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Systemic Risk: A Comparative Study between Public and Private Banks

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ABSTRACT

This paper aims to study the capital insufficiency in various Tunisian banks which are on the list of the Tunisian stock exchange market. Basing our work on the various measures of systemic risk, we have modeled the shortfall capital of the Tunisian banking sector in order to compare private banks and public ones in terms of exposure to systemic risk. We have also studied the effect of stock market shocks on the banks' marginal expected shortfall. The results obtained show that the systemic risk for the period 2006 and 2013 is mainly conveyed by the three public banks.

Keywords: Systemic Risk, Marginal Expected Shortfall, Public Bank, Private Bank
JEL Classifications: G21 G30 G32 G33

1. INTRODUCTION

The subprime crisis has confirmed the fragility of banking systems. Banks were unable to maintain the funds needed to deal with financial turmoil and under-funding. Thus, the amplification of the size of banks assets accompanied by the problem of capital shortfall led to systemic crises in the banking sector, where the bankruptcy of an institution affects the entire sector. As a result, banks are required to build capital reserves to offset capital shortfall in times of financial distress. In order to determine the requisite amount for the recapitalization and financing of capital insufficiency, a set of systemic risk measures are made available.

The financial investigations carried out by "Attac and Basta" (2015) show that the size of banks assets has increased dramatically in relation to the GDP of OECD countries for the period between 1995 and 2013. This difference is mainly due to the orientation of the banks' main activity (i.e., the collection of deposits from individuals and companies as well as the funding of the economy) to more speculation and security of corporate debts. It might be also the consequence of the development of more complex derivatives. In this respect, Kirkpatrick (2009) confirms the presence of the paradigm "too big to fail." He postulates that banks with a high level of total assets are related with higher systemic risk, while Mayordomo et al. (2014) do not obtain a significant relationship between total assets and systemic risk.

Cerutti et al. (2015) and Alin and Simona (2016) indicate that the increase in volatility of total assets increases the banks contribution to the total systemic risk of the financial sector.

Research has led to the development of new methods aimed at bringing the financial sphere closer to real life. In this respect, the Basel III agreement has taken into consideration the latter connection by pushing analyzes and research towards a more generalized world. It is for this reason that current research has shifted to new more complex system risk measurement methods. Acharya and Volpin. (2010) validate that the MES was a good predictor of the decline of the stock prices. Idier et al. (2014) have tried to evaluate the MES method and its capabilities to estimate the contribution of systemic risk to the financial sector risk compared to other measures.

Through this research, we try to identify the Tunisian systemic banks in order to classify them according to their contribution to the sector systemic risk. Furthermore, we try to compare the public and private banks as a function of their contribution to the total systemic risk.

According to the modern financial theory, there are three main methods of quantifying systemic risk, such as "the Marginal Expected Shortfall (MES), Acharya and Volpin (2010)," "the Systemic Risk Index (SRISK), Acharya et al. (2012)" and "the Variation in Conditional Value-at-Risk (ΔCoVaR), Adrian and Brunnermeier (2011)."

2. DATA

2.1. Measures Overview

This section outlines the construction of systemic risk indicators. To study the systemic risk in the Tunisian banking sector, on the one hand, and to rank banks according to their contribution to the systemic risk of financial sector, on the other hand, we decided to proceed by the measures conceived by Acharya et al. (2012). These include the MES, the LRMES and the SRISK. The financial data corresponding to the construction of the systemic risk indicators are collected manually from the Tunis Stock Exchange website and the annual reports of the various banks listed on the BVMT[1].

Formally, Acharya et al. (2012) illustrate the marginal expected shortfall as the forecasted equity loss when market falls below a 2% in a single day. This measure has a more realistic predictive ability than other measures. It provides a more reasonable economic interpretation than the conditional VaR. In addition, the general index of systemic risk came into being with the work of Acharya et al. (2012). The SRISK is considered as the extension of the MES. This involves taking into consideration both the financial commitments and the size of the financial institution. It corresponds to the expected capital deficit of a financial institution, depending on a crisis affecting the entire financial system. It estimates the amount of capital that the institution would need to obtain, in equity, during a severe financial crisis. Furthermore, the SRISK of an institution, during a financial crisis, is calculated according to the MES. For example, companies with large SIFIs under-fund the financial market in the event of a crisis. As a result, they would be the most vulnerable to risk.

Therefore, the RISK% index measures the share of the expected deficit of each bank related to the overall deficit of the banking sector.

2.2. Methodology

In order to quantify the systemic risk of Tunisian banks, we first adopt the Engle model (2002) "DCC-MGARCH," in order to calculate the conditional volatility and the conditional correlation peer (i.e., stock price performance of banks and the performance of the general index of the Tunis Stock Exchange "Tunindex"). After calculating the variances and conditional correlations of the various performance peers for the period between 2006 and 2013, we secondly use the methodology of Acharya et al. (2012) to determine the level of systemic risk MES of each bank. Finally, we study the dynamic relationship between stock price shocks of banks and the stock index level TUNINDEX.

