The impact of political instability driven by the Tunisian revolution on the relationship between Google search queries index and financial market dynamics

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Abstract

Purpose – This paper examines the impact of political instability on the investors' behavior, measured by Google search queries, and on the dynamics of stock market returns.

Design/methodology/approach – First, by using the DCC-GARCH model, the authors examine the effect of investor sentiment on the Tunisian stock market return. Second, the authors employ the fully modified dynamic ordinary least square method (FMOL) to estimate the long-term relationship between investor sentiment and Tunisian stock market return. Finally, the authors use the wavelet coherence model to test the co-movement between investor sentiment measured by Google Trends and Tunisian stock market return.

Findings – Using the dynamic conditional correlation (DCC), the authors find that Google search queries index has the ability to reflect political events especially the Tunisian revolution. In addition, empirical results of fully modified ordinary least square (FMOLS) method reveal that Google search queries index has a slightly higher effect on Tunindex return after the Tunisian revolution than before this revolution. Furthermore, by employing wavelet coherence model, the authors find strong comovement between Google search queries index and return index during the period of the Tunisian revolution political instability. Moreover, in the frequency domain, strong coherence can be found in less than four months and in 16–32 months during the Tunisian revolution which show that the Google search queries measure was leading over Tunindex return. In fact, wavelet coherence analysis confirms the result of DCC that Google search queries index has the ability to detect the behavior of Tunisian investors especially during the period of political instability.

Research limitations/implications – This study provides empirical evidence to portfolio managers that may use Google search queries index as a robust measure of investor's sentiment to select a suitable investment and to make an optimal investments decisions.

Originality/value – The important research question of how political instability affects stock market dynamics has been neglected by scholars. This paper attempts principally to fill this void by investigating the time-varying interactions between market returns, volatility and Google search based index, especially during Tunisian revolution.

Keywords Political instability, Investor sentiment, Tunindex, DCC GARCH model, Wavelet coherence model, FMOL method

Paper type Research paper

1. Introduction

Political instability is one of the most important impediments to economic development. It is related to decreased welfare (Dupas and Robinson, 2010), increased propensity to engage in violence (Blattman and Miguel, 2010) and increased risk-taking (Dupas and Robinson, 2012).

The politically unstable events often lead to radical and sudden changes in property rights laws and rules governing the conduct of business (Gyimah-Brempong (1999)). As a result, the political risk remains valued by investors because this risk often has a strong impact on investor confidence, usually their feelings and emotions, and has a greater impact on the economy, performances and volumes of financial market transactions (Beaulieu *et al.* (2006), Bailey *et al.* (2005) and Frey and Waldenstrom (2004).

Several studies have looked at the effects of political instability on financial market performance. However, Frieden *et al.* (2000) study the impact of political economy factors on exchange rate policy in Latin America. Arfan *et al.* (2012) concludes that the political instability is one of the main causes that affects the capital inflows in Pakistan.

Investor sentiment is an important topic in behavioral finance that plays a fundamental role in predicting returns and volatilities of financial markets. As outlined in a literature review by Lee *et al.* (2002), investor sentiment is a significant factor that explains excess returns and conditional volatility shocks.

Hence, a great amount of literature has approved the positive or negative impact of investors' sentiment on market dynamics (Brown and Cliff, 2005; Baker and Wurgler, 2007; Hengelbrock *et al.*, 2009; Grigaliuniene and Cibulskiene, 2010).

Investor sentiment also plays a crucial role in the transmission of economic, financial and political crises from one country to another, as well as the transmission of political shocks to financial markets. Perotti and Oijen (2001) have shown that political shocks have an effect on stock markets; their results show strong changes in excess returns with the fluctuation of political risk.

Motivated by the critical period, which is characterized by the starting of the Tunisian revolution in 2011, the objective of this study is to empirically examine the impact of political instability on the return, volatility and sentiment of the Tunisian stock market. Meanwhile, it also analyses the transmission of shocks between the Tunisian stock market and investor's sentiment during periods characterized by turmoil and political instability. It is of interest, therefore, to consider a recent measure of investor sentiment. This paper uses the volume of Google search to proxy the investor attention due to the reason that Google's search data are easy accessible and free available to investors. It is a direct methodology of collecting trend data that has not been used in the prior literature for Tunisian stock market. In addition; this general and broad measure reflects the rapidly changing interests of millions of Internet users especially whom that access to huge amounts of economic and financial information online.

In terms of methodology, varieties of models have been employed to explore the link between the stock market returns, volatility and investor's sentiment. First, by using the DCC-GARCH model, we examine the effect of investor sentiment on the Tunisian stock market return. The DCC-GARCH models are comprehensive tools and provide intriguing insights to understand the interdependence between variables over time. The parameters of this model can easily be estimated, and the model can be evaluated and used in straightforward way.

Second, we employ the fully modified dynamic ordinary least square method (FMOL) to estimate the long-term relationship between investor sentiment and Tunisian stock market return. More precisely, this particular model intent to identify the long-run cointegration among Google search queries index and return index. Finally, we use the wavelet coherence model to test the comovement between investor sentiment measured by Google Trends and Tunisian stock market return. The continuous wavelet decomposition technique has been proposed to improve the forecasting accuracy of financial time series. This method can

provide a matrix to accommodate correlation at each time and frequency point. This advantage makes it useful for observing the shift of coherency between Google search index and Tunindex. Meanwhile, it also empirically analyses the direction and intensity of comovement in the Tunisian stock market in different time-frequency domains. As compared to other standard methods, the advantage of wavelet coherence is that allows us to understand the lead–lag relationships between Google search index and Tunindex over the sample period.

The important research question of how political instability affects stock market dynamics has been neglected by scholars. This paper attempts principally to fill this void by investigating the time-varying interactions between market returns, volatility and Google search based index, especially during Tunisian revolution.

The remainder of this paper is organized as follows. Section 2 presents the literature review. Section 3 describes the methodology as well as the descriptive statistics. Section 4 provides the empirical findings and Section 4 concludes.

