

Structural Breaks, Asymmetry and Persistence of Stock Market Volatility: Evidence from Post-Revolution Tunisia

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Abstract

This paper analyses the impact of political uncertainty on the volatility of the Tunisian stock market from November 2010 to February 2016. In particular, it examines structural breaks in the variance by using the Iterated Cumulative Sums of Squares (ICSS) and modified ICSS algorithms. Asymmetric GARCH models are then extended by taking account regime shifts. Our results suggest that Tunisian stock market volatility is sensitive to local and political events. Large shifts coincide with civil uprisings and periods of political turbulence during the democratic transition and argue that the relationship between volatility and returns reflects the common effects of political factors. Diagnostic tests emphasize the asymmetric volatility response to news. However, there is no evidence that taking into account regime shifts reduces the volatility persistence which leads to think that the Tunisian stock market is well controlled and supervised.

Keywords: structural breaks, ICSS algorithm, modified ICSS, Tunisian stock market, persistence, asymmetry, civil uprisings

1. Introduction

For decades, the impacts that major political events have on stock prices have been a topic of interest for financial economists. Turbulent political situation has a high systematic investment risk, discourages capital investment, growth and reduces overall economy's performance. As the occurrences of political and civil unrests signal possible shift in policy which may create market-wide assessment changes, it is very common for stock markets to experience an increase in volatility levels (Karolyi, 2006). The generalized autoregressive conditional heteroskedasticity (GARCH) family models are useful processes, implemented by many researchers, to model time-varying volatility in asset returns. However, most of these models do not account for structural breakpoints in the variance which may overestimate the variance persistence and cause spurious volatility modeling (Lamoureux & Lastrapes, 1990; Malik, 2003).

In this context, the Tunisian revolution was an enormous and unprecedented event arising from overthrown in government as a result of pacific civil uprisings. Intuitively, a major political event like this can have an explosive impact on stock market volatility. It may cause structural breaks in volatility and, as a result, influence its persistence as well as the asset's current price. Therefore, it is imperative and entirely justified to examine whether, and to what extent the political turmoil has impacted the overall Tunisian stock market.

The disrupting effects of political uncertainty such as military invasion/ wars, presidential elections and terrorist attacks have been widely documented in literature on financial markets and economy. Little studies have analyzed the potential effect of an important source of political uncertainty arising from civil uprisings. Using Tunisian revolution as a unique test environment, this study represents the latest attempt in assessing the influence of political turmoil on the stability of the Tunisian stock market by considering sudden changes in volatility. To reach this objective, initially the time periods of volatility shifts are identified endogenously using Inclan and Tio's (1994) iterated cumulative sums of squares (ICSS) algorithm. This choice can be explained for two reasons. On the one hand, this approach seems to have already given satisfactory results on real data (Aggarwal, Inclan, & Leal, 1999; Ewing & Malik; 2005, 2010, 2015; Malik, 2011; Hammoudeh & Li, 2008) and on the other hand, the performance of the results seems very close to those obtained with parametric methods

such as Bayesian methods or those based on maximum likelihood (Inclan & Tio, 1994; Ahamada et al., 2005). Moreover, to overcome the problems of homoskedasticity and mesokurtosis of ICSS algorithm, we apply the modified ICSS developed by Sansó et al. (2004) based on kappa-1 and kappa-2 tests. Indeed, κ_1 test corrects for non-mesokurtosis, while κ_2 test takes into account the fourth moment and the persistence in variance. Political events surrounding the breakpoints in volatility are then analyzed. These regime shifts are then introduced in a number of symmetric and asymmetric GARCH models to measure the effect of a given shock on volatility persistence.

The remainder of this paper is structured as follows: Section 2 presents the literature review. Section 3 and 4 respectively describe the methodology and data. Section 5 provides the results. The concluding remarks are given in Section 6.

2. Literature Review

Dramatic rises and falls of security prices during turbulent times have long intrigued researchers. Political uncertainty can create more stress in stock markets and investors may lose their ability to assess rationally the event implications (Aktas & Oncu, 2006). Several studies focus on the impact of specific political events and find that political uncertainty presents a significant source of market volatility. Chau et al. (2014) investigate the effect of political uncertainty in MENA countries caused by the civil uprising and find a significant increase in the volatility of Islamic indices. They conclude that political unrests are closely linked to financial volatility. Wang and Lin (2009) find that political conflicts negatively affect returns and increase market volatility. French and Porterba (1991) note that since investors mainly hold domestic assets, their portfolios are exposed to a very significant political risk specific to the country. Lobo (1999) examines the US markets during the 1998 election, after the discovery of the political scandal. He finds a sense of insecurity among investors. Brooks et al. (1997) conduct a similar study in South Africa after the crucial political change and find similar results which indicate that equity market volatility is closely related to political instability.

Goodell and Vähämaa (2013) attempt to explore the impact of political uncertainty on the stock market caused by the presidential elections in the United States. Their results indicate that the presidential election process causes market anxiety and prompts investors to revise their hopes and expectations in light of future macroeconomic policy. In the same context, Smales (2015) seeks to examine the influence of political uncertainty. He finds that a high (low) level of uncertainty around elections leads to an increase (decrease) in market uncertainty. Thus, a high probability of winning by the outgoing party, whose economic policy is well known, helps reduce market uncertainty. It is in this sense that the author uses the proverb “Better the Devil you know”.

Previous studies are mainly concerned with political events such as elections, wars, and terrorist attacks. Little research is conducted to examine the impact of political uncertainty resulting from civil movements like that of the Arab revolution on the stability and efficiency of financial markets. By relating this question to previous research, three hypotheses are formulated:

H1: According to Goodell and Vähämaa (2013) and Smales (2015), an increase (decrease) in political uncertainty will lead to an increase (decrease) in market uncertainty as measured by volatility.

H2: Taking into account structural breakpoints reduces the persistence of conditional volatility.

H3: Negative shocks impact volatility more than positive shocks of the same magnitude.

3. Methodology

3.1 Detection of Structural Breakpoints in the Variance

The approach used to detect sudden discrete change in the variance in time series is based on the Inclan and Tiao's (1994) ICSS algorithm. This latter assumes that data display a stationary unconditional variance during the starting time period till a structural break takes place. The cumulative sum of squared residuals is given as:

$$C_k = \sum_{t=1}^k \varepsilon_t^2, \quad k = 1, \dots, T \quad (1)$$

Where $\varepsilon_t \sim \text{i.i.d. } N(0, \sigma^2)$.

