ON REVERSE STRESS TESTING FOR WORST CASE SCENARIOS: AN APPLICATION TO CREDIT RISK MODELING OF TUNISIAN ECONOMIC SECTORS

AMIRA DRIDI, MOHAMED EL GHOURABI, MOHAMED LIMAM

Abstract:

In Tunisia substantial economic and financial vulnerability are mainly caused by the civil unrest and the subsequent regime change after the Tunisian revolution in 2011. In order to quantify this fragility, in this paper, we use reverse stress testing (RST) based on combination of relevant risk factors that lead to the worst case in which the bank becomes unviable and insolvent. Given the financial stress testing scenarios shortcomings (i.e. plausibility, subjectivity), the use of RST methodology is explained by the fact that it identify the probability of realization of such scenarios. We apply this new methodology on Tunisian banks which are the core for financial stability; more specifically, we focus on credit risk RST. We choose the upper bound for value at risk (VaR) in order to identify worst VaR at probability of realization a. Our proposed framework relies on the logistic regression to identify stress probability and the linear regression of financial stress index output gap versus macroeconomic risk factors in order to search for scenarios at 1%, 3% and 5% levels of plausibility. Empirical results show that Tunisian banks have likely to reach the WVaR in 2012 at 5% level. Besides the more extreme the scenarios which are considered the less plausible they become. Our reverse FST is a complement, and never a substitute for risk manager and what matters most is the mindset of those employing it.

Keywords:

reverse stress testing, worst case scenarios, credit risk, value at risk, generalized Pareto distribution.

JEL Classification: C19, G01, C10

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1.   Introduction

Tunisia has opted for a gradual liberalization of the financial market, with limited access granted to foreign companies' to the Tunisian market. Thus, there was no collapse in securities from 2008 as a result of the financial crisis (from 2008, there was a decline in the market capitalization of all developed countries and in emerging countries with significant foreign participation). However, after the Tunisian revolution that caused political changes and revealed many social problems, Tunisia has a clear financial stability difficulties experienced by certain sectors. This substantial economic and financial vulnerability are mainly caused by the civil unrest and the subsequent regime change. This fragility can be measured using financial stress testing (FST) defined as "a generic term describing various techniques used by financial firms to gauge their potential vulnerability to exceptional but plausible events" (Bank of International Settlements committee on the global financial system). Mainly, there are four steps for any micro or macro FST namely the set of risk exposures, the scenario defining the exogenous shocks, the model and the measure of the outcome. However, for several researchers, there are difficulties involved in estimating an exact risk model, especially for multi-period FSTs. The selection of scenarios should be based on a measure of plausibility (Breuer et al. 2009). In fact, the choice of scenarios is very important, they should be extreme and plausible at the same time, and more extreme scenarios are considered the less plausible ones. Institutions should avoid the "illusion of safety" if it does not choose the worst scenarios like in the Irish FST case in 2010 (Breuer et al., 2012). FST can be conducted by simulating historical stress episodes or by constructing hypothetical events built by stressing one or a group of risk factors.

Traditional FSTs can be criticized for being conducted outside the context of a risk model, hence the probability of an extreme event is unknown. Many FSTs also fail to incorporate the characteristics that markets are known to exhibit in crisis periods, namely, increased probability of further large movements, increased co-movement between markets, greater implied volatility and reduced liquidity. To solve those problems, practitioners rely on an exact measure of stress that should be integrated in the FST process, this measure is called financial stress index (FSI) that will be used to overcome the drawbacks of FST. A measure of an institution's stress gives a better picture of its financial condition than a simple binary crisis indicator. Illing and Liu (2006) computed an index for Canada. Cardarelli et al. (2009) computed an FSI for developed economies, and Balakrishnan et al. (2009) proposed an FSI for emerging countries and compared it with that for developed countries, Dridi et al. (2012) proposed an FSI based on EVT and control chart to determine stress periods in the Tunisian banking system.