2. Literature review

In the literature, we found a number of research studies that have studied the effect of investor sentiment on stock returns and the effect of investor sentiment on realized volatility, respectively. Brown and Cliff (2004) have found that investor sentiment has a negligible impact on subsequent monthly market returns, while Huang *et al.* (2014) have concluded that investor sentiment is a reliable contrarian predictor of subsequent monthly market. Naik and Padhi (2016) explored the relationship between investor sentiment and stock return volatility using monthly data from National Stock Exchange (NSE) of India from July 2001 to December 2013 period. They show that sentiment index has a significant effect on market excess returns and negative effect on the conditional volatility. Whereas, when the sentiment index is decomposed into positive sentiment and negative sentiment changes, the study reveals that positive and negative sentiments have asymmetric impacts on excess return volatility. Along these lines, Cheema and Nartea (2018) have found that investor sentiment indexes of both Baker and Wurgler (2006) and Huang *et al.* (2014) were contrarian predictor of aggregate stock market returns at all horizons but only during high sentiment states. Trichilli *et al.* (2018) have studied the impact of googling investor's sentiment on the monthly Islamic and conventional index returns during the period 2004–2016. They have indicated that investors can use googling investor's sentiment as an indicator to predict returns and volatility of MENA financial markets.

As far as the impact of political instability on financial market dynamics is concerned, the financial literature has been recently enriched with several empirical studies that show divergent results. For example, Bittlingmayer (1998) concluded that political uncertainty has an impact on stock market volatility and output in post-WWI Germany. Aggarwal *et al.* (1999) showed that political shocks contribute to large fluctuations in the volatility of emerging stock market returns. Chesney *et al.* (2011) studied the effect of terrorism that occurs in 25 countries on the global economy over an 11-year time period. They demonstrate that a majority of the events have a negative effect on the financial markets. By way of example, Ikizleri and Ülkü (2012) indicated that political risk influences stock market returns, net external flows and macroeconomic activity in Turkey. Abdelbaki (2013) used the recently developed techniques of time series data cointegration: vector error correction model (VECM) to investigate the impact of political instability, economic instability and external events associated with the Egyptian revolution that started on 25th January 2011 on the stock market performance. They find that political instability has a negative impact on the EGX30 index.

In a more related study, Murtaza *et al.* (2015) investigated the association of stock market returns with political instability in Pakistan stock market during the period of 2007–2012.

They have showed that political events that cause change in government policy have significant effect on stock market returns that proves our hypothesis. These results give an insight into the price behavior of KSE in response to various political events of different natures. As for Jeribi *et al.* (2015), they have concluded that the 2011 Tunisian revolution has a substantial impact on the volatility of sector index returns. Suleman *et al.* (2017) have found that global country risk and its economic, financial and political components play an important role in predicting the movements of returns and financial market volatility in about half of all cases.

Recently, using EGARCH (1.1) model, Zaiane (2018) has investigated the impact of the political uncertainty on return and volatility of major sectorial stock indices in the Tunisian Stock Exchange. She has concluded that both of good and bad news have increased the volatility of major selected indices, including the TUNINDEX. However, the political news hasno impact on return of all indices. Ben Moussa and Talbi (2019) investigate the impact of political instability and terrorist attacks on the Tunisian stock market dynamics. The results of the estimation of EGARCH model showed that these two events have a negative impact on the performance of the Tunisian stock market and positive impact on the volatility of the Tunindex market especially after the revolution. However, the impact of these events on the behavior of the stock market was lower for the period before the revolution.

Only one prior study specifically examines the relationship between investor sentiment and the Tunisian stock return (Soltani *et al.*, 2017). These authors have employed simultaneous equations and GMM 2S method to study the impact of political instability on stock market dynamics by comparing the interaction between market returns, volatility and investor sentiments before and after the Tunisian revolution. They show that during the period of political stability, investor sentiment did not affect market return and volatility. Whereas, they show a significant bidirectional relationship between investor sentiment, market volatility and return during the period of the Tunisian revolution.

Political instability has recently struck all continents around the world. In fact, it has an effect on the psychology of investors and any change in their sentiment is reflected in stock market performance and volatility. Overall, compared to the previous research studies, given the growing importance of the Tunisia's picture worldwide and in the Arab world, in particular, this study is the first that aims at exploring the impact of political instability on the investors' behavior, measured by Google search queries and on the dynamics of stock market returns.

3. Methodology
Our objective in this paper is to study the effect of investor sentiment on the return of the Tunindex by analyzing the correlation between these two variables during the period of the Tunisian revolution. In this respect, we use a methodology based on four steps: in a first place, we explain the methodology for constructing Google search queries index in details. In a second place, we use the DCC-GARCH model to study the impact of investor sentiment on the returns of Tunisian stock market. In a third place, we attempt to estimate the long-term relationship between investor sentiment and Tunisian stock market e using the modified dynamic ordinary least square (FMOL) method. Finally, we apply the wavelet coherence model to examine the comovements between these two variables.

3.1 Constructing the Google search queries index
To understand the key to the construction of a search queries index, we followed Da *et al.* (2015). First, among 743 words with the "Econ @" or "ECON" markers, we gathered only words related to a positive and negative sentiment, and we removed noneconomic words that not revealed sentiment toward economic conditions. Second, using Google Translate, we

translate the set of 149 primitive terms, which are "economic" words that are specified by the widely used dictionaries in the literature on finance ("Harvard IV-4 Dictionary" and «Lasswell Dictionary ») into Tunisian's corresponding language. We have employed the Arabic and French languages. Third, we put these 149 translated words into Google Trends product, and we identified the top ten terms associated with each word. Indeed, after removing terms that produced insufficient data and that were not semantically related to economics or finance, we have considered only search terms with at least 100 monthly SVI files. Fourth, we download the monthly search volume index (SVI) for each of the search terms during our sampling period from January 2004 to April 2018. Fifth, we calculate the monthly change in SVI (ΔSVI) for each search term. Then we optimize the extreme observations, eliminate the seasonality and normalize the time series to make them comparable to finally get the change weekly adjusted search volume (ΔASVI) (Trichilli *et al.*, 2018; Trichilli *et al.*, 2019; Trichilli *et al.*, 2020a; Trichilli *et al.*, 2020b).