2.3. Sample of the Study

Our sample includes eleven Tunisian banks (both public and private). Our study covers the period between 2006 and 2013. This survey focuses on a daily frequency for calculating stock market returns and a half-yearly frequency for the calculation of the risk index. The chosen period is considered as representative since it encompasses the main facts observed, namely the fallout from the global sub-prime crisis, the European sovereign debt crisis, the political disturbances as well as the "Tunisian revolution" triggered from December, 2010.

3. SYSTEMIC RISK MODELING

3.1. Volatility Modeling and Conditional Correlation

3.1.1. The estimation of DCC-MGARCH model

In this sub-section, we first attempt to present the DCC-MGARCH model proposed by Engle (2002) in order to make estimates of the volatility and conditional correlation of Tunisian banks daily yields of stock market prices between 2006 and 2013.

The above model minimizes the number of parameters by making the correlation matrix dynamic over time. In this respect, we can model the conditional variances, on the one hand, and the conditional correlations of several series of returns, on the other hand. The stated model is as follows:

$$H_t = D_t R_t D_t \quad (1)$$

With $D_t = diag\left(\sqrt{h_{11t}}, \sqrt{h_{22t}}, \ldots\ldots, \sqrt{h_{NNt}}\right)$

$$R_t = \left(diagQ_t\right)^{-1/2} Q_t \left(diagQ_t\right)^{-1/2}$$

With:

$D_t R_t D_t$: The variance-co-variance matrix

$diag\ (\sqrt{h_{it}})$: The designation of the diagonal matrix of standard deviations that vary over time.

R_t: The representation of the conditional correlation coefficient matrix.

Q_t: The representation of the co-variance matrix of standardized residuals, of the dimension (N*N).

3.1.2. Preliminary empirical tests of modeling DCC-MGARCH

The estimation of the DCC-MGARCH model consists in exploiting the presence of similar movements between the index of the Tunis Stock Exchange (TUNINDEX) and the various stock prices in Tunisian banks.

1 BVMT: Tunis Stock Exchange

In fact, we try to examine the conditional correlations between Tunisian banks stock market returns and the TUNINDEX index returns. First of all, we must proceed by testing the heteroscedasticity of the errors to validate the existence of the ARCH effect. Then we have to test the normality of stock market returns.

The tests cited above inform us about the robustness of the estimation in order to decide on the law of distribution (i.e, Gaussian or Student) with which we have to begin our regressions. In order to study volatility and conditional correlation based on the Engle model (2002), we first test the heteroscedasticity of errors.

The test postulates that under the null hypothesis of homoscedasticity, the statistics associated with the Chi-square test follow a Chi-square law with (q) degrees of freedom. The results of the ARCH-LM test are shown in the following table:

Reading this table shows us that the probabilities associated with the test statistics (X^2) are null. As a result, our series of stock market returns are heteroscedastic, hence we confirm the presence of the ARCH effect for all series.

3.1.3. Model Estimation Results "DCC- MGARCH"

The relevance of this modeling lies in the use of the multivariate GARCH model from the GARCH family, retaining the hypothesis of the dynamic variation of the variances and correlations of the series over time. Indeed, the modeling of these correlations takes into account all the financial information available, at a given moment. The results of the DCC-MGARCH model are reproduced in the following table: [Supplementary Table 1].

We proceeded by the dynamic conditional correlation model developed by Engle (2002) to explore the evolution of the dependence between stock market returns and the TUNINDEX index returns.

The estimation of the DCC-MGARCH model for the period between 2006 and 2013 confirms the significance of all the parameters. Therefore, we validate the adoption of the GARCH specification of the different variables. Moreover, the persistence of the coefficient (α), in the short term, remains low and statistically significant for most of the conditional variance equations, with the exception of two series, that of the BTE bank and the UBCI bank. However, the sum of the two parameters (α+β) is very close to unity, which reveals the importance of the persistence of the conditional variance of the series of stock market returns[2]. However, we note that both banks, that is Attijari bank and ATB bank admit the highest conditional correlation coefficients, in terms of dependence between stock price performance and the Tunindex index. On the other hand, Amen bank and the Bank of Tunisia are the least market-dependent, with correlation coefficients equal to 0.0583 and −0.0066 respectively.

2 Our structure of analysis of the different parameters of the estimation of the DCC-MGARCH models is based on the work of Rouabah (2007), "Co-variation of sectoral growth rates in Luxembourg: The contribution of dynamic conditional correlations", Working Paper No. 25, Central Bank of Luxembourg.

At the same time, we notice the presence of two shocks. Actually, the interconnection between the general index of the stock market (Tunindex) and most Tunisian banks stock exchange prices has amplified to reach spectacular levels. The first shock was recorded between 2008 and 2009. This reflects the impact of the global financial crisis "sub-prime" on the Tunisian economy, while the second phase of interdependence began in 2011, reaching extreme levels in early 2012. In this respect, the strong correlation between the different stock market returns of the banks and the TUNINDEX index returns, during the downward phases of the financial market, has had a negative impact on the diversification strategies which, therefore, would reduce investment gains.

We present, below, the different DCC curves between the TUNINDEX returns and banks stock market returns.

