fell sharply, in just one trading session, the BET index lost about 12%, and the BET-NG index - 10%.

Although until December the evolution of the indices was a positive one, following the issuance of the ordinance, they ended the year with decreases. The downward evolution continued at the beginning of 2019, but after consultations between the Ministry of Finance, specialists, representatives of The National Bank, and economists, were amended and clarified the ordinance, and investors returned to better sentiment.

And the onset of the Covid pandemic, the state of emergency in March 2020 led to high volatility of stock indices. The indices lost approximately 8% (BET-NG) to 10% (BET) in one single trading session.

The results of our study show that ordinary and predictable political events, such as presidential, parliamentary, and local elections produced at the time of their occurrence reduced volatility. Regarding the censorship motions or the resignations of the prime ministers, these events did not produce significant variations of the indices, 1% - 2%. These events had a minimal impact on the financial market probably because the information was in the market before this was reached. Everyone distilled it until the event happened.

Conclusion

Using a database of daily quotations of BET and BET-NG indices for 2010-2021, this study analyses the effects of political events on the capital market evolution. By applying econometric models such as ARIMA, ARCH / GARCH, to emphasize volatility, our findings confirm our hypothesis, that political events and economic policies influence the stock exchange indices evolution.

Our study shows that the magnitude of the impact of policy measures is stronger than the impact of political events such as presidential, local, or European parliamentary elections, cabinet formation, and dissolution.

Unexpected "shock" type events with negative impacts resulted in much higher volatility than positive events. When there were events that had fiscal connotations, they had a much greater power of penetration in the investment environment because it comes down to figures and calculations that had a direct, measurable impact.

Investors want to see political involvement, certainty, lack of ambiguity, and predictability, both from a legislative point of view and how it is applied.

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