Next, we identify search terms that are the most important for the Tunisian stock returns. Hence, we determine the historical correlation between each term and contemporaneous Tunisian market returns.

The final step in the construction of the Google search queries index was calculating the ΔASVI average of the top 30 positively correlated and the top 30 negatively correlated search terms for each month. Then the formula is presented as follows:

$$\text{Google search queries index} = \sum_{i=1}^{30} R^i_+(\Delta \text{ASVI}_i) - \sum_{i=1}^{30} R^i_-(\Delta \text{ASVI}_i) \tag{1}$$

With $\sum_{i=1}^{30} R^i_{\pm}(\Delta \text{ASVI}_i)$ is the *t*-statistic-weighted average of the top 30 positively (negatively) correlated search items.

3.2 Fully modified ordinary least square (FMOLS) approach

This method corresponds to the Engel–Granger approach for which estimation can be done by OLS when there is a cointegration relationship between the dependent variable and its fundamentals.

For nonstationary panels, Pedroni (2000) demonstrates that MCO estimators are asymptotically biased. Indeed, the Group-Mean Fully Modified OLS (GM-FMOLS) panel technique proposed by Pedroni (1996, 2000) solves this problem in the sense that it allows the use of heterogeneous cointegrating vectors.

For Maeso-Fernandez *et al.* (2004), the FMOLS estimator takes into account the presence of the constant term and the possible existence of correlation between the error term and the differences of the regressors. Adjustments are made for this purpose on the dependent variable and the long-term coefficients obtained by regressing the adjusted dependent variable. In the case of panels, the long-term coefficients resulting from the technique GM-FMOLS are obtained by the "group mean" of the estimators relative to the sample size (*N*).

Thus, the GM-FMOLS estimator is written as follows:

$$\widehat{\beta}^{\text{GM–FMOLS}} = N^{-1} \sum_{i=1}^{NT} \left[\sum_{t=1}^{T} \left(x'_{it} x_{it} \right)^{-1} \left(\sum_{t=1}^{T} x'_{it} Y^*_{it} - T \widehat{\lambda}_i \right) \right] \tag{2}$$

where

Y^*_{it} represents the regressands adjusted for the covariance between the error term and the vector x_{it}.

$T \widehat{\lambda}_i$ represents the adjustment due to the presence of the constant term. The term in the brackets is the individual FMOLS estimator for the *K* fundamentals.

3.3 DCC-GARCH model

Engle (2002) proposed the DCC-GARCH, model to estimate the dynamic conditional correlations between series. This model is a generalization of Bollerslev's (1990) constant conditional correlation model (CCC), where volatilities vary over time, but conditional correlations are assumed to be constant.

In this context, the estimated time-varying correlation coefficient helps us in analyzing the correlation between Google search queries index and Tunindex return.

In the DCC-GARCH (1.1) model, the variance covariance matrix, H, is giving by

$$A(L)Y_t = \varepsilon_t \tag{3}$$

where A denotes the matrix, L denotes the lag polynomial matrix, ε_i denotes the innovations vector with $\varepsilon_t|\Omega_{t-1} \sim N(0, H_t)$ and $t = 1, \cdots T$.

Accordingly, the conditional covariance matrix of the vector ε_i is specified as

$$H_t = D_t R_t D_t \tag{4}$$

and

$$h_{i,t} = \omega_i \sum_{p=1}^{p_i} \alpha_{ip}\varepsilon_{it-p}^2 + \sum_{q=1}^{Q_i} \beta_{iq}h_{it-q} \text{ with } i = 1, 2 \tag{5}$$

where $D_t = diag\sqrt{h_{it}}$ denotes the 2×2 matrix including the time-varying standard deviations from estimating GARCH model. $R_t = \rho_{ijt}$ denotes the 2×2 matrix of conditional correlations with $i, j = 1, 2$.

Therefore, we obtain the DCC structure which is defined as follows:

$$R_t = Q_t^{*-1}Q_tQ_t^{*-1} \tag{6}$$

$$\text{where } Q_t = \left(1 - \sum_{k=1}^{K} \alpha_k - \sum_{l=1}^{L} b_l\right)\overline{Q} + \sum_{k=1}^{K} \alpha_k(\varepsilon_{t-k}\varepsilon_{t-k}) + \sum_{l=1}^{L} b_l Q_{t-1} \tag{7}$$

where $\overline{Q}$ denotes the matrix of unconditional covariances of the standardized errors, Q_t^* denotes the 2×2 diagonal matrix consisting of the square root of the diagonal elements of Q_t.

The resulting time-varying correlation can be written as follows:

$$\rho_{ij} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \text{ with } i, t = 1, 2 \tag{8}$$

3.4 Wavelet coherence model

By using signal processing, the wavelet coherence model is a powerful tool that offers a single chance to assess simultaneously the comovement between two series at different frequencies and over many time scales.

In tune with Tiwari *et al.* (2013) and Torrence and Webster (1999), wavelet coherence coefficient is defined as:

$$R_n^2(s) = \frac{\left|S\left(s^{-1}W_n^{XY}(s)\right)\right|^2}{S\left(S^{-1}\left|W_n^X(s)\right|^2\right)S\left(s^{-1}\left|W_n^Y(s)\right|^2\right)} \tag{9}$$

with S represents a smoothing operator . W^X and W^Y represent the wavelet transforms for the time series X and Y, respectively. W^{XY} represents the cross wavelet transform. s^{-1} is employed to convert to energy density (n denotes time position and s denotes scale) .