From the graph above, the estimated dynamic conditional correlations seem important. In addition, we can see strong intensity between the banking sector and the Tunisian securities market. Even more, it appears that dynamic conditional correlations have increased during the crisis period and the period of political turmoil (2011) [Supplementary Figure 1].

3.2. Systemic Risk Modeling

3.2.1. The marginal expected shortfall

We try, through the modeling of the MES, to quantify the probability of occurrence of the marginal expected shortfall of the banks stock market value, on the basis of the work of Acharya et al. (2012).

We try, through the model below to determine the expected marginal shortfall of the banks stock market value, based on the work of Acharya et al. (2012). In this respect, the marginal expected shortfall MES is defined as follows:

$$\begin{aligned} MES_{i,t} &= E(\text{-}R_{i,t} \left| R_{m,t} < C\right.) \\ &= \sigma_{i,t}\rho_{i,m,t}E\left(\varepsilon_{m,t} \left| \varepsilon_{m,t} < C/\sigma_{m,t}\right.\right) \\ &+\sigma_{i,t}\sqrt{1-\rho_{i,m,t}^2}\,E\left(\xi_{i,t} \left| \varepsilon_{m,t} < C/\sigma_{m,t}\right.\right) \end{aligned} \quad (2)$$

If (ξ_{it}) and (ε_{mt}) are independent, we have:

$$MES_{i,t} = \sigma_{i,t}\rho_{i,m,t}E\left(\varepsilon_{m,t} \left| \varepsilon_{m,t} < C/\sigma_{m,t}\right.\right)$$

where from $MES_{i,t} = \sigma_{i,t}\rho_{i,m,t}E\left(\varepsilon_{m,t} \left| R_{m,t} < C\right.\right)$ (3)

With $R_{i,t} = \ln(\frac{P_{i,t} + Div}{P_{i,t-1}})$

$$R_{m,t} = \ln(\frac{P_{m,t}}{P_{m,t-1}})$$

And ($P_{i,m}$) represents the closing prices of the stocks and the TUNINDEX index.

$C = VaR_{m,t}(\alpha)$

$\sigma_{i,t}$ = Conditional volatility of the securities (i)

$\rho_{i,m,t}$ = Conditional correlation of peers (i and m)

In order to model the systemic risk, it is necessary to determine certain variables such as the Tunindex returns, the banks stock market returns, the dynamic conditional correlation between the banks stock market returns and the market index returns, the conditional volatility of the banks stock market returns and finally the historical VaR of the market index.

After calculations, we obtained a historical VaR of the Tunisian market index almost equal to that found by Acharya et al. (2012). Hence, the historical VaR of the TUNINDEX for the period (2006-2013) is equal to:

$$C = VaR_{m,t}^{(\alpha=1\%)} = -1.98\% \approx -2\% \quad (4)$$

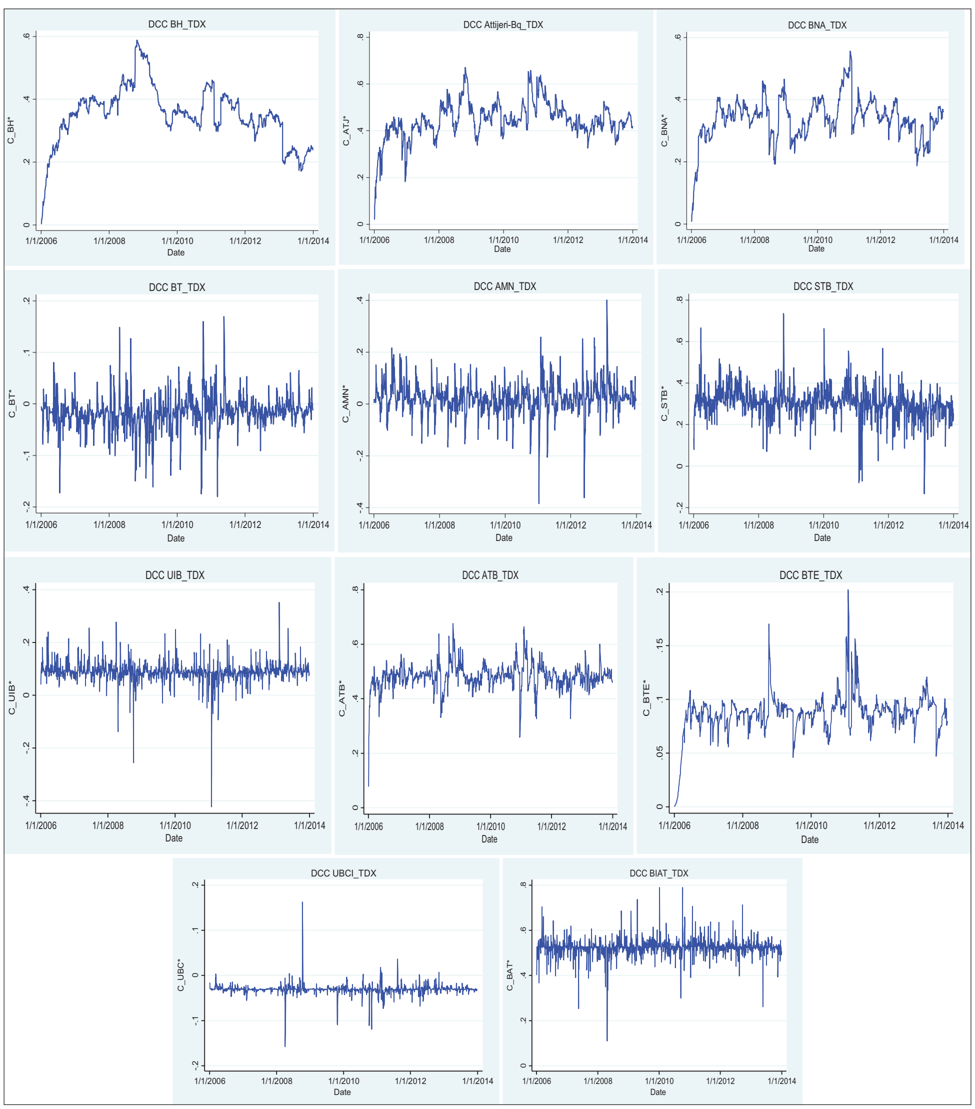
After setting the VaR, in a first time, and the MES of the different Tunisian banks listed on the BVMT in a second time, we can then proceed to the classification of these institutions on the basis of the degree of risk assigned to each of them. The ranking of Tunisian banks according to the MES for the period between 2006 and 2013 gave us the following results:

The Figure 1 ranks the banks by their exposure to the risk of marginal expected loss when the stock index falls by −2%, in a single day. Therefore, UBCI bank appears to be the riskiest bank with an average MES equal to 6.69%. However, BTE bank appears to be the least exposed to risk, with an average MES equal to 0.11%. At the same time, we can see that the banks status (whether public or private) is not significant. In addition, the above rankings are, indeed, heterogeneous in terms of the banks status.

3.2.2. Long-run marginal expected shortfall

The Long-Run Marginal Expected Shortfall appeared, for the first time, with the study of Brownlees and Engle in 2010. This risk measure is defined as the long-term MES calculated over a period of 6 months or more. This is the long-run MES calculated on the basis of 6 months. The LRMES forecasts provide insight into long-term financial risk. Brownlees and Engle (2011) show that LRMES can be estimated through two approaches, a direct approach and

Figure 1: Dynamic conditional correlation between the TUNINDEX return and Banks' stock market return



an indirect approach. The direct approach allows the LRMES to be calculated when the return of the Tunindex index falls by −40%, in a single semester. This method is particularly difficult to estimate because, in reality, the most dynamic stock markets in the world such as the US Stock Exchange Market, during the last century, had only three stock market crashes, where the index got deteriorated to more than -40%, in 1930, 2000 and 2008. Thus, this method is estimated, according to Monte Carlo's simulation, as follows:

$$LRMES_{i,t:t+T} = -\frac{\sum_{s=1}^{S} R_{i,t:t+T}^{(s)}\, I\left(R_{M,t:t+T}^{(s)} \le C\right)}{\sum_{s=1}^{S} I\left(R_{M,t:t+T}^{(s)} \le C\right)} \quad (5)$$

$R_{i,t:t+T}^{(s)}$ and $R_{M,t:t+T}^{(s)}$ represent stock market returns (i) for a 6-month period (t: T) and the return of the TUNINDEX index for the same semester.

C = 40% Brownlees and Engle (2011) define a stock market crash as a rebound in the market index of −40%, in one semester.

I (x) = (1) if true otherwise (0)

The indirect approach is to determine the long-run marginal expected shortfall, without the market declining by −40%. In this case, the Monte Carlo simulation is not necessary because the LRMES is determined through the modeling of the MES. Therefore, the LRMES is defined as follows:

$$SRMES_{i,t} = -E\left[R_{i,t+1} \middle| R_{M,t+1} \le -2\%\right] \quad (6)$$

The SRMES (Short-Run Marginal Expected Shortfall) represents the MES. Moreover, the final approximation of the LRMES proposed by Brownlees and Engle (2011) is defined as follows:

$$LRMES_{i,t:t+T} \approx 1 - \exp\left(-k \times MES_{i,t}\right) \quad (7)$$

For the calculation of the long-run marginal expected returns of the stock market returns, we proceed with the indirect approach, since the index of the BVMT (TUNINDEX) has not bounced below 40% during the study period 2006-2013.

3.2.3. Systemic risk measure

According to the (Risk Management Center of the University of Lausanne), the systemic risk index was first reported by Acharya and Volpin (2010). The SRISK is defined as the capital that a company would need in the event of a subsequent financial crisis. Depending on Brownlees and Engle (2011), the systemic risk of a financial institution is defined as follows:

$$SRISK_{i,t:t+T} = \max\left(CS_{i,t:t+T}, 0\right) \quad (8)$$

Our objective is to validate the assumption that the capital requirement of financial institutions increases when the stock market performance decreases.