Define the centered normalized cumulative sum of squares as follows:

$$D_k = \frac{C_k}{C_T} - \frac{k}{T}, \quad k = 1, \dots, T \quad \text{with} \quad D_0 = D_T = 0 \quad (2)$$

If there are no changes in variance, then D_k statistic oscillates around zero; otherwise, if the series contains more shifts in variance, then it will depart from zero.

The critical values, under the null hypothesis of stationary variance, determine the significant change in variance. If the maximum absolute of the statistic D_k is larger than the critical value then the null hypothesis is rejected. k^* is a breakpoint at the 95% threshold when $IT = \sup_k \left| \sqrt{T/2} D_k \right|$ is outside the critical interval of ± 1.358 . The asymptotic distribution is given as follows:

$$IT \Rightarrow \sup_r |W^*(r)| \quad (3)$$

Where $W^*(r) \equiv W(r) - rW(1)$, $W(r)$ is a Brownian Bridge. Since the financial data generally exhibit an excess of kurtosis (which exceeds 3) and a non-constant variance, the IT test has certain drawbacks. Indeed, the original version of the ICSS algorithm assumes that $\varepsilon_t \sim i.i.d. N(0, \sigma^2)$, it can be overestimated when the error terms follow a GARCH process. Furthermore, Rodrigues and Rubia (2011) show that the asymptotic distribution of the ICSS statistics changes in the presence of additive outliers.

Sansó et al. (2004), based on the ICSS algorithm of Inclán and Tiao (1994), develop a more general test than that of Kokoszka and Leipus (2000). They propose two other tests, Kappa 1 (κ_1) and Kappa 2 (κ_2) which consider the fourth order moment.

3.2 GARCH Models Without and with Structural Failures

With the generalized ARCH model (GARCH) of Bollerslev (1986), a process ε_t satisfies a GARCH representation (p, q) if σ_t^2 can be expressed as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^p \beta_j \sigma_{t-j}^2 \quad (4)$$

where $\omega > 0$, $\alpha_i \geq 0$, $i = 1, \dots, q$ and $\beta_j \geq 0$, $j = 1, \dots, p$. Under the condition of second-order stationarity $\alpha_1 + \beta_1 < 1$. The equation of the conditional variance of the GARCH model with structural changes is expressed as follows:

$$\sigma_t^2 = \omega + d_1 D_1 + \dots + d_n D_n + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^p \beta_j \sigma_{t-j}^2 \quad (5)$$

where D_1, D_2, \dots, D_n are dummy variables, with

$$D_t = \begin{cases} 1, & \text{if there is a structural breakpoint} \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

The conditional variance of the EGARCH model with structural changes is given by the following equation:

$$\log \sigma_t^2 = \omega + d_1 D_1 + \dots + d_n D_n + [1 - \beta(L)^{-1}][1 + \alpha(L)]g(z_{t-1}) \quad (7)$$

The conditional variance equation of the GJR model with structural changes is given as follows:

$$\sigma_t^2 = \omega + d_1 D_1 + \dots + d_n D_n + \sum_{i=1}^q (\alpha_i \varepsilon_{t-i}^2 + \gamma_i S_{t-i}^- \varepsilon_{t-i}^2) + \sum_{j=1}^p \beta_j \sigma_{t-j}^2 \quad (8)$$

where S_{t-i}^- is a dummy variable taking the value 1 when ε_t is negative and 0 otherwise.

3.3 Conditional Distributions

GARCH models do not fully capture the property of heavy tails of high-frequency financial. In addition to the normal distribution, we consider the Student distribution, the Skewed-Student distribution and the GED distribution. For standard normal distribution, the log-likelihood function can be illustrated as follows:

$$l_n = -\frac{1}{2} \sum_{t=1}^T [\log(2\pi) + \log(\sigma_t^2) + z_t^2] \quad (9)$$

where T is the number of observations. The log-likelihood function for Student distribution is given as follows:

$$l_t = T \left\{ \log \Gamma\left(\frac{v+1}{2}\right) - \log \Gamma\left(\frac{v}{2}\right) - \frac{1}{2} \log[\pi(v-2)] \right\} - \frac{1}{2} \sum_{t=1}^T \left[\log(\sigma_t^2) + (1+v) \log\left(1 + \frac{z_t^2}{v-2}\right) \right] \quad (10)$$

With v is the degree of freedom and $\Gamma(\cdot)$ is the gamma function. The log-likelihood function for a Skewed Student, is as follows:

$$l_{skst} = T \left\{ \log \Gamma\left(\frac{v+1}{2}\right) - \log \Gamma\left(\frac{v}{2}\right) - 0.5 \log[\pi(v-2)] + \log\left(\frac{2}{\xi + \frac{1}{\xi}}\right) + \log(s) \right\} - 0.5 \sum_{t=1}^T \left\{ \log \sigma_t^2 + (1+v) \log \left[1 + \frac{(sz_t + m)^2}{v-2} \xi^{-2} \right] \right\} \quad (11)$$

GED density is often used to account for excess kurtosis.

$$l_{GED} = \sum_{t=1}^T \left[\log\left(\frac{v}{\lambda v}\right) - 0.5 \left| \frac{z_t}{\lambda v} \right|^v - (1+v^{-1}) \log(2) - \log \Gamma\left(\frac{1}{v}\right) - 0.5 \log(\sigma_t^2) \right] \quad (12)$$

3.4 The News Impact Curve

This useful tool illustrates how new information is affecting volatility estimates. In the GARCH (1, 1) model, the functional form of the news impact curve provided by Engle and Ng (1993) can be constructed as follows:

$$\sigma_t^2 = A + \alpha \varepsilon_{t-1}^2 \quad (13)$$

with

$$A = \omega + \beta \vartheta \quad (14)$$

ϑ being the unconditional variance which is equal to:

$$\vartheta = \frac{\omega}{1-(\alpha+\beta)} \quad (15)$$

Where the coefficients ω , α , and β are the parameters of the equation of the conditional variance of the standard GARCH process.