Interestingly, the wavelet coherence coefficient $R_n^2(S)$, a localized correlation coefficient in time frequency space, ranges from 0 (weak dependence) to 1 (strong dependence) (Grinsted *et al.*, 2004).

Monte Carlo simulations are used to determine the 5% statistical significance level of the wavelet coherence (Torrence and Compo, 1998).

4. Data and variables analysis

This section describes the data used throughout the analysis. From the Morgan Stanley Capital International (MSCI) database, we obtain monthly close price of Tunindex. Moreover, we construct a monthly Google search queries proxy measured by Google Trends which is the main source of data that provides a search volume index (SVI) for search items in different countries in different languages since 2004.

4.1 Tunindex return
The closing prices of the Tunindex data cover the period between January 2004 and June 2018. Tunisian monthly index return is measured as follows:

$$R_t = In\left(\frac{P_t}{P_{t-1}}\right) \qquad (10)$$

with P_t presents the closing index price on month t, and P_{t-1} presents the closing index price on month $t-1$.

Figure 1 plots the dynamics of Tunindex return in the period 2004–2018.

Graphical analysis reveals that there has been an enhanced decrease in the return of the Tunindex from 2008 which correspond to the global financial crisis. This result is in favor of the phenomenon of contagion between markets in periods of crisis and, it identifies the transmission of the effects of the global financial crisis on the Tunisian stock market.

This chart also shows a remarkable fall in Tunindex return in 2011. There are major possible explanations justifying this fall. First, the starting of the Tunisian revolution since the Bouazizi's desperate self-immolation in Sidi Bouzid at this year, Tunisia still suffers from sudden events and serious political turbulence that continuously and severely affect the economy on all sides. Second, the lack of investor's confidence sustained by the information regarding the new provisions of the Finance Bill, 2011 related to direct taxes which stipulates for the capital gains tax on the sale of shares. Third, Tunisian and Arab investors' confidence was shaken by the political uncertainty that emanating from Arab spring revolution.
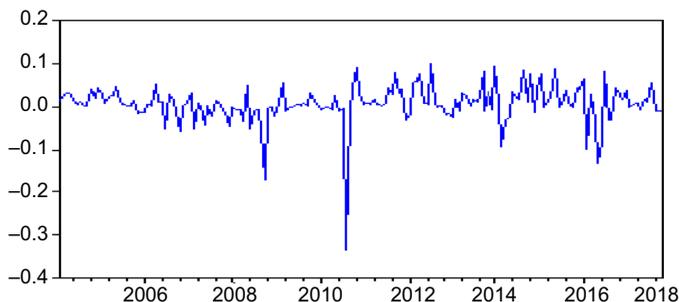

Figure 1.
Dynamics of Tunindex
return in the period
2004–2018

In addition, there is a sharp fall in return in 2014. This result is not due to the impact of oil crisis on the Tunisian stock market; it is rather due to the Tunisian legislative elections of the month of October 2014, which resulted in a new political landscape. This sharp also can be explained by the political turmoil that manifests after the killing of 15 Tunisian soldiers on Mount Chaambi by jihadists.

Nonetheless, we can see a sharp fall in return in 2017. We explain this result by the fact that the state of emergency was extended by one month throughout Tunis. Also, this result may be due to the death of a police officer and two of his colleagues were injured in a terrorist attack in Jenoura.

4.2 Google search queries index

Figure 2 presents a plot of the evolution of Google search queries index covering period starting from January 2004 to June 2018.

Referring to Figure 2, it can easily be noticed that during the year 2009, the Google search queries index dropped until it reached the lowest level of a negative value of −40%. This finding can be explained by the transmission of the US shock, generated by the stock market crashes of the Suprimes, by the phenomenon of contagion between the markets in periods of crisis. Moreover, Google search queries index has sharply decreased during the Tunisian revolution of 2011. This finding shows that sentiment is bearish. Therefore, we can conclude that pessimism dominates the Tunisian stock market. Following to this sharp decline, Google search queries index fluctuates slightly around the interval of −10 and 10. This result can demonstrate that the investor becomes very indifferent toward all events after the revolution.

4.3 Volatility of the tunindex

Figure 3 illustrates Tunindex volatility during 2004–2018. Figure 3 clearly indicates a sharp upward peak between 2006 and 2008, indicating a high level of volatility during this period,
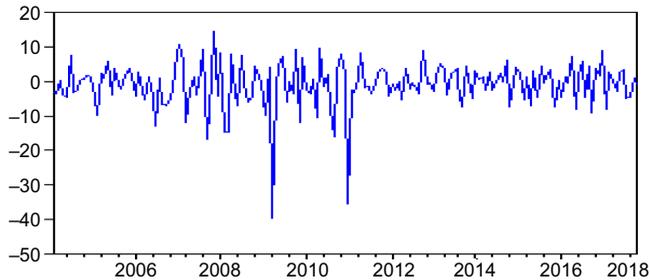
Figure 2.
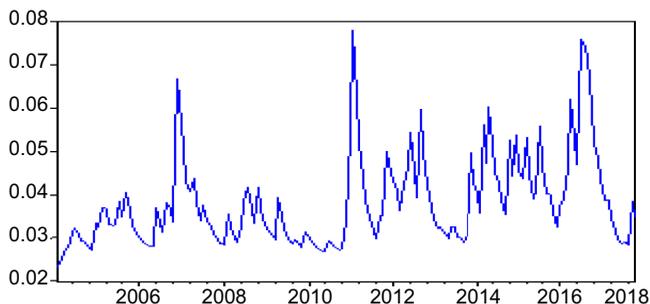Evolution of Google
search queries index

Figure 3.
Tunindex volatility
during 2004–2018

which can be explaining by the presence of a strong financial imbalance. In fact, during this period, the global financial crisis spread to Tunisia through the contagion effect between the American market and the Tunisian market. This finding can be also due to the Soliman affair in 2007. In 2011, we can see that volatility has significantly and strongly increased, reflecting the important impact of the Tunisian revolutionary movement on the volatility of market index return. Even after 2011, other peaks are observed which may explain the successive turbulence after the Tunisian revolution leading to a situation where the economy was no longer able to operate properly. The figure also shows a peak in 2012. This result can be explained by the curfew instituted by the Prime Minister Hamadi Jebali in Tunis and seven other governorates in the country because of violent clashes between Salafists and police. Similarly, the figure reached a peak in 2013, which is due to the political assassination of the two leftist nationalist opponent; Chokri Belaid and Mohamed Brahmi. These murders have plunged the country into a new political crisis.