Acharya et al. (2017) show that it is possible to directly calculate the capital shortfall value using the following variables (the book value of debts for a period of 6 months, the market capitalization of the bank and the long-run marginal expected shortfall. In this regard, the SRISK is calculated as follows:

$$SRISK_{i,t} = kD_{i,t} - (1-k)\left(1 - LRMES_{i,t}\right)E_{i,t} \quad (9)$$

k =The prudential ratio, assumed equal to 8%

$D_{i,t}$ = The book value of the debts of the institution (i) for semester (t)

$E_{i,t}$ = The market capitalization of the institution (i) for semester (t)

thus, we can determine the sectoral systemic risk through the aggregation of the SRISK of each bank listed on the BVMT. The following formula represents the sectoral SRISK:

$$\sum_{j \in J} SRISK_{j,t} \quad (10)$$

The space (J) refers to all the bank institutions whose systemic risk is positive for period (t).

To assimilate the share of each bank in the sectoral systemic risk, we then calculate the contribution of each bank in the total deficit of the banking sector (in other words, the systemic risk as a percentage). According to Acharya et al. (2012), the individual banking contribution (in percentage) in sectoral systemic risk is determined as follows:

$$SRISK(\%)_{j,t} = \frac{SRISK_{j,t}}{\sum_{j \in J} SRISK_{j,t}} \quad (11)$$

The calculation of the individual contribution of each bank in the overall systemic risk illustrates the following results:

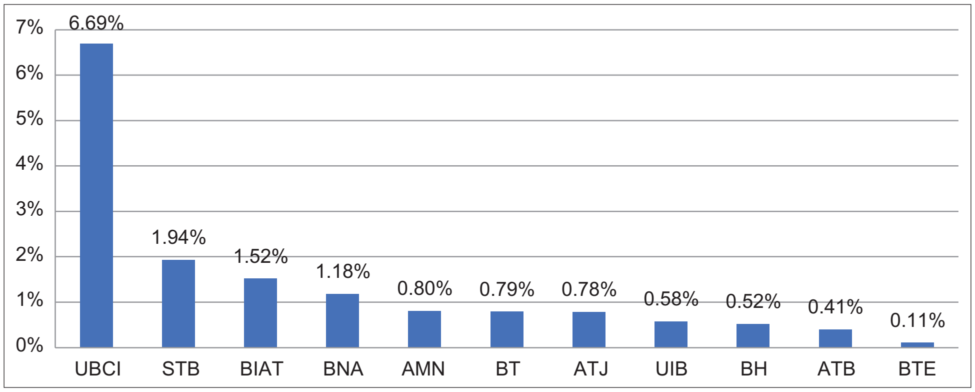
According to this Figure 2, we can see that the three public banks "STB, BNA and BH" contribute to sector systemic risk, in a significant way.

3.3. The Sensitivity Coefficient Beta

In parallel with the work of Brownlees and Engle (2011), Acharya et al. (2012), Benoit et al. (2014), we first try to determine the sensitivity coefficient Beta of the various banks stock market. Secondly, we try to compare this coefficient of sensitivity with the different risk measures previously treated such as MES, LRMES and SRISK. Indeed, Beta is considered as the sensitivity coefficient associated with the risk premium derived from the famous Capital Asset Pricing Model (CAPM). However, it is the ratio between the co-variance of the banks stock returns (i), the return of the TUNINDEX index (m) as well as the variance (m). Mathematically, Beta is defined as follows:

$$\beta_{i,t} = \mathrm{cov}\left(R_{i,t}, R_{m,t}\right) / \mathrm{var}\left(R_{m,t}\right) \quad (12)$$

Figure 2: Ranking of Tunisian banks according to the MES for the period between 2006 and 2013



$$= \frac{\rho_{i,t}\sigma_{i,t}}{\sigma_{m,t}}$$

In addition, the cross-sectional analysis revealed that the coefficient Beta reached its highest level in times of political upheaval (2010-2011). The graph below describes the evolution of Beta of different banks during the period between 2006 and 2013 [Supplementary Figure 2].

The coefficient Beta recorded significant levels on two occasions and the effect of the (2007-2008) subprime crisis is clearly visible. While those of the year 2011 are dictated by a purely political upheaval. In addition, the coefficient Beta associated with the performance of private banks was larger and more significant than that associated with public banks. A priori, we can see that the portfolio of private banks was riskier than that of public banks. We, then, analyze the average Beta throughout the reference period between 2006 and 2013. This is illustrated through the Supplementary Figure 3.

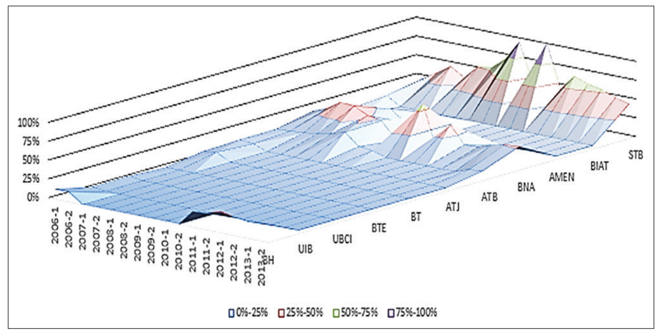
The analysis of the average Beta shows that BT bank (public bank) is qualified as the riskiest bank with a coefficient equal to 0.26. However, Amen bank ranks second with a coefficient equal to 0.22, followed by ATB bank, Attijari bank and UBCI, with risk coefficients around 0.12.