In this paper, we apply a new FST framework on banks which are the core for financial stability; more specifically we focus on credit risk FST. In order to avoid the shortcomings for FST scenarios (i.e. plausibility, subjectivity) we rely on the reverse stress testing (RST) that identify the combinations of relevant risk factors or risk parameters that lead to the worst case scenario (WCS) under which the bank

becomes unviable and insolvent; it also finds the probability of realization of such scenarios. RST is done by starting with a worst case outcome and working backward to identify different scenarios under which such failure may occur. Our framework is applied on the Tunisian banks as they play a key role in financing the Tunisian economy. Indeed, more than 95% of lending to the economy goes through these financial institutions. Moreover Tunisian economic sectors are typically intermediated, as the share of banks in total assets held by all financial institutions exceeds 80%. Banks are the main vectors of intermediation because they provide most of the credit to the economy. However, political and social changes in Tunisia made a substantial transformation in the basic foundations of banks business. The rapid expansion in the level of non-performing loans (NPL) and the importance of the losses incurred by banks on their loan portfolios have shown interest to understand the determinants of credit risk ensuring proper management of this risk and maintaining macroeconomic financial stability. Several studies have considered the interaction of microeconomic and macroeconomic shocks as an explanatory factor in risk credit modeling. However, these studies have focused on developed countries. In Tunisia, to our knowledge, the literature on this topic is limited. We still lack clear answers, because the authors are unanimous in recognizing that there is no proven effect of the macroeconomic shocks on credit risk FST. The purpose of this study is to analyze the effect of macroeconomic shocks on the Tunisian deposit banks using RST. First we identify the worst case outcome and next we rely on the regression of the financial stress index (FSI) output gap versus macroeconomic risk factors in order to search for scenarios at 1%, 3% and 5% levels of plausibility.

The remainder of this paper is structured as follows. Section 2 presents an overview for credit risk stress testing modeling. The worst case search is presented in Section 3. The corresponding empirical study and results are discussed in section 4 and the main conclusions are summarized in section 5.

2.   Credit Risk Stress Testing Modeling

Credit risk is the most significant source of risk; it is defined as the loss associated with unexpected changes in credit quality. The largest source of credit risk is loans that involve the risk of default of the counterparty. Measuring credit risk is an estimation of a number of different parameters namely probability of default, loss given default, which may involve estimating the value of collateral and the exposure at default. Some authors link credit risk to macroeconomic variables using econometric models. Pesola (2005) presents an econometric study of macroeconomic determinants for credit risk and other sources of banking fragility and distress in Finland. For Austria, Boss (2002) provides estimates of the relationship between macroeconomic variables and credit risk. For Norway, the Norges Bank has single equation models for household debt and house prices, and a model of corporate bankruptcies based on annual accounts for all Norwegian enterprises (Eklund et al., 2001). For Hong Kong, Gerlach et al. (2004) proposed an FST credit risk model based on a panel using bank-by-bank data. For the Czech Republic, Babouček and Jančar

(2005) estimate a vector autoregression model with NPL and a set of macroeconomic variables. Similar models are also common in Financial Sector Assessment Program missions (FSAP). For example, the technical note from the Spain FSAP includes an estimate of a regression explaining NPL on an aggregate level with financial sector indicators and a set of macroeconomic indicators.

Jiménez and Mencía (2009) consider corporate loans and loans to households in their credit risk model and they introduce latent factors in order to model the correlations between different types of loans, Breuer et al. (2012) propose a new method for analysing multi-period stress scenarios for portfolio credit risk.

Several shortcomings need to be considered when interpreting macroeconomic models of credit risk stress testing. In particular, the literature is dominated by linear statistical models. The linear approximation is reasonable when shocks are small, but for large shocks non-linarites are likely to be important. Moreover, the models are subject to the Lucas critique (that is it is naive to try to predict the effects of a change in economic policy entirely on the basis of relationships observed in historical data, especially highly aggregated historical data) since their parameters or functional forms may become unstable, especially if exposed to a major stress. In order to overcome those shortcomings, in this paper, we apply the method of worst case search over risk factor domains of certain plausibility to the analysis of portfolio credit risk for each sector.

The type of model widely used in credit risk modeling is the Credit Portfolio View (CPV) model developed by Wilson (1997a and 1997b). In CPV, the default and other rating migration probabilities are explicitly linked to some macroeconomic variables and distribution of portfolio losses are calculated by using Monte Carlo simulations. The basic idea of the CPV model is to link default and migration probabilities to macro variables. There are four steps for the CPV model. In the first step, average default rates are linked to macro indices. These indices can be seen as functions of different macro variables. In the second step, the evolutions of macro variables are described by using time series models. The third step is the construction of the correlation structure of model. In the fourth step, new values for macro variables and average default rates are simulated and portfolio loss distribution is generated.

Our credit risk model is inspired from CPV methodology and following the same ideas of Wilson.