Moreover, we observe a rising peak during 2014–2015 period. This finding can be attributed to the oil crisis.

5. Empirical results

5.1 Descriptive statistics

Table 1 displays descriptive statistics of Google search queries index (Panel A) and the Tunindex return (Panel B).

We find that mean value of Google search queries index is positive indicating a negative investor sentiment for the sample period. While the Tunindex has positive mean return over the sample period with a maximum return of 21.13% and a minimum −13.29%.

The Kurtosis values are higher than three for Tunindex return and Google search queries index suggesting that the distributions are leptokurtic.

Regarding skewness statistic, we can indicate well that marginal distributions appear to be asymmetrical to the right for the two variables.

The Jarque–Bera test confirms the results of the skewness and Kurtosis coefficients. According to the results, the normality hypothesis turns out to be rejected with regard to the two series, given the Jarque–Bera test.

5.2 Long-term relationship between Google search queries index and Tunindex return

Table 2 presents the estimation of the long-term relationship between Google search queries index and Tunindex return using the modified dynamic ordinary least square (FMOL) method for three periods, namely: full-sample period, before Tunisian revolution period and after Tunisian revolution period

Panel A reports the impact of Google search queries index on the Tunindex return. However, Panel B reports the impact of Tunindex return on Google search queries index.

As shown in Table 2, the Google search queries index has a significant positive effect at the 10 and 1% of level on the Tunindex return before and after the revolution, respectively. This result can be explained by the feeling of fear that pushes Tunisian investors to make extensive use of the Internet during and after the revolution to follow the news affecting their portfolios. So, investors can increase the frequency of Internet searches, thus explaining the positive relationship between Google search queries index and Tunindex return.

This finding corroborates the ideas of Soltani *et al.* (2017), who suggested that after the Tunisian revolution, the investor sentiment has a close relationship with market return.

Google search queries index has a slightly higher effect on Tunindex return after the Tunisian revolution than before this revolution. These findings can be explained by the fact that the Google search queries index has become increasingly disrupted during the

Mean	Median	Maximum	Minimum	Standard deviation	Skewness	Kurtosis	Jarque–Bera	Probability
Panel A : Google search queries index								
−0.723409	0.014108	57.48070	−40.78741	10.76593	0.385738	10.27508	383.5745	0.000000
Panel B : Tunindex return								
0.010174	0.006502	0.211342	−0.132909	0.040754	0.740697	7.182679	141.1069	0.000000

Table 1.
Descriptive statistics

Variables	Full-sample period	Before Tunisian revolution period	After Tunisian revolution period
Panel A: dependent variable: Google search queries index			
Tunindex return	35.566	47.388	23.050
	(2.793)***	(1.649)*	(2.598)***
Constant	−0.997	0.2064	0.90433
	−1.858	0.1844	(2.2378)**
R^2	0.022	0.0235	0.064
Adj.R^2	0.0161	0.0126	0.0524
S.E. of regression	10.7592	13.563	3.7498
Panel B: dependent variable: Tunindex return			
Google search queries index	0.000594	0.00049	0.0033
	(1.9183)**	(1.745)*	(2.574)***
Constant	0.00059	0.0059	0.0111
	(3.1408)***	1.5599	(2.1138)**
R^2	0.02215	0.03392	0.0625
Adj.R^2	0.01626	0.02319	0.0501
S.E. of regression	0.0408	0.00135	0.042

Note(s): *significant at 10%, **significant at 5% and ***significant at 10% level

revolution, and consequently the effect of this variable on the return is higher during this period.

Results also show that Tunindex return has a significant effect on the Google search queries index before the revolution at the level of 10% and after the revolution at the level of 1%. Indeed, this effect is about 0.00049 before the revolution, and it is about 0.0033 after the revolution.

5.3 Dynamic conditional correlation between Google search queries index and Tunindex return

Figure 4 provides a plot of the dynamic correlation between Google search queries index and Tunindex return during the period 2004–2018. We observe a high negative correlation between investor sentiment and Tunindex return with an extremely high negative peak that exceeded −0.8 during the 2007–2008 financial crises supporting the presence of contagion effect. This result can be due to the negative emotions and overpessimism among American investors during this period, which is spilled over Tunisian financial market. In fact, Tunisian investors became instantly followers and rapidly searchers of political news via Internet that may affect their investment decisions and may be are reinforced to sell their equities.
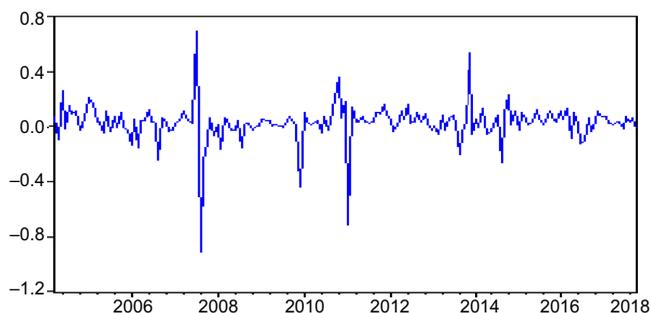

Figure 4.
Dynamic conditional
correlation between
Google search queries
index and Tunindex
return

Moreover, the figure shows a negative peak that is close to −0.8, following the starting of the Tunisian revolution of 2011, which indicate a dynamic conditional correlation between the two variables but they do not move in the same direction, this be due to the instability that characterizes this period because of the increase in political friction. Consequently, the Tunisian investors are more frightened about this political instability event that affect their country so they increase their searched frequency on Internet, searching all information associated to the economic and financial conditions, in order to make the successful portfolio decision. Indeed, we can also see that there is a positive conditional dynamic correlation between investor sentiment and Tunindex return in 2014. This correlation is explained by Tunisian 2014 elections.