In this case, The curve is a quadratic function, typically centered on $\varepsilon_{t-1} = 0$. For the EGARCH, the curve can be plotted as follows:

$$\sigma_t^2 = A \cdot \exp\left(\frac{\theta_2 + \theta_1}{\sqrt{\vartheta}} \varepsilon_{t-1}\right), \text{ pour } \varepsilon_{t-1} > 0 \quad (16)$$

and

$$\sigma_t^2 = A \cdot \exp\left(\frac{\theta_2 - \theta_1}{\sqrt{\vartheta}} \varepsilon_{t-1}\right), \text{ pour } \varepsilon_{t-1} < 0 \quad (17)$$

where

$$A \equiv \vartheta^\beta \cdot \exp\left(\omega - \theta_2 \sqrt{2/\pi}\right) \quad (18)$$

with $\vartheta = \exp\left(\frac{\omega}{1-\beta}\right)$ is the unconditional variance of the EGARCH model. Here the news impact curve is asymmetric around zero which suggests that a negative shock has a greater influence on volatility than positive shock. The news curve for the GJR-GARCH model depicts a steeper slope of its negative side compared to its positive side. The news impact curve of the GJR-GARCH model, as proposed by Engle and Ng (1993), is given as follows:

$$\sigma_t^2 = A + \alpha \varepsilon_{t-1}^2, \text{ if } \varepsilon_{t-1} > 0 \quad (19)$$

and

$$\sigma_t^2 = A + (\alpha + \lambda) \varepsilon_{t-1}^2, \text{ if } \varepsilon_{t-1} < 0 \quad (20)$$

Where

$$A = \omega + \beta \vartheta \quad (21)$$

with $\vartheta = \frac{\omega}{1-\alpha-\frac{\gamma}{2}-\beta}$ is the unconditional variance of the GJR-GARCH model.

4. Descriptive Data and Statistics

We consider the daily returns of the TUNINDEX. The returns are defined as: $r_t = 100 * [\log(p_t) - \log(p_{t-1})]$, for $t = 1, 2, \dots, 1296$. The total study sample spans the period from 02/11/2010 to 04/02/2016. The results in Table 1 report descriptive statistics. The average of the returns is positive indicating that positive changes in the index outnumber negative changes. As in emerging markets, stock values tend to rise.

The results of conventional ADF and KPSS unit root reveal that the TUNINDEX series is stationary. The unconditional density function of the returns visualized in Figure 1 appears symmetrical, which proves that the skewness coefficient is influenced by the time dependence detected in the square of the returns of the index. We can thus affirm that the distribution of the series is far from being the normal distribution. Also, our distribution is symmetric, which may exclude the choice of the Skewed Student distribution.

Table 1. Statistical properties

TUNINDEX returns	
Panel A : basic descriptive statistics	
Mean	0.0059
Median	
Std. dev	0.5767
Skewness	-0.54936***
Kurtosis	12.762***
JB	8217.6 [0.0000]
Q(50)	265.207***
Q ² (50)	1440.1***
Q _L (20)	1157.37***
Panel B: unit root and stationarity tests	
ADF	-6.07924***
KPSS	0.0626602
Panel C: heteroskedasticity test	
ARCH LM test	16.240 [0.000]

Note. **, *** denote statistical significance at 5% and 1% levels respectively. Q(.) and Q²(.) are Box-Pierce statistics applied on returns and the square of returns. Q_L(.) are the Ljung-Box robust statistics.

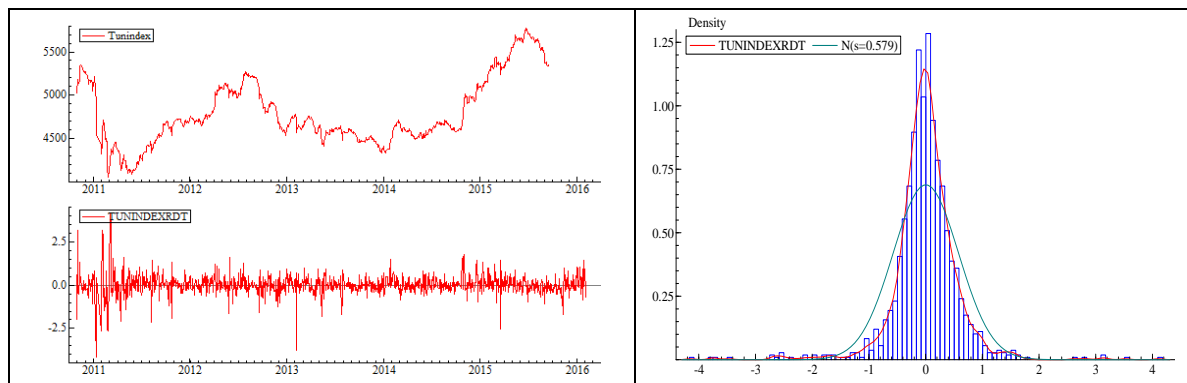


Figure 1. Daily TUNINDEX index prices and returns (on the left) and Empirical distribution of the TUNINDEX returns and the best normal distribution (on the right): 2010-2016

5. Results

5.1 Detection of Regime Change Points in the Variance News Impact Curve

The presence of regime changes can be indicative of major events. Fig. 2, Fig. 3 and Fig. 4 show for the TUNINDEX returns, the breaking points determined by the ICSS algorithm according to the three statistics namely: IT, kappa 1, and kappa 2. The upper and lower limits denote 3 times the standard deviations on either side of the returns. As postulated in Table 2, the number of breakpoints ranges from 1 to 7. The time points according to the IT statistic and the kappa 1 and kappa 2 statistics are not the same, but there is however a coincidence of a very high volatility regime.

Table 2. Structural breakpoints in volatility as detected by the ICSS and modified ICSS algorithm

Statistic	Number of change point	Time period	Standard deviation
Inclin-Tiao	1	02 November 2010 – 07 January 2011	0.681
	2	08 January 2011-08 March 2011	2.151
	3	09 March 2011-26 October 2011	0.644
	4	25 October 2011- 30 March 2012	0.299
	5	31 March-2012- 05 February 2013	0.473
	6	06 February 2013 - 28 April 2013	0.624
	7	28 April 2013- 04 February 2016	0.403
Kappa 1	1	02 November 2010 – 07 January 2011	0.630
	2	08 January 2011- 08 March 2011	2.263
	3	09 March 2011- 04 February 2016	0.467
Kappa 2	1	02 November 2010 – 09 April 2011	1.300
	2	10 April 2011- 04 February 2016	0.443

Regime 1: High volatility

This regime is marked by the immolation of Mohamed Bouazizi. Demonstrations and insurrectional protests return to the capital. President Ben Ali addresses the people and speaks for the first time to denounce “a minority of extremists who act against the interests of their country”. He promises solutions. Two days later, three governors were dismissed and the Prime Minister dismissed four ministers from his government.