The stress rate which is the credit risk indicator (CRI) for each sector is linked to macro-variables by using a logistic transformation

$$CRI = \pi_t = p(y_t = (FSI_t > 0)/x_t) = \frac{1}{1+e^{-y_t}}, \tag{1}$$

where π_t is the stress rate at time t, y_t is a categorical variable that indicates either the presence or the absence of stress and x_t is the set of explanatory macroeconomic factors (GDP growth, interest rate, coverage rate…). The logistic transformation ensures that values of stress rates are in the range [0,1]. CRI is the probability of the

occurrence of stress periods given specific macro-variables x. From equation (1), the value of Logit (y) given stress rate is calculated as:

$$Logit(y_t) = \ln(odds) = \ln\left(\frac{\pi_t}{1-\pi_t}\right),$$

(2)

where odds are ratios of probabilities π_t of occurred y (i.e. the year is stressed) to probabilities $1-\pi$ (of non-occurred y).

In order to find the empirical macro-variables, the logit transformation is assumed to be determined by a number of macro variables, i.e.:

$$Logit(y_t) = \alpha + \beta X + \upsilon_t,$$

(3)

where α is the intercept, β is a set of regression coefficients to be estimated, X is a macroeconomic risk factors vector and u_t is a random error assumed to be independent and identically normally distributed. The equations (1) to (3) define the relationship between stress rates and macro variables. In equation (3), the systematic effect is captured by macroeconomic variables X and u_t defines an economic specific surprise.

The next step is the determination of the worst case value for the credit risk model which is presented in the next section.

3.   Proposed Worst Case Search Methodology for Credit Risk Modeling

Let (Ω,F,P) a fixed probability space and consider n continuous risk random variables ($X_1,…,X_n$) with given marginal distributions functions $F_1,…,F_n$, such that

$F_i(x)=IP(X_i \le x), i=1,…,n.$

Let Ψ some function defined as follow:

$$\Psi : IR^n \rightarrow IR;$$
$$\Psi(x) = X_1 + … + X_n$$

be the total credit risk indicator, for our case it indicates the overall FSI with some modifications. Following the methodology proposed by Wang et al (2013), the problem here is to find the best possible sharp bound of the distribution function (*df*) of $\Psi(x)$ where the upper bound indicates the worst value at risk (WVaR). When the dependence structure is unspecified, the stochastic bounds for the *df* $F_\Psi(x)$ easily obtained from the multivariate version presented by

$$m_+(s) \le F_\Psi(s) \le M_+(s) \;,$$

where

$$m_+(s) = \inf\left\{P(S<s) : X_i \sim F_i; i=1,\ldots,n\right\};$$
$$M_+(s) = \sup\left\{P(S<s) : X_i \sim F_i; i=1,\ldots,n\right\};$$

For more details about deriving the sharps bounds $m_+(s)$ one can see references such that Wang et al (2013), Embrechts et Puccetti (2010) and Embrechts et al (2003). These authors deal with the problems of finding $m_+^{-1}(s)$ as the WVaR for any corresponding aggregate position. The so-called VaR at level *α* is defined as:

$$VaR_\alpha(S) = \inf\left\{s \in IR : P(S \le s) \ge \alpha\right\}$$

It is well noticed in Wang et al (2013) for *n≥3* exact bounds were only found for the homogenous case ($F_1=\ldots=F_n=F$).

Define $\Psi(t) = IE(X > F^{-1}(t))$

For $t \in (0,1)$,

$$\psi(1) = \lim_{t\to 1^-} \psi(t),$$

$$\psi(0) = \lim_{t\to 0^+} \psi(t)$$

and $\qquad \psi^{-1}(x) = \inf\left\{t \in [0,1] : \psi(t) \ge x\right\} \qquad$ for $\qquad x \in \psi(1)$ and $\psi^{-1}(x) = 1$ for $x \ge \psi(1)$

In this paper, we will consider *F* as a generalized Pareto distribution which is a decreasing density function.

Wang et al. (2013) define $Q_n^F(c_n), (n \ge 2)$ as the copula used to calculate $m_+(s)$, where c_n is the smallest possible *c* such $c \in \left[0, \dfrac{1}{n}\right]$ and a copula Q_n^F that satisfies the following criteria:

a)   for each *i=1,…,n*, given $U_i \in [0,c]$ we have $U_j = 1 - (n-1)U_i; \forall j \ne i$

b) $F^{-1}(U_1) + \ldots + F^{-1}(U_n)$ is a constant when any of U_i lies in the interval $[c, 1-(n-1)c]$

Proposition

Assume that $X_i \sim F$ with a density function $\qquad f(x,\sigma,\zeta) = \dfrac{1}{\sigma|\zeta|}(1 + s\dfrac{1x}{\sigma})^{-\frac{(1+\zeta)}{\zeta}}$, where