5.4 Comovement between Google search queries index and Tunindex return
Wavelet coherence is used as a descriptive tool to examine the level of comovement between Google search index and Tunindex return at different times and different time scales. It also allows us to depict the lead–lag relationship between these two variables.

Figure 5 plots the wavelet coherence between Google search queries index and Tunindex return. Time is represented on the horizontal axis, while the frequencies are on the vertical axis. In the wavelet coherence picture, code color ranges from deep blue (weak correlation between Google search index and Tunindex return) to deep red (strong correlation between Google search index and Tunindex return). The arrows indicate the different relative phases of the time series at a given scale, in fact when these arrows are pointing to the right hand side, this means that the two series are in-phase (positively correlated), whereas they are out-of-phase when the arrows are directed toward the left hand side (negatively correlated).

Indeed, if the arrow is pointing east and downwards (↘), Tunindex return is leading Google search queries index, whereas if the arrow is pointing upwards (↗), Tunindex return is lagging Google search queries index. The reverse is in fact true if, the arrow is pointing west and upward (↖), Tunindex return is leading Google search queries index in a negatively correlated situation, whereas Tunindex return is lagging Google search queries index if the arrow is pointing downwards (↙).

By examining Figure 5, it is clear that in 2011, for lower frequency (large time scales) and especially for scales less than four months, the red color dominates this period, which shows us the strong correlation between Google search index and Tunindex return at the starting of the Tunisian revolution. This result is consistent with that of the DCC-GARCH results that the correlation between Google search queries and Tunisian return index is very significant during the Tunisian revolution. Moreover, we note that the arrows are pointing to the right and upwards, which shows us Google search queries index and Tunindex return are antiphase and that Google search queries index is the leader. Indeed, corresponding to 16–32-month time scales, we show a strong co movement between investor sentiment and Tunisian
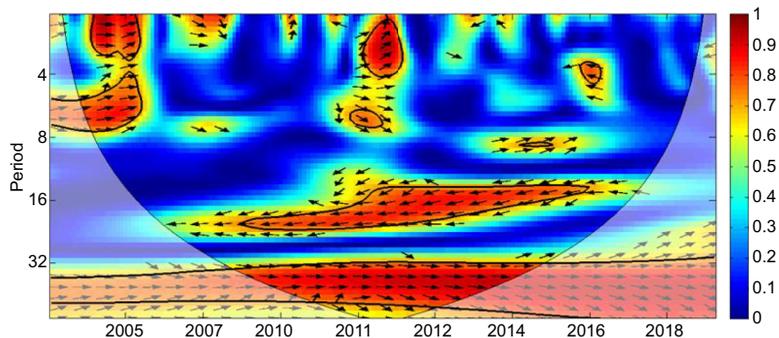

Figure 5.
Comovement between Google search queries index and Tunindex return

stock market return. The arrows are pointing to the left and down indicating that these two variables are antiphase and the Google search queries index remains the leader. These findings are explained by the emotions of fear that drive Tunisian investors. In fact, during the Tunisian revolution, the Tunisian investor is increased his connections to Internet to get access to the new information concerning his investment and consequently his searched frequency has increased which lead to an significant high correlation between Tunindex return and investor's sentiment. Furthermore, these empirical findings are consistent with those obtained by Trichilli *et al.* (2018), in which the googling investor's sentiment leads its stock market returns in the almost of MENA financial markets since wavelet coherency analysis indicates that investor's sentiment and returns are strongly correlated.

During 2011–2016, in the frequency band from 16 to 32 months, there is a strong correlation between the Google search index and Tunindex return proved by the appearance of the red color throughout this band. These results are ascribed to the extensive and successive dominance of political events that have had a major impact on the country's economy during this period. The arrows point to the left and the down; indicating that Google search index and Tunindex return are antiphase. Consequently, search queries index was leading.

Over the same time interval, a strong correlation is also noted on the frequency band of more than 32 months, with arrows pointed to the right. This strong correlation between these two variables is still due to the significant political instability that has characterized this period since 2011, the year that ended the authoritarian regime, but has become a benchmark for the new ungovernable political discourse putting Tunisia always in search of political stability.

This fact sounds consistent with that of Trichilli *et al.* (2019) indicating that the lead–lag relationship between investor sentiment and market indexes returns is affected by political, social and economic instability in MENA financial markets.In addition, these results are far more similar to Abdelhédi and Boujelbène -Abbes, 2019 suggesting a substantial co-movement between oil and Chinese stock markets during the crisis periods.

Additional interesting aspect arising from the wavelet correlation analysis is that Tunisian stock market indexes return is strongly influenced by Google search queries index in both directions, which indicate that the lead–lag structure, in fact, seem to show a bidirectional causality at different scales, specifically, medium- and high-frequency bands of scales over the period 2010– 2014. In fact, these findings indicate that Google search queries index serves as a transmission channel of financial contagion between the investor sentiment and Tunisian equity markets. Interestingly, the results indicate the capability of Google search queries index to detect investor's behavior during political instability.

6. Conclusion
The objective of the paper is to study the impact of political instability on the relationship of shock between investor sentiment and Tunisian stock market returns using monthly data of Tunindex from January 2004 to June 2018. In this paper, we have used the DCC-GARCH model, the FMOLS model and the wavelet coherence analysis.

Results from FMOLS method reveal that Google search queries index has a significant positive effect at the 10 and 1% of level on the Tunindex return before and after the revolution, respectively. More specially, Google search queries index has a slightly higher effect on Tunindex return after the Tunisian revolution than before this revolution. Results also show that has an effect of Tunindex return significant on the Google search queries index before the revolution at the level of 10% and after the revolution at the level of 1%. Indeed, this effect is about 0.00049 before the revolution, and it is about 0.0033 after the revolution.