3.4. Comparing the Different Measures of Systemic Risk and Beta

After analyzing the different facets of systemic risk such as (MES, LRMES, SRISK in value and SRISK in %), we proceed to classify the different institutions according to the nature of the risk. The ranking of the different institutions is represented in the following table:

The table above shows the classification of Tunisian financial institutions (banks) according to their contribution to systemic risk (SRISK) and this concerns the period between 2006 and 2013. The above LRMES and Beta are calculated according to their average during the same period. In this respect, the classification of the various establishments has allowed us to note that public banks (STB, BNA and BH) are the riskiest in terms of SRSIK. Nevertheless, the ranking according to other systemic risk measures such as LRMES and Beta did not lead to the same results.

Figure 3: Individual contribution in % to systemic risk of banking sector



Thus, the results we have obtained show that the banks ranking differs from one measure to another, since each measure deals with a particular aspect of systemic risk. Therefore, the divergence in classifications of banks on the basis of systemic risk is due to the difference in the fundamentals of each measure and not to the instability of a particular measure. In addition, the ranking based on the SRISK is mainly sensitive to the importance of the level of indebtedness of each bank. Brownlees and Engle (2011) show that the SRISK can be considered as a "*compromise between the two paradigms (too big to fail) and (too interconnected to go bankrupt)*". However, they have shown, through their empirical study, that the two measures (SRISK and BETA) differ in the definition of their contribution to systemic risk. In contrast, these two measures are qualitatively very similar in explaining cross-sectional differences in contribution to systemic risks. In addition, they are closely related to certain financial variables such as VaR, size and financial leverage. Afterwards, we try to illustrate the degree of agreement between the two measures of systemic risk LRMES and Beta through the following graphical representation:

From the Figure 3, we note that both risk measures increase in times of economic downturn. This is explained by Sylvain et al. (2013). They explain how these two measures (i.e., LRMES and BETA) tend to increase in times of economic slowdown, which is the case for our study. Apart from that, the measure Beta seems to be more sensitive to periods of economic and political disturbances. In addition, we note that the two risk measures followed the same trend for the period between 2006 and 2013.

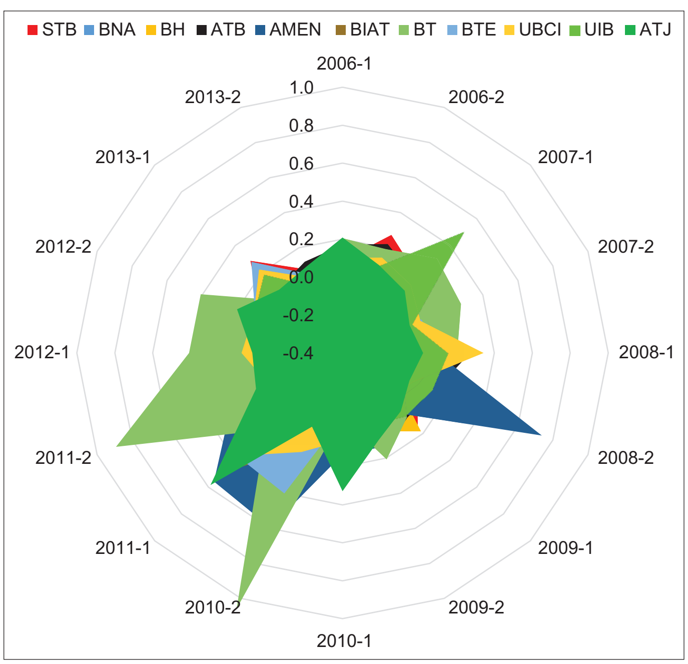
Table 1: ARCH effect presence test "ARCH-LM test"

Bank	AB	ATB	ATJ	BH	BIAT	BNA	BT	BTE	STB	UBCI	UIB
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 2 : The results of the estimation of the model DCC GARCH [1.1]