$s = sign(\zeta).$

Then

$$F(x) = 1 - \frac{N}{n}(1 + \frac{\zeta}{\sigma}(x-u))^{-\frac{1}{\zeta}},$$

$$F^{-1}(a) = u + \frac{\sigma}{\zeta}((\frac{n}{N}(1-a))^{-\zeta} - 1)$$

and $\phi(a)$ defined in (7). Then for *a≥F(b)*, the WVaR of $S = X_1 + ... + X_n$ is

$$\sup_{X_i \sim F} VaR_\alpha(S) = m_+^{-1}(s) = \phi(a)$$

Sketch of the Proof

Now we are able to give a computable formula for $m_+(s)$. For a decreasing density *F* and $a \in [0,1]$ define

$$WVaR = H_a(x) = (n-1)F^{-1}(a + (n-1)x) + F^{-1}(1-x) \qquad (4)$$

$$c_n(a) = \min\left\{ c \in \left[0, \frac{1}{n}(1-a)\right] : \int_c^{\frac{1}{n}(1-a)} H_a(t)dt \geq (\frac{1}{n}(1-a) - c)H_a(c) \right\}$$

and $\phi(a) = \begin{cases} H_a(c_n(a)) & if \ c_n(a) > 0 \\ n\psi(a) & if \ c_n(a) = 0 \end{cases}$ \qquad (5)

Further we have that *cₙ (a)* is the smallest $c \in \left[0, \frac{1}{n}(1-a)\right]$ such that

$$u(1 - a - nc) + \frac{N}{n}\frac{\sigma}{\zeta(1-\zeta)}((\frac{n}{N}(1-a-(n-1)c))^{1-\zeta} - c) - \frac{N}{n}\frac{\sigma}{\zeta(1-\zeta)}((\frac{n}{N}c)^{1-\zeta} - c)$$

$$\geq (\frac{1}{n}(1-a) - c)\left[u + \frac{\sigma}{\zeta}((\frac{n}{N}(1-a-(n-1)c))^{-\zeta} - 1) + u + \frac{\sigma}{\zeta}((\frac{n}{N}c)^{-\zeta} - 1)\right] \qquad (6)$$

4.   Empirical Study

4.1 Data

Due to the annual frequency of some series, we compute a yearly index for the Tunisian banking sector from 1980 to 2012. We use mainly aggregate balance sheet data. For our case study, we choose five loan variables relative to five sectors: agriculture and fishing, industry, manufacturing, extractive industry and services. The choice of those variables is not restrictive and it is limited to the availability of the data

as NPL which is not available for Tunisian banks for the studied period (i.e. the NPL that we had started from 1996). We have 33 observations for each variable from 1980 to 2012. To compute the FSI we use a widely used technique namely variance-equal weight method.

Following Table 1, the FSI distribution is right-skewed and Platykurtic distribution (flatter than a normal distribution with a wider peak). The Jarque-Bera test shows that data are not normally distributed. Moreover, Figure 1 shows that credit FSI shrank in 2007 but still increasing since 2008.

Figure 1: Time Series Plot for Credit FSI
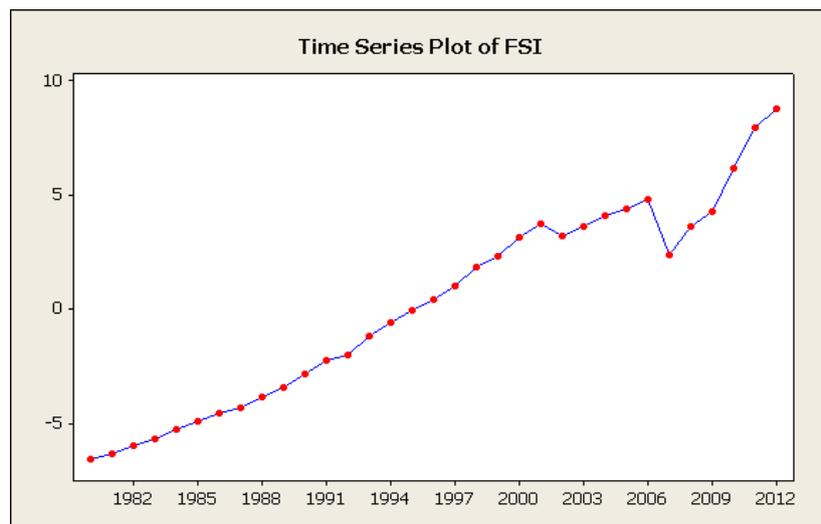
We use the five credits for each sector named above. Figure 2 shows the continuous increasing evolution of all credits across time except for extractive industry that shrank since 2007 which is caused by " mineral basin" events occured in Gafsa (south Tunisia) in response to the general concerns of rising unemployment, poverty and increasing living costs, as well as the corruption widely believed to have contributed to the region's poverty committed by the executives of the Gafsa phosphate company, in their recruitment operations, arousing disillusionment and disappointment among the youths concerned by these operations.