Regime 2: The most turbulent regime

The United States summons the Tunisian ambassador to express concern over the repression of demonstrators by the police. In France, the Minister of Foreign Affairs talks with his Tunisian counterpart. President Ben Ali delivers a second speech.

Schools and universities suspend classes and the UGTT (Tunisian General Labor Union) organizes a three-day general strike. The interior minister is sacked. The International

Federation for Human Rights speaks of at least 66 deaths. President Ben Ali delivers the third speech. He decides to dissolve the government.

Thousands of demonstrators claim the departure of Ben Ali. The latter leaves the country and takes refuge in Saudi Arabia. Curfew is being imposed across the country. A provisional government of national unity was then formed. The UN assesses the toll of the Tunisian revolt at 219 dead and 510 wounded. On February 27, 2011, Mohamed Ghannouchi resigned from his post, and Bêji Caïd Essebsi was then appointed head of government. The same day, Michèle Alliot-Marie left her post as Minister of Foreign Affairs, following controversies over her vacation in Tunisia.

Regime 3

The third regime is characterized by high market volatility. However, this regime is less violent than the two previous ones. During this period, several political events occurred, including:

- Final dissolution of the RCD (Democratic Constitutional Assembly Party) of the ex-president Ben Ali.
- Alain Juppé, head of French diplomacy, announces 350 million Euros aid to Tunisia and thus revives the relationship between the two countries.
- 55 political parties have been created in Tunisia.
- Prime Minister Bêji Caïd Essebsi confirms that the elections for the Constituent Assembly will be postponed until October 23, 2011.
- Election of the National Constituent Assembly (NCA). The Ennahdha movement wins the elections with 89 seats out of a total of 217.

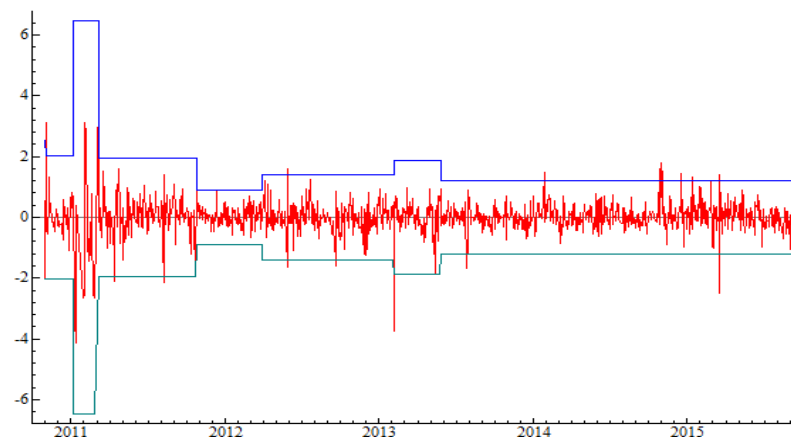


Figure 2. Structural breakpoints detected by ICSS (IT) for the post-revolution period

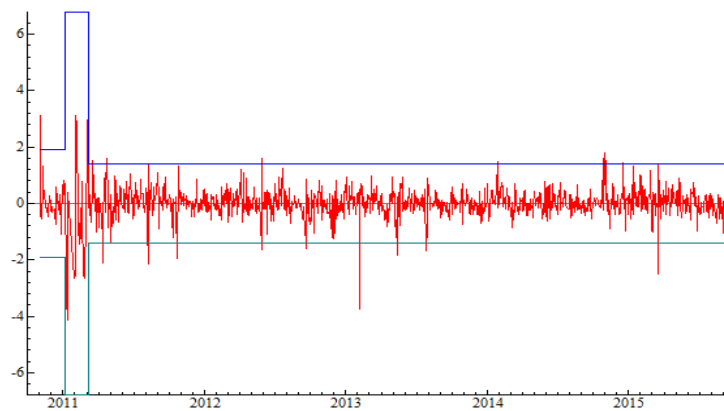


Figure 3. Structural breakpoints detected by ICSS (*Kappa-1*) for the post-revolution period

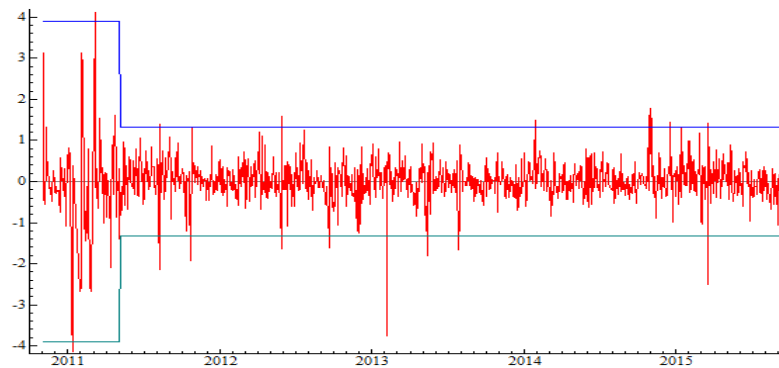


Figure 4. Structural breakpoints detected by ICSS (*Kappa-2*) for the post-revolution period

Note. Bands represent ± 3 standard deviations.

Regime 4

This is the calmest volatility regime. The most notable political events are as follows:

- Election of Mustapha Ben Jaafar, head of the ANC.
- The ANC adopts the constitutive law on the provisional organization of public powers (small Constitution).

Regime 5

In this regime, there has been a relative increase in the volatility of the stock market. The political events associated with this regime are as follows:

- The national commission for establishing the facts on the overruns committed during the events that accompanied the revolution publishes its report.
- Announcement of the birth of a new party called “Nidaa Tounes” by B ħi Ca ĩl Essebsi.
- Creation of a left coalition called “The Popular Front”.
- Attacks on the premises of the US Embassy in Tunis.
- Launch of the National Dialogue Congress, at the initiative of the UGTT, intended to get Tunisia out of the deep political dead end.
- Disassembly of a gang and seizure of a large number of weapons in two warehouses in Medenine.