Bank	The coefficients of the estimation of the DCC GARCH model				Conditional correlations	Adjustment DCC MGARCH		Distributions
	ARCH (1)	ARCH (1)	GARCH (1)	GARCH (1)		M-GARCH	M-GARCH	
	$\alpha_{1.1}$	$\alpha_{2.1}$	$\beta_{1.1}$	$\beta_{2.1}$	$\rho(i, j)$	DCC^1	DCC^2	
AMN	0.2758	0.1407	0.4764	0.6994	0.0583	0.0367	0.7164	Gaussienne
	(0.000)	(0.000)	(0.000)	(0.008)	(0.043)	(0.068)	(0.000)	
ATB	0.2306	0.1850	0.5191	0.5955	0.4360	0.0218	0.8263	Gaussienne
	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.011)	(0.000)	
ATJ	0.2344	0.1941	0.5364	0.2647	0.4493	0.0190	0.9386	Gaussienne
	(0.000)	(0.000)	(0.000)	(0.056)	(0.000)	(0.006)	(0.000)	
BH	0.2491	0.3064	0.5265	0.4844	0.2643	0.0066	0.9862	Gaussienne
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
BIAT	0.5939	0.7547	0.5566	0.6566	0.4156	0.0700	0.2208	Student
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.171)	(0.678)	
BNA	0.4675	0.5969	0.6139	0.6805	0.2843	0.0139	0.9675	Student
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.065)	(0.000)	
BT	0.2723	0.4984	0.4805	0.1494	-0.0066	0.0242	0.6813	Gaussienne
	(0.000)	(0.000)	(0.000)	(0.005)	(0.809)	(0.169)	(0.006)	
BTE	517.9314	250.6698	0.4096	0.2366	0.0795	0.0637	0.9346	Student
	(0.690)	(0.691)	(0.000)	(0.000)	(0.003)	(0.000)	-	
STB	0.2624	0.1923	0.5140	0.6807	0.3000	0.0572	0.5352	Gaussienne
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.014)	(0.097)	
UBCI	-	-	-	-	-0.0373	0.0077	0.4860	Student
					(0.155)	(0.329)	(0.264)	
UIB	1.0291	1.0757	0.4594	0.5514	0.0928	0.0593	0.5150	Student
	(0.002)	(0.003)	(0.000)	(0.000)	(0.001)	(0.223)	(0.144)	

Figure 4: Biannual Beta of Tunisian banks (2006-2013)



The difference between the two measures stems from the fact that the systemic risk calculated according to the LRMES is based on the tail dependence rather than the average co-variance, Acharya (2010). In other words, the systemic risk measurement LRMES calculated according to the MES, is modeled on the assumption that stock market returns fall by <2% in a single day. Thus, the risk measurement LRMES is considered as more relevant than Beta. Unlike LRMES, the risk measure Beta is based on the co-variance dependence of the average returns on the banks financial assets. Finally, the weakness of the Tunisian banking sector, in terms of capital deficiency, has not disrupted the Tunisian real economy, unlike in the case of Systemic Multinational Financial Institutions (SIFs) where the systemic risk holds an important place in the GDP. This can be explained by the absence of the paradigm TBTF in the Tunisian banking system. Afterwards, we try to study the effect of impulse shocks, in terms of the marginal expected shortfall of the stock market performance of the banking sector.

4. THE STUDY OF IMPULSE SHOCKS

To minimize the systemic risk, a government must act on the performance and governance variables in banking institutions in order to reduce the budget devoted to the recapitalization of the banking sector, in the event of a financial crisis.

After identifying systemic institutions, a government could downplay the systemic risk by referring to more stringent regulations in terms of prudential ratios. In other words, by identifying the financial and economic variables that affect the measure of systemic risk, we could avoid the spread of this risk across the entire financial sector that could subsequently affect the real economy. The key assumption of Acharya et al. (2010)

Table 3: Ranking of Banks by SRISK %, SRISK (one million Tunisian dinars), LRMES and Beta

Bank	Rank	SRISK in (%)	SRISK in (MDT)	Bank	LRMES (%)	Bank	β
STB	1	43.57	3,401,361	BIAT	19.90	BT	0.270
BNA	2	24.19	1,889,003	BNA	17.70	AMEN	0.217
BH	3	14.96	1,167,810	ATJ	11.90	ATB	0.138
ATB	4	7.18	560,419	UIB	8.50	ATJ	0.123
AMEN	5	3.47	270,970	BH	8.40	UBCI	0.117
ATJ	6	1.99	154,987	BT	7.20	STB	0.115
BT	7	1.96	153,306	UBCI	6.80	BNA	0.107
BIAT	8	1.92	149,557	STB	6.70	BH	0.089
UBCI	9	0.43	33,325	AMEN	5.60	BTE	0.086
UIB	10	0.34	26,757	BTE	1.80	BIAT	0.074
BTE	11	0.00	0	ATB	1.20	UIB	0.062
Total		100	7,807,494				

Figure 5: Average Beta of Tunisian banks (2006-2013)