Figure 2: Time Series Plot of Sectorial Credits
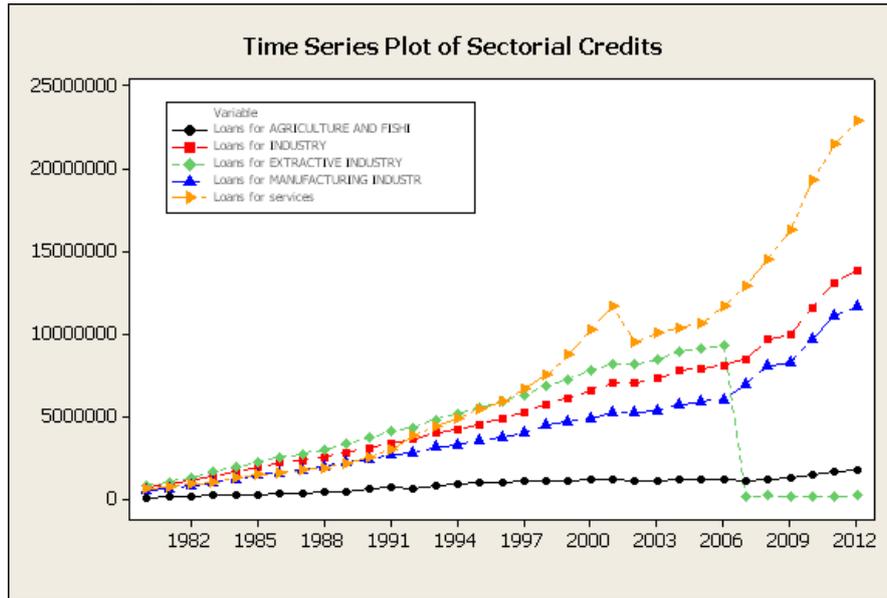
Indeed, the five sectors are far from being independent, and there is a specific dependence structure as shown in Figure 2 that needs a careful study to identify its nature.

	Agriculture	Industry	Extractive	Manufacturing
Industry	0,952			
Extractive	0,251	0,024		
Manufacturing	0,936	0,997	-0,053	
Services	0,928	0,993	-0,039	0,993

The correlations matrix shows that all sectors are strongly correlated to each other except the extractive sector which presents a weak correlation with the remained sectors.

In the empirical model, four macroeconomic risk variables are tested for their explanatory power. These are import/export coverage rate (CR), gross domestic product growth (GDP) interest rate (IR) and inflation rate (IFR). These data are obtained from the central bank of Tunisia. The choice of those macro-variables is not restrictive and it is limited to the availability of the data. The descriptive statistics for macro-variables are given in Table 2 which shows that all macro variables have right skewed distribution except the CR which has left skewed distribution. All macroeconomic risk factors have Leptokurtic distributions.

4.2   Results

4.2.1 Credit Risk Logistic Regression Model

We find that an association between different macroeconomic risk variables at the same time in order to predict the stressful periods is not significant. But, the association between the binary variable and each macroeconomic risk variable

separately, gives very satisfying results as shown in Tables 3 to 6. The equations that describe the logistic regression function can be written as follows for each risk factor:

For CR:

$$\begin{cases} \ln(odds) = -38.6062 + 0.5584CR \\ \pi = \dfrac{1}{1 + e^{-\ln(odds)}} \end{cases}$$

where π is the probability that the year is stressed given a specified value of CR.

We know that a logistic model is said to provide a better fit to the data if it demonstrates an improvement over the intercept-only model (also called the null model).

Then, following Table 3, the logistic model was more effective than the null model at 0.01 (log likelihood = -9.304 and p-value = 0.000). Goodness-of-fit statistics assess the fit of a logistic model against actual outcomes.

Three inferential goodness-of-fit tests are conducted, the Hosmer–Lemeshow (HL) test, Pearson test and deviance test. These three tests suggest the null hypothesis of a good model fit to data was tenable (all p-value are greater than 0.1). Goodman-Kruskal Gamma is summary of the table of concordant and discordant pairs. This measure is about 83% which indicates that the model has a good predictive ability.