Regime 6

This regime is characterized by increased volatility in the stock market as a result of:

- Assassination of Chokri Belaïd, the general coordinator of the Unified Democratic Patriots Party and leader of the Popular Front.
- The UGTT calls for a general strike.
- Hamadi Jebali presents his resignation to the President of the Republic.

- Discovery of an arms warehouse in M'nihla.
- Election of Ali Larayedh as head of government.
- Explosion of three landmines at Mount Chaambi.
- The UGTT organizes the second round of the national dialogue with the participation of the three presidents and several components of civil society.

Regime 7: return to the relative calm

- Assassination of the constituent and general coordinator of the popular movement Mohamed Brahmi.
- The sponsors of the dialogue propose a roadmap to end the crisis.
- Adoption of the new Constitution of the Republic of Tunisia.
- ANC votes confidence in Mehdi Jomaa's government.
- The main anti-Islamist formation Nidaa Tounès wins the first legislative elections.
- Béji Caïd Essebsi wins the second round of the presidential election.

The results obtained seem to be very significant since the breakpoints in variance coincide with the important political events. The episode of increased volatility occurs particularly during popular uprisings in 2011. This result corroborates those of Schwert (1989a), Schwert (1989b), Hamilton and Lin (1996), Charles and Darné (2014) and Song et al. (2019) who find that the volatility of equity returns increases during severe recessions. This confirms research hypothesis 1: increasing (decreasing) political uncertainty leads to increasing (decreasing) volatility and the results support that the relationship between volatility and returns reflects the common effects of political factors.

5.2 Estimation and Diagnostics

The synthetic statistics presented in Table 3 affirm that the models with dummy variables are more relevant and confirm that the distribution of the series is far from the normal distribution. One of the study's most interesting findings is that the heavy-tailed distributions perform better when dummy variables are included. Besides, the domination of Student distribution cannot then be called into question, for models without and with dummy variables.

Table 4 reveals that the parameters α and β of the GARCH model are all positive and statistically significant at the 1% level for the four specifications. This indicates that the GARCH model is an interesting representation of daily returns behavior, as it successfully captures the temporal dependence of the return volatility of TUNINDEX. α coefficients are less than β coefficients which indicates that the conditional variance is primarily affected by the lagged variance and that previous shock significantly affects current volatility. These results also mean that the Tunisian stock market is not efficient in the weak form. Also, the sum of the parameters ($\alpha + \beta$) for all of these specifications is on average equal to 0.83, which proves the presence of a volatility clusters indicating further support for the inefficiency of the market.

Table 3. Synthetic statistics for the models with and without dummy variables

	ARMA (1, 0) - GARCH (1, 1)				ARMA (1, 0) - EGARCH (1, 1)				ARMA (1, 0) - GJR-GARCH (1, 1)			
	Normal	Student	GED	SKST	Normal	Student	GED	SKST	Normal	Student	GED	SKST
Without dummy												
LB(20)	48.5327	51.7072	53.1794	51.7134	48.8067	49.2013	52.7964	49.1908	47.5965	51.5167	53.0818	51.5180
LB ² (20)	4.11295	4.84467	4.64177	4.84191	10.5907	5.05501	5.34323	5.04715	5.44051	5.92417	5.74272	5.93881
Akaike	1.253406	1.094102	1.123230	1.095765	1.247865	1.101789	1.129073	1.103448	1.246508	1.092677	1.121803	1.094333
Schwarz	1.270350	1.115282	1.144411	1.121181	1.273281	1.131442	1.158725	1.137337	1.267688	1.118093	1.147219	1.123985
ARCH (10)	0.17636	0.22577	0.21338	0.22561	0.32378	0.24862	0.22423	0.24868	0.19689	0.25085	0.23735	0.25153
Log-vrais	-749.297	-652.555	-670.061	-652.555	-743.967	-655.175	-671.573	-655.173	-744.151	-650.699	-668.204	-650.694
Inclin Tiao												
LB(20)	52.8817	54.8663	56.1350	54.7247	48.4703	51.6330	53.6850	51.6157	52.4741	55.1186	56.0623	55.0862
LB ² (20)	13.5927	14.8582	14.2111	14.8867	14.2283	11.8913	13.2765	11.8785	17.0242	17.5822	17.0532	17.6044
Akaike	1.173861	1.087180	1.103726	1.088680	1.199648	1.101861	1.118956	1.103496	1.168191	1.085102	1.101564	1.086538
Schwarz	1.220458	1.138012	1.154559	1.143749	1.254717	1.161166	1.178261	1.167037	1.219023	1.140171	1.156633	1.145842
ARCH	0.23059	0.36258	0.31918	0.36486	0.35822	0.41071	0.40634	0.41283	0.33862	0.40824	0.38138	0.40912
Log-vrais	-694.491	-641.395	-651.339	-641.297	-707.989	-648.219	-658.492	-648.201	-690.083	-639.146	-649.040	-639.009

Kappa 1

LB(20)	48.4818	51.3567	52.7148	51.2682	48.6704	49.8897	52.0137	49.8798	48.4054	51.9321	53.2494	51.9037
LB ² (20)	4.73959	5.72684	5.39174	5.75471	10.0486	5.04294	5.60365	5.03495	6.86208	7.03913	6.85868	7.10434
Akaike	1.234574	1.089692	1.117097	1.091272	1.243231	1.104391	1.130729	1.106050	1.223830	1.088206	1.114867	1.089692
Schwarz	1.259991	1.119344	1.146749	1.125161	1.277119	1.142516	1.168854	1.148411	1.253482	1.122095	1.148756	1.127817
ARCH	0.19034	0.27149	0.24708	0.27342	0.24426	0.24603	0.22098	0.24607	0.23619	0.30698	0.28436	0.31056
Log-vrais	-735.979	-647.905	-664.375	-647.854	-739.182	-654.739	-670.568	-654.736	-728.522	-646.012	-662.035	-645.905