From DCC-GARCH model, we conclude that, following the starting of the Tunisian revolution of 2011, the dynamic conditional correlation between investor sentiment and Tunindex return is negative. This result is explained by the fact that the Tunisian investors are more frightened about this political instability event that affect their country, so they

increase their searched frequency on Internet, searching all information associated to the economic and financial conditions, in order to make the successful portfolio decision.

Indeed, we show that there is a positive conditional dynamic correlation between investor sentiment and Tunindex return in 2014. This correlation is explained by Tunisian 2014 elections. Results obtained by the wavelet coherence analysis shows a strong correlation between Tunindex return and Google search queries index which is due to the significant political instability that has characterized this period since 2011, the year that ended the authoritarian regime, but has become a benchmark for the new ungovernable political discourse putting Tunisia always in search of political stability. In particular, in 16–32 months, we show a strong comovement between investor sentiment and Tunisian stock market return. The arrows are pointing to the left and down indicating that these two variables are antiphase and the Google search queries index remains the leader.

Generally, our results provide that there is that Google search queries index has the ability to detect the behavior of Tunisian investors especially during the period of political instability.

Examining the impact of political instability on the investors' behavior, measured by Google search queries, and on the dynamics of stock market returns has critical implications for policymakers, investors and scholars. Hence, the results of this paper are important in understanding the role of political instability on stock market return and are of great significance to local and international investors and market regulators. Thus, investors should take that into account the dynamic of investor sentiment when making market investment during turmoil periods.

References

Abdelbaki, H.H. (2013), "The impact of Arab spring on stock market performance", *British Journal of Economics, Management & Trade*, Vol. 3 No. 3, pp. 169-185, available at: https://ssrn.com/abstract=2886858.

Abdelhédi, M. and Boujelbène -Abbes, M. (2019), "Transmission shocks between Chinese financial market and oil market", *International Journal of Emerging Markets*, Vol. 15 No. 2, pp. 262-286.

Arfan, Dawood, Abdullah and Faudziah (2012), "Political stability and the foreign direct investment , inflows in Pakistan", *British Journal of Arts and Social Sciences*, Vol. 9, p. 2.

Aggarwal, R., Inclan, C. and Leal, R. (1999), "Volatility in emerging stock markets", *The Journal of Financial and Quantitative Analysis*, Vol. 34 No. 1, pp. 33-55.

Bailey, J.E., Argyropoulos, S.V., Kendrick, A. and Nutt, D.J. (2005), "Behavioural and cardiovascular effects of 75% CO2 in human volunteers", *Depression and Anxiety*, Vol. 21, pp. 18-25.

Baker, M. and Wurgler, J. (2006), "Investor sentiment and the cross-section of stock returns", *Journal of Finance*, Vol. 61, pp. 1645-1680.

Baker, M. and Wurgler, J. (2007), "Investor sentiment in the stock markets", *Journal of Economic Perspectives*, Vol. 21 No. 2, pp. 129-151.

Beaulieu, M.C., Coggins, F. and Gendron, M. (2006), "Mutual fund daily conditional performance: selectivity and timing measurements", *Journal of Financial Research*, available on the SSRN website.

Bittlingmayer, G. (1998), "Output, stock volatility, and political uncertainty in a natural experiment: Germany, 1880–1940", *Journal of Finance*, Vol. 53 No. 6, pp. 2243-2257.

Blattman, C. and Miguel, E. (2010), "Civil war", *Journal of Economic Literature*, Vol. 88 No. 48, pp. 3-57.

Bollerslev, T. (1990), "Modelling the coherence in short-run nominal exchange rates: a multivariate generalised ARCH model", *Review of Economics and Statistics*, Vol. 72, pp. 498-505.

Brown, G.W. and Cliff, M.T. (2004), "Investor sentiment and the near-term stock market", *Journal of Empirical Finance*, Vol. 11 No. 1, pp. 1-27, doi: 10.1016/j.jempfin.2002.12.001.

Brown, G.W. and Cliff, M.T. (2005), "Investor sentiment and asset valuation", *Journal of Business*, Vol. 78 No. 2, pp. 405-440.

Cheema, M.A. and Nartea, G.V. (2018), "Investor sentiment dynamics, the cross-section of stock returns and the MAX effect", *Presented at the New Zealand Finance Meeting 2018*, Queenstown.

Chesney, M., Reshetar, G. and Karaman, M. (2011), "The impact of terrorism on financial markets: an empirical study", *Journal of Banking & Finance*, Vol. 35 No. 2, pp. 253-267.

Da, Z., Engelberg, J. and Gao, P. (2015), "The sum of all fears investor sentiment and asset prices", *Review of Financial Studies*, Vol. 28 No. 1, pp. 1-32.

Dupas, P. and Robinson, J. (2010), "Coping with political instability: micro evidence from Kenya's 2007 election crisis", *The American Economic Review*, Vol. 100 No. 2, pp. 120-124.

Dupas, P. and Robinson, J. (2012), "Why don't the poor save more? Evidence from health savings experiments", NBER Working Paper #17255.

Engle, R. (2002), "Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models", *Journal of Business and Economic Statistics*, Vol. 20 No. 3, pp. 339-350.

Frey, B.S. and Waldenstrom, D. (2004), "Markets work in war: world war II reflected in the Zurich and Stockholm bond markets", *Financial History Review*, Vol. 11 No. 1, pp. 51-67.

Frieden, J., Ghezzi, P. and Stein, E. (2000), "Politics and exchange rates: a cross-country approach to Latin America", IDB Working Paper No. 137, doi: 10.2139/ssrn.1814683.

Grigaliuniene, Z. and Cibulskiene, D. (2010), "Investor sentiment effect on stock returns in Scandinavian stock market", *Economics and Management*, Vol. 15, pp. 929-940.