From Table 3, it is clear that the estimated coefficients for both intercept and the risk factor CR have p-values less than 0.05, indicating that there is sufficient evidence that the coefficients are not zero using α-level of 0.05. The value of the CR coefficients is positive, this indicates that the CR is associated with the presence of the stressful period for Tunisian economic sectors. To better understand this finding, we look at the odds ratios.

Following Table 3 the odds of the CR is 1.75 and when interpreting this value we compare it to value of 1 (which indicates no effect). As this value is greater than 1, this indicates that a year with a significant CR is 1.75 times more likely to be stressful than years without significant CR.

As for stress probabilities π, it is shown in Table 7 that if the CR increases than π decreases (i.e. for a CR= 90%, the probability of stress approaches 1).

Figure 3 Time Series Plot of CR
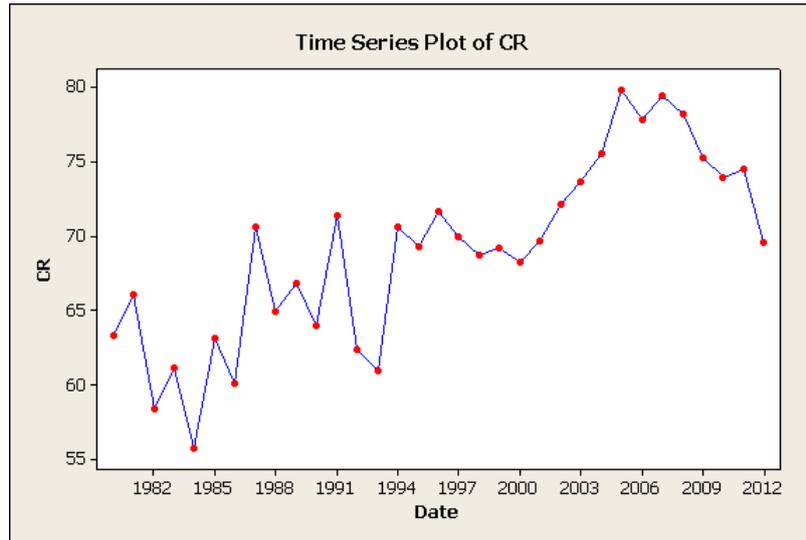
For the CR variations in Figure 3 mainly caused by the continued decline in production and exports of the industrial sector especially for export-oriented manufacturing industries and that, as a result of the economic downturn in the area Euro.

For GDP Growth:

$$\begin{cases} \ln(odds) = 1{,}23411 - 11{,}5276\,GDP \\ \pi = \dfrac{1}{1 + e^{-\ln(odds)}} \end{cases}$$

Table 4 gives a different type of results. The coefficients for both intercept and the risk factor, GDP, are negative and significant only at 0, 1. Since logistic regression allows us to directly measure the increased risk associated with the binary variable Y, the negative sign of the GDP coefficient indicates that the year with significant GDP is associated with the absence of stress periods. Moreover, Table 4 indicates that the logistic model was more effective than the null model only at 0.1 (log likelihood = -21,460and p-value = 0.094). The three inferential goodness-of-fit tests suggest the null hypothesis of a good model fit to data was tenable (all p-value are greater than 0.1). Goodman-Kruskal Gamma is about 33% which indicates that the model has a fairly predictive ability.

In addition, the odd ratio is less than 1. Though, there is a reduced risk to belong to the   group of stressful years. Figure 4 depicts the GDP growth variations that dropped off in 2011 after the Tunisian revolution.

Figure 4: Time Series Plot for GDP Growth
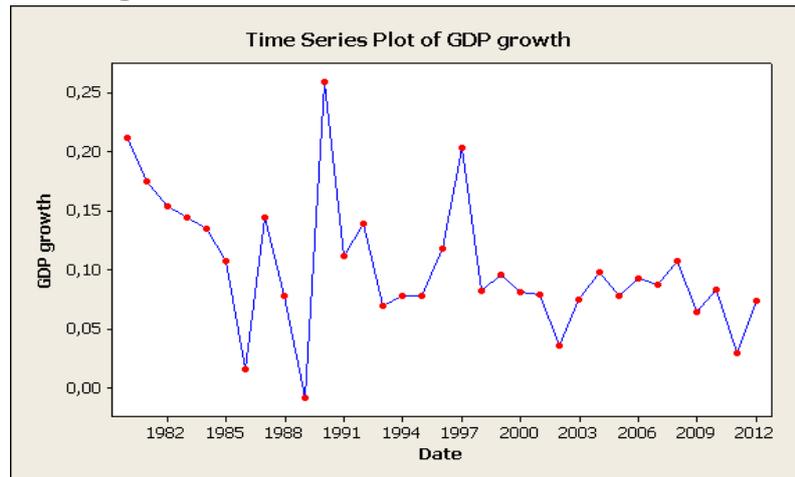
As for stress probabilities π, it is shown in Table 7 that if the GDP growth decreases than π increases (i.e. for a GDP= 0.90%, the probability of stress approaches 0). For IR:

$$\begin{cases} \ln(odds) = 23.8976 - 3.01435 IR \\ \pi = \dfrac{1}{1 + e^{-\ln(odds)}} \end{cases}$$

Table 5 indicates that the IR has good association with the financial stress. The value of odds ratio outline that the year with low controlled IR is associated with the presence of stress periods and a high level of IR is associated with tranquil periods.

In fact, IR may have a positive or negative effect on the level of credits. An increase in the IR results in higher costs of refinancing for banks and lenders. The increase in the debt rate may cause certain credits become nonperforming. Indeed, a rise in IR means that non risky borrowers will have better access to bank financing which can limit the exposure to credit risk. Moreover, Tunisian Central Bank began by strongly lowering interest rates in front of the economic downturn caused by the financial turmoil. According to standard economic models, lower real interest rate which is believed to be sustainable accelerating credit expansion. It adds further assets as it reduces the discount factor for future cash flows. All things being equal, the value of collateral increases, which may encourage financial institutions to make more money and increase their own leverage to buy riskier assets which may explain the increase in credit risk.

As for stress probabilities π, it is shown in Table 7 that if the IR increases than π decreases (i.e. for an IR= 10%, the probability of stress approaches 0).

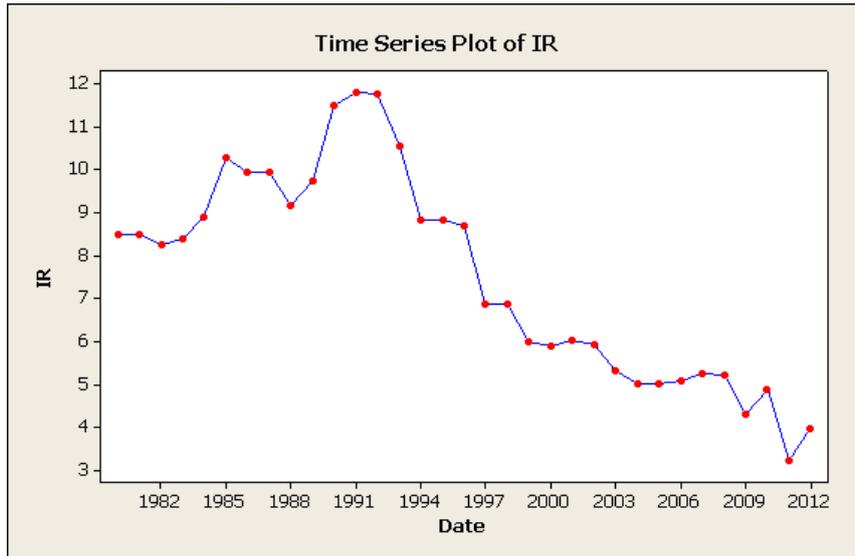**Figure 5: Time Series Plot for IR**

Figure 5 shows the remarkable decrease in the IR level in 2011 due the political and social events related to the revolution. Once again this confirmed that low level of IR is associated to high level of stress.
For IFR:

$$\begin{cases} \ln(odds) = 7.54401 - 1.55924 INF \\ \pi = \dfrac{1}{1 + e^{-\ln(odds)}} \end{cases}$$

Figure 6 and Table 6 outline that low level of IFR is registered during the stressful periods. Indeed, financial stress depicted during the period of low interest rate and in a context of decelerating inflation.