Kappa 2

LB(20)	48.5162	51.5234	53.0718	51.5260	48.8041	49.0976	52.6685	49.0907	47.6304	51.3619	53.0145	51.3605
LB ² (20)	4.11254	4.84942	4.64192	4.84842	10.5666	4.95872	5.22942	4.95357	5.44451	5.91105	5.73428	5.92762
Akaike	1.255068	1.095620	1.124843	1.097284	1.249512	1.102890	1.130372	1.104551	1.248166	1.094255	1.123447	1.095908
Schwarz	1.276248	1.121037	1.150259	1.126936	1.279164	1.136778	1.164260	1.142675	1.273582	1.123907	1.153099	1.129796
ARCH	0.17639	0.22692	0.21393	0.22686	0.32308	0.24455	0.22073	0.24460	0.19698	0.25109	0.23736	0.25187
Log-vrais	-749.296	-652.468	-670.030	-652.468	-743.957	-654.837	-671.353	-654.835	-744.148	-650.647	-668.191	-650.641

5.3 Persistence of Volatility

The comparison of volatility persistence before and after the revolution reveals a surprising result. Table 5, Table 6 and Table 7 reveal that volatility persistence decreased significantly after the revolution. This observation holds for the three models selected and for the different distributions except for EGARCH under the Gaussian distribution. This result can be explained by the closure of the Tunisian stock exchange at the most critical moments of the revolution. Indeed, the departure of Ben Ali which occurred on Friday, January 14, 2011, is announced after the closure of the trading session. The financial market authorities decided to suspend quotations from Monday, January 17, 2011, to Sunday, January 30, 2011 (i.e. 17 days). The second suspension of quotations also took place from Monday, February 28, 2011, to Friday, March 4, 2011, because of the Kasbah demonstrations. Therefore, the impact of popular uprisings on stock market volatility was neutralized by the suspensions of quotations.

Table 4. Results of estimating models with and without dummy variables, 2010-2016

	without dummies	IT*	$\kappa 1$	$\kappa 2$
AR(1) - GARCH (1, 1)				
Cst(M)	-0.001264	0.000702	-0.000472	-0.001145
AR(1)	0.215899***	0.226966***	0.219025***	0.215606***
Cst(M)	0.050548***	0.041236***	0.045208***	0.050 50***
d1IT		0.000000		
d2IT		23.516601		
d3IT		-4.491708***		
d4IT		-1.478223		
d5IT		0.691656		
d6IT		8.064127		
d7IT		0.180199		
d1kun			26.068879	
d2kun			-4.540307	
d1kdeux				0.360321
ARCH(Alpha1)	0.390137***	0.326112***	0.345293***	0.389203***
GARCH(Beta1)	0.443434***	0.503838***	0.486746***	0.443003***
Student(DF)	4.742894***	5.495037***	4.951808***	4.740801***
AR(1) -EGARCH (1, 1)				
Cst(M)	-0.004920	-0.011410	-0.005019	-0.004766
AR(1)	0.229682***	0.224708***	0.226609***	0.229643***
Cst(V)	-1.640862***	-1.649230***	-1.641460***	-1.641907***
d1IT		-7.414974		
d2IT		-0.120654		
d3IT		1.104422***		
d4IT		-0.170269		
d5IT		-2.151301**		

d6IT		-6.383050***		
d7IT		1.404749***		
d1kun			0.047595	
d2kun			1.163455***	
d1kdeux				1.157568***
ARCH(Alpha1)	-0.286247	-0.335995	-0.280582	-0.298148
GARCH(Beta1)	0.878872***	0.891108***	0.878118***	0.880758***
EGARCH(Theta1)	-0.051265	-0.081087**	-0.054004	-0.051057
EGARCH(Theta2)	0.561284***	0.608587***	0.555567***	0.562086***
Student(DF)	4.691056***	5.000743***	4.679715***	4.678861***
AR(1) –GJR-GARCH (1, 1)				
Cst(M)	-0.005832	-0.004410	-0.005066	-0.005698
AR(1)	0.219397***	0.229662	0.221841***	0.219201***
Cst(v)	0.048496***	0.039101	0.044034***	0.048665***
d1IT		0.000000		
d2IT		17.979733		
d3IT		-3.139151		
d4IT		-1.361335***		
d5IT		1.069892		
d6IT		7.435530		
d7IT		0.200036		
d1kun			20.077404	
d2kun			-3.316645	
d1kdeux				0.287768
ARCH(Alpha1)	0.296359***	0.238705***	0.265933***	0.296674***
GARCH(Beta1)	0.463097***	0.525948***	0.498053***	0.462067***
GJR(Gamma1)	0.163040*	0.148639**	0.147995*	0.161619*
Student(DF)	4.798966***	5.582960***	5.024983***	4.796653***

In the literature, the results document that accounting for breakpoints in the variance significantly reduces volatility persistence (Alfreedi et al., 2012; Malik, 2011; and Ewing & Malik, 2015). In our case, the results remain mixed and suggest that regime changes in variance do not significantly reduce persistence. This invalidates research hypothesis 2. The lowest persistence comes from the GJR-GARCH model estimate. These results corroborate those of the study by Alfreedi et al. (2012).

The heavy-tailed distributions play a moderate role in reducing persistence in models that incorporate dummy variables. As Table 8 shows, the four distributions marginally reduce the persistence of volatility. The distribution hypothesis does not appear to play an important role in estimating persistence.

5.4 Leverage Effect and Asymmetry

Taking into account the leverage effects in the GJR-GARCH model during the pre-revolutionary period as presented in Table 6, gives us insignificant parameters. The revolution and the myriad of political turbulence events may have resulted in a significant change in the parameters of asymmetry. The positive and significant coefficient γ makes it possible to justify the presence of a leverage effect.

It is important to note that once regime changes (according to ICSS (*IT*)) are introduced into the variance equations of the two models, all skewness parameters become statistically significant at the 5% level. This leads us to conclude that the asymmetric behavior of volatility is affected by regime changes. A negative shock leads to a greater increase in conditional variance than a positive shock of the same magnitude, which confirms research hypothesis 3. The results of Table 9 show that the impact of negative news on volatility is greater than positive news for all models under the different distributions used. It is crucial to note that the magnitude of the negative news effects increases when we take into consideration dummy structural changes in variance calculated according to *IT* and *kappa 1*. This proves that the market is affected, during political uncertainty, by bad news more than good news. Our results are indeed consistent with those of Kartsonakis-Mademlis (2020).