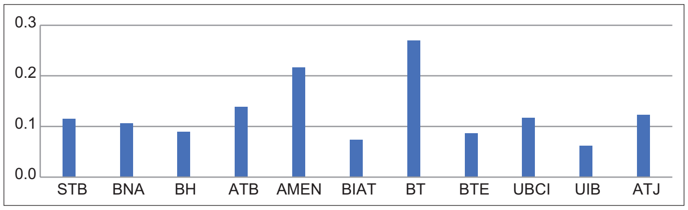


Figure 6: Concordance between LREMS and BETA

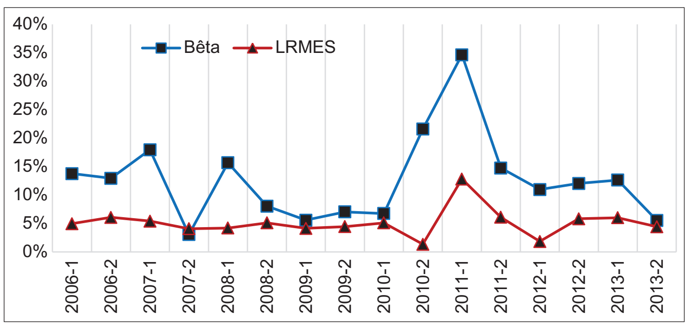
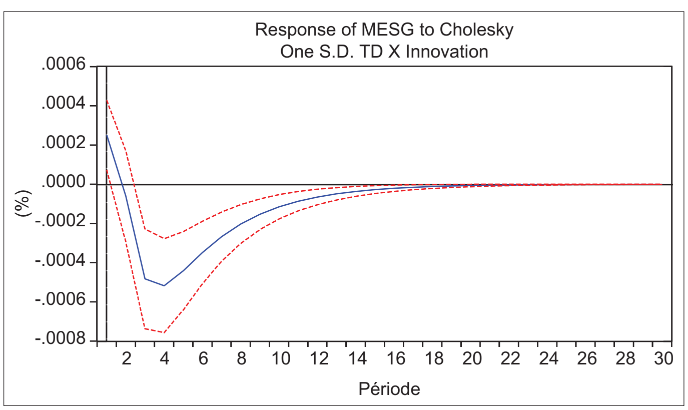


Figure 7: Response of Global MES to Cholesky One S.D. TDX Innovation



is that undervaluation of the capital of a financial institution imposes external costs on the real economy when it occurs during a period of financial distress. Indeed, these costs are borne by taxpayers. However, it also includes externalities that are particularly severe. However, the bankruptcy of a financial institution cannot be absorbed by competitors when a country's economy is in a recession. In other words, when the system is underfunded, it will no longer provide liquidity on a regular basis. This phenomenon can be analyzed by impulsive shocks in the Tunisian banking sector.

4.1. Approach to the Study

In order to study the impulse shocks on the Tunisian banking sector, we looked at two variables such as the daily market index returns "TUNINDEX" and the overall marginal expected shortfall of the banks stock exchange markets "Global MES." The analysis will cover the period from 2006 to 2013.

4.2. The Pulse Function

Yun and Moon (2014) conducted an impulse study to investigate the impact of financial shocks on the real economy during periods of economic stability and instability. To do this, they proceeded by the structural threshold model VAR of Balke (2000).

In this respect, we adopt this same methodology, except that, instead of studying the effect of financial shocks on the real economy, we analyze the effect of stock market shocks on the MES.

The graph below illustrates the impulse response of market index shocks "TUNINDEX" to the overall marginal expected shortfall of the banking book (i.e., the aggregate MES).

The blue curve represents the impact of the stock index returns "Tunindex" shock on the marginal expected shortfall of the banking sector while the dashed lines represent the confidence interval (Figure 4).

We will be focused in the impacts of the impulse shock on a horizon of thirty trading days. This period represents the time needed for the two indicators to regain their long-term equilibrium.

As a result, a positive stock market index shock lowers the overall "Global MES" to a level of 0.00076 for four trading days. This impact, then, disappears gradually until it returns to a long-term equilibrium after a period of three trading weeks.

In this regard, we can make a final judgment on the reaction of the sector MES in the face of the stock market index shock. Indeed, the results obtained demonstrate that the absorption of the impulse shock is a gradual process that lasts three trading weeks.

5. CONCLUSION

Since the advent of the sub-prime crisis, academic and professional research on systemic risk management of financial institutions has proliferated. The failure of micro-prudential regulations prompted several questions about the reliability of rules and measures of systemic risk. Some researchers describe this failure as the result of the sophistication of financial risk modeling techniques. Others consider the weakness of the financial system as the consequence of the inefficient governance structures of banks.

The study of the above-mentioned systemic risk measures highlights three periods of disruption in which the overall marginal expected shortfall "global MES" has reached extreme levels. In this regard, we note that the Tunisian banking system has reached critical levels, in terms of the overall marginal expected shortfall for the period 2010 and 2011, when the latter measure exceeded 10%. In addition, the disturbances observed in 2008 represent the result of the fallout from the subprime crisis on the Tunisian economy.

Thus, we can notice that LRMES recorded significant proportions during the study period. Indeed, it has reached more than 25%. In fact, this is explained by the fallout from the Tunisian political crisis triggered in December 2010. Thus, we find that public and private banks were exposed to prudential risk in the same way.

Even more, cross-sectional analysis has found that public banks "STB, BNA and BH" have contributed to the systemic risk of the banking sector in a more significant way than private banks. Moreover, the systemic risk is mediocre for most private banks except the ATB and Amen bank.

In addition, the examination of the overall systemic risk of the Tunisian banks revealed two important phases for the period between 2006 and 2013. Indeed, we note that the marginal expected shortfall of the sector increased between 2006 and 2010. The second episode of increase in SRISK is caused by political turmoil from January 2011. The banking sector capital shortage widened between the period 2011 and 2013. Finally, the results obtained show that the systemic risk for the period 2006 and 2013 is mainly conveyed by the three public banks.

Finally, the fallout from the subprime crisis (2007-2008), on the one hand, and the Tunisian political events triggered at the end of 2010, on the other hand, have revealed the deficiency of the Tunisian banking system.

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