Grinsted, A., Moore, J.C. and Jevrejeva, S. (2004), "Application of the cross wavelet transform and wavelet coherence to geophysical time series", *Nonlinear Processes in Geophysics*, Vol. 11, pp. 561-566, doi: 10.5194/npg-11-561-2004.

Gyimah-Brempong, K. (1999), "Political instability, investment and economic growth in Sub-Saharan Africa", *Journal of African Economics*, Vol. 8 No. 1, pp. 52-86, doi: 10.1093/jae/8.1.52.

Hengelbrock, J., Theissen, E. and Westheide, C. (2009), "Market response to investor sentiment", available at: www.ssrn.com.

Huang, C., Yang, X., Yang, X. and Sheng, H. (2014), "An empirical study of the effect of investor sentiment on returns of different industries", *Mathematical Problems in Engineering*, Vol. 2014 No. 45, pp. 1-11.

İkizlerli, D. and Ülkü, N. (2012), "Political risk and foreigners' trading: evidence from an emerging stock market", *Emerging Markets Finance and Trade*, Vol. 48, pp. 106-121.

Jeribi, A., Fakhfekh, M. and Jarboui, A. (2015), "Tunisian revolution and stock market volatility: evidence from FIEGARCH model", *Managerial Finance*, Vol. 41 No. 10, pp. 1112-1135, doi: 10.1108/mf-12-2014-0310.

Lee, W.Y., Jiang, C.X. and Indro, D.C. (2002), "Stock market volatility, excess returns, and the role of investor sentiment", *Journal of Banking and Finance*, Vol. 26, pp. 2277-2299.

Maeso-Fernandez, F., Osbat, C. and Schnatz, B. (2004), "Towards the estimation of equilibrium exchange rates for CEE acceding countries: methodological issues and a panel cointegration perspective", Working Paper No. 353, European Central Bank, Frankfurt.

Moussa, F.B. and Talbi, M. (2019), "Stock market reaction to terrorist attacks and political uncertainty: empirical evidence", *International Journal of Economics and Financial Issues*, Vol. 9 No. 3, pp. 48-64.

Murtaza, H., ulhaq, M.A. and Ali, R. (2015), "Impact of major political events on stock market returns of Pakistan", *Public Policy and Administration Research*, Vol. 5 No. 4, pp. 69-83.

Naik, P.K. and Padhi, P. (2016), "Investor sentiment, stock market returns and volatility: evidence from national stock exchange of India", *International Journal of Management Practice*, Vol. 9 No. 3, p. 213.

Pedroni, P. (1996), "Human capital, endogenous growth, and cointegration for multi-country panels", Working Paper, Department of Economics, Indiana University.

Pedroni, P. (2000), "Fully modified OLS for Heterogeneous cointegrated panels", Department of Economics Working Papers 2000-03, Department of Economics, Williams College.

Perotti, E.C. and Oijen, P.V. (2001), "Privatization, political risk and stock market development in emerging economies", *Journal of International Money and Finance*, Vol. 20 No. 1, pp. 43-69.

Soltani, H., Aloulou, A. and Abbes Boujelbène, M. (2017), "The impact of political instability on investor sentiment and market performance: evidence from Tunisian revolution", *The IUP Journal of Applied Finance*, Vol. 23 No. 4, pp. 5-17.

Suleman, T., Gupta, R. and Balcilar, M. (2017), "Does country risks predict stock returns and volatility? Evidence from a nonparametric approach", *Research in International Business and Finance*, Elsevier, Vol. 42 C, pp. 1173-1195.

Tiwari, A., Dar, A. and Bhanja, N. (2013), "Oil price and exchange rates: a wavelet based analysis for India", *Economic Modelling*, Vol. 31, pp. 414-416.

Torrence, C. and Compo, P. (1998), "A practical guide to wavelet analysis", *Bulletin of the American Meteorological Society*, Vol. 79, pp. 61-78.

Torrence, C. and Webster, P.J. (1999), "Interdecadal changes in the ensomonsoon system", *Journal of Climate*, Vol. 12, pp. 2679-2690.

Trichilli, Y., Abdelhédi, M. and Boujelbène Abbes, M. (2018), "Googling investor's sentiment: powerful measure in conventional and Islamic MENA financial markets", *International Economic Journal*, Vol. 32 No. 3, pp. 1-16.

Trichilli, Y., Abbes, M.B. and Masmoudi, A. (2019), "Islamic and conventional portfolios optimization under investor sentiment states: Bayesian vs Markowitz Portfolio analysis", *Research in International Business and Finance*, Vol. 51, 101071, doi: 10.1016/j.ribaf.2019.101071.

Trichilli, Y., Boujelbène Abbes, M. and Masmoudi, A. (2020a), "Predicting the effect of Googling investor sentiment on Islamic stock market returns: a five-state hidden Markov model", *International Journal of Islamic and Middle Eastern Finance and Management*, Vol. 13 No. 2, pp. 165-193.

Trichilli, Y., Abdelhédi, M. and Boujelbène Abbes, M. (2020b), "The thermal optimal path model: does Google search queries help to predict dynamic relationship between investor's sentiment and indexes returns?", *Journal of Asset Management*, Vol. 21, pp. 261-279, doi: 10.1057/s41260-020-00159-0.

Zaiane, S. (2018), "The impact of political instability driven by the Tunisian revolution on stock market volatility: evidence from sectorial indices", *Journal of Applied Business Research (JABR)*, Vol. 34 No. 2, pp. 339-354.

Further reading

Ester, Massimo and Michele (2007), "Political pressures and exchange rate stability in emerging market economies", *Journal of Applied Economics*, Vol. XI No. 1 (May 2008), pp. 1-32.

Frieden, J. and Stein, E.H. (2000), "The political economy of exchange rate policy in Latin America: an analytical overview", *SSRN Electronic Journal*.

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