Table 5. Persistence and half-life of volatility shocks for the EGARCH model

	Before the revolution				After the revolution			
	Normal	Student*	GED	SkSt	Normale	Student	GED	SkSt
<i>Sans dummies</i>								
θ_1	0.044514	-0.041870	0.025012	0.003448	-0.046046	-0.051265	-0.050001	-0.051890
θ_2	0.584210***	0.573417***	0.568592***	0.544060***	0.457987***	0.561284***	0.531849***	0.560800***
β	0.954167***	0.894225***	0.929637***	0.894874***	0.986466***	0.878872***	0.844635***	0.877906***
persistence	0.954167***	0.894225***	0.929637***	0.894874***	0.986466***	0.878872***	0.844635***	0.877906***
Half-life	14.77	6.20	9.50	6.24	50.86	5.36	4.10	5.32

Table 6. Persistence and half-life of volatility shocks for the GJR model

	Before the revolution				After the revolution			
	Normal	Student	GED	SkSt	Normale	Student	GED	SkSt
<i>Sans dummies</i>								
α	0.178330***	0.208746***	0.189599***	0.202095***	0.199343**	0.296359***	0.269536***	0.293757***
β	0.752852***	0.660568***	0.716526***	0.669096***	0.477712***	0.463097***	0.465507***	0.463804***
γ	-0.004647	0.019805	0.007341	0.024169	0.220214*	0.163040*	0.172009**	0.164776**
persistence	0.9288585	0.8792165	0.9097955	0.8832755	0.787162*	0.840976*	0.8210475**	0.839949**
Half-life	9.39	5.38	7.33	5.58	2.89	4	3.51	3.97

Table 7. Persistence and half-life of volatility shocks for the GARCH model

	Before the revolution				After the revolution			
	Normal	Student	GED	SkSt	Normale	Student	GED	SkSt
<i>Sans dummies</i>								
α	0.176142	0.217602	0.192856	0.213084	0.328076	0.390137	0.368521	0.389359
β	0.752365	0.662111	0.717250	0.670957	0.446162	0.443434	0.444028	0.443889
persistence	0.92851	0.87971	0.91011	0.88404	0.77424	0.83357	0.81255	0.83325
Half-life	9.34	5.40	7.35	5.62	2.70	3.80	3.33	3.79

5.5 News Impact Curves

The effects of news asymmetry before and after regimes are taken into account and can be identified by visualizing news impact curves. Under the normal distribution, Fig. 5 shows that the news impact curves meet the following conditions:

$$\omega > 0, \quad 0 \leq \alpha < 1, \quad 0 \leq \beta < 1, \quad \alpha + \beta < 1 \quad \text{and} \quad (\gamma > 0 \text{ for the GJR-GARCH})$$

Where ω , α , and β are the parameters of the variance equations. The presence of leverage hypothesis is easy to detect. In the Tunisian market, the new impact curves are asymmetrical for the GJR-GARCH model without and with dummy variables. This asymmetry appearance indicates that bad news from the past has more impact on current volatility than good news from the past. In particular, the same effect is amplified by taking into account the breakpoints in the variance detected by ICSS (IT) and ICSS (κ I).

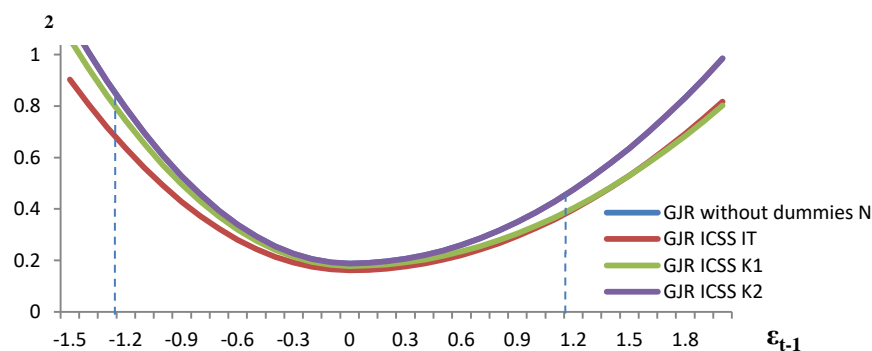


Figure 5. News impact curve of the Tunisian stock market, 2010-2016

6. Conclusion

The main objective of this article is to explore the impact the Tunisian revolution on the stability of the Tunisian stock market. Financial instability is approximated by the volatility of the returns of the TUNINDEX. To achieve this objective, we endogenously detect structural breaking points using the ICSS algorithm developed by Inclan and Tiao (1994). However, the use of the ICSS algorithm can overestimate the structural breaking points. To overcome the problems of homoskedasticity and mesokurtosis, we applied the modified ICSS developed by Sans ó et al. (2004) based on the Kappa-1 and the Kappa-2 tests. Indeed, κ_1 fixes non-mesokurtosis, while κ_2 fixes both for non-mesokurtosis and persistence.

The results obtained show that political events at the national level are a significant source of volatility and prove that the relationship between volatility and return reflects the common effects of political factors. Post-revolutionary volatility is marked by at least one structural change in conditional volatility. The structural breaking point detected by the three statistics seems to coincide with March 2011.

We have investigated the market volatility using symmetric and asymmetric GARCH models with the presence of structural variance breaks. We found that the asymmetric models are helpful in differentiating the significant impact of shocks. Taking into account the asymmetry by estimating the GJR model shows that there is a leverage effect. The impact of bad shocks on conditional variance is stronger than that of the good ones. The persistence of volatility decreased significantly after the revolution. This result can be explained by the closure of the Tunisian stock exchange at the most critical moments of the revolution. Political uncertainty has become certain in Tunisian's life, requiring greater coordination between regulators, investors and policy makers.

Table 8. Persistence and half-life of volatility shocks for the GARCH models, 2010-2016

	GARCH				GJR				EGARCH			
	Normal	Student	GED	SkSt	Normal	Student	GED	SkSt	Normal	Student	GED	SkSt
<i>Without dummies</i>												
α	0.328076	0.390137	0.368521	0.389359	0.199343**	0.296359***	0.269536***	0.293757***	-	-	-	-
θ_1	-	-	-	-	-	-	-	-	-0.046046	-0.051265	-0.050001	-0.051890
θ_2	-	-	-	-	-	-	-	-	0.457987***	0.561284***	0.531849***	0.560800***
β	0.446162	0.443434	0.444028	0.443889	0.477712***	0.463097***	0.465507***	0.463804***	0.986466***	0.878872***	0.844635***	0.877906***
γ	-	-	-	-	0.220214*	0.163040*	0.172009**	0.164776**	-	-	-	-
persistence	0.77424	0.83357	0.81255	0.83325	0.787162*	0.840976*	0.8210475**	0.839949**	0.986466***	0.878872***	0.844635***	0.877906***
Half-life	2.70	3.80	3.33	3.79	2.89	4	3.51	3.97	50.86	5.36	4.10	5.32
<i>ICSS</i>												
α	0.285212	0.326112	0.308748	0.323335	0.164011	0.238705***	0.211935**	0.235503***	-	-	-	-
θ_1	-	-	-	-	-	-	-	-	-0.085962**	-0.081087**	-0.076634*	-0.080865**
θ_2	-	-	-	-	-	-	-	-	0.586309***	0.608587***	0.606491***	0.608759***
β	0.479843	0.503838	0.496529	0.506874	0.544960**	0.525948***	0.530843***	0.527464***	0.858719***	0.891108***	0.878460***	0.891571***
γ	-	-	-	-	0.165506**	0.148639**	0.151246**	0.149441**	-	-	-	-
persistence	0.9881	0.9956	0.9910	0.9963	0.791724	0.8389725**	0.818401**	0.8376875**	0.858719***	0.891108***	0.878460***	0.891571***
ratio	2.58	3.71	3.20	3.72	1.0057	0.9976	0.9967	0.9973	0.8705	1.0139	1.0400	1.0155
Half-life	0.9881	0.9956	0.9910	0.9963	2.96	3.94	3.45	3.91	4.55	6.01	5.34	6.03
<i>Kappa 1</i>												
α	0.288491	0.345293	0.326270	0.341563	0.156189***	0.265933***	0.231745***	0.260865***	-	-	-	-
θ_1	-	-	-	-	-	-	-	-	-0.078308	-0.054004	-0.054348	-0.054523
θ_2	-	-	-	-	-	-	-	-	0.485750***	0.555567***	0.537673***	0.555078***
β	0.473760	0.486746	0.482076	0.490638	0.500246***	0.498053***	0.496737***	0.501569***	0.655926***	0.878118***	0.839435***	0.877184***
γ	-	-	-	-	0.235921**	0.147995*	0.174002**	0.149150*	-	-	-	-
persistence	0.76225	0.83204	0.80835	0.83220	0.7743955**	0.8379835*	0.815483*	0.837009*	0.655926***	0.878118***	0.839435***	0.877184***
ratio	0.984515	0.998163	0.994826	0.998741	0.9837	0.9964	0.9932	0.9964	0.6649	0.9991	0.9938	0.9991
Half-life	2.55	3.76	3.25	3.77	2.71	3.92	3.39	3.89	1.64	5.33	3.96	5.28
<i>Kappa 2</i>												
α	0.328012	0.389203	0.368252	0.388341	0.199265**	0.296674***	0.269824***	0.294028***	-	-	-	-
θ_1	-	-	-	-	-	-	-	-	-0.045728	-0.051057	-0.055557	-0.051680
θ_2	-	-	-	-	-	-	-	-	0.458389***	0.562086***	0.532566***	0.561557***
β	0.446012	0.443003	0.443254	0.443435	0.478132***	0.462067***	0.464645***	0.462672***	0.986432***	0.880758***	0.848934***	0.879737***
γ	-	-	-	-	0.220413*	0.161619*	0.171450*	0.163307*	-	-	-	-
persistence	0.77402	0.83221	0.81151	0.83178	0.7876035*	0.8395505*	0.820194*	0.8383535*	0.986432***	0.880758***	0.848934***	0.879737***
ratio	0.9997	0.9983	0.9987	0.9982	1.0005	0.9983	0.9989	0.9981	0.9999	1.0021	1.0050	1.0020
Half-life	2.70	3.77	3.31	3.76	2.90	3.96	3.49	3.93	50.73	5.45	4.23	5.40

Table 9. News Impact extent on the volatility of the GJR and EGARCH models with and without dummy variables, 2010-2016

	EGARCH				GJR			
	Normal	Student	GED	SkSt	Normal	Student	GED	SkSt
without dummies								
Negative news	0.504033	0.612549	0.58185	0.61269	0.419557	0.459399	0.441545	0.458533
Positive news	0.411941	0.510019	0.481848	0.50891	0.199343	0.296359	0.269536	0.293757
Relative asymmetry	122.355%	120.103%	120.753%	120.392%	210.469%	155.014%	163.816%	156.092%
IT								
Negative news	0.672271	0.689674	0.683125	0.689624	0.329517	0.387344	0.363181	0.384944
Positive news	0.500347	0.5275	0.529857	0.527894	0.164011	0.238705	0.211935	0.235503
Relative asymmetry	134.360%	130.743%	128.926%	130.636%	200.911%	162.268%	171.364%	163.456%
Kappa 1								
Negative news	0.564058	0.609571	0.592021	0.609601	0.39211	0.413928	0.405747	0.410015
Positive news	0.407442	0.501563	0.483325	0.500555	0.156189	0.265933	0.231745	0.260865
Relative asymmetry	138.438%	121.534%	122.489%	121.785%	251.048%	155.651%	175.083%	157.175%
Kappa 2								
Negative news	0.504117	0.613143	0.588123	0.613237	0.419678	0.458293	0.441274	0.457335
Positive news	0.412661	0.511029	0.477009	0.509877	0.199265	0.296674	0.269824	0.294028
Relative asymmetry	122.162%	119.982%	123.293%	120.271%	210.613%	154.476%	163.541%	155.541%

Note. For the GJR- GARCH model, the effect of good news is measured α and that of bad news is measured by $(\alpha + \gamma)$. For EGARCH, the effect of good news (positive shock) is measured by $(\theta_2 + \theta_1)$ and that of bad news (negative shock) is measured by $(\theta_2 - \theta_1)$.

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