Figure 6: Time Series Plot for IFR
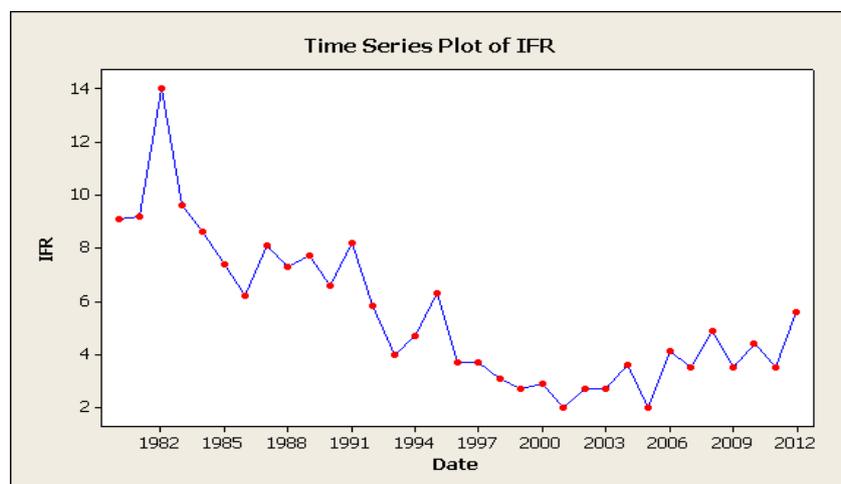
As for stress probabilities π, it is shown in Table 7 that if the IFR increases than π decreases (i.e. for an IFR= 10%, the probability of stress approaches 0).

In stress testing, it is important to know the probability of the occurrence of the stress given macroeconomic risk variables. Table 7 gives the stress rate π for those risk variables.

We have stressed year for a level of CR > 69.1372%, for a GDP growth < 0.11%, for an IR<7.92%, for an IFR < 4.83826%   with probabilities of occurrence π given in Table 7.

4.2.2 Reverse Stress Testing Framework: Worst Case Scenarios

In order to estimate the WVaR for the Tunisian credit risk we use equation (4), results are summarized in Table 8 which presents WVaR s at a given level of plausibility *a.* We can see that the probability that the WVaR reach 9.8092 is 1%.

Figure 7 present the WVaR which goes in the opposite direction which means that the more extreme value of stress correspond to the low probability of occurrence. The very severe extreme scenario has a lower probability and usually tends to zero as depicted in Figure 7.

Figure 7: Time Series Plot of WVaR
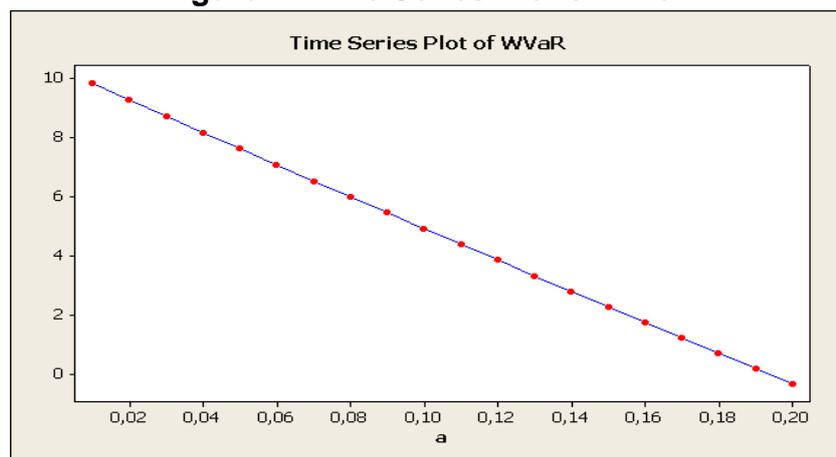
Following Figure 8 which presents 1%, 3% and 5% plausibility levels, Tunisian banks achieved the WVaR in 2012 at 5% level. As the WVaR increases, the level of plausibility decreases and approaches to zero. Here, we talk about the trade-off between severity and plausibility outlined by Breuer et al. (2012), " the more extreme the scenarios which are considered the less plausible they become: There is a trade-off between severity and plausibility of stress scenarios ".

Once our WCVs are found, we move to the next step which is scenarios identification. We first estimate the output gap as follows

$$Gap = FSI_t - WVaR_a$$

The computation of the output gap is motivated by the fact that worst scenario is reached when the FSI is greater than WVaR (i.e. Gap>0). We choose a simple regression model that relates the Gap to macroeconomic risk variables in order to search scenarios.

However, as mentioned above the association between different macroeconomic risk variables at the same time did not reach significant results. That is why our reverse FST search for scenario gives significant regression results only for two combinations of macro-variables namely CR and GDP growth and IR and IFR.

Regression analysis estimates for the first combination CR versus GDP Growth are summarized in Table 9 for 1%, 3% and 5% plausibility levels. We choose the period 2010-2011-2012 as reference period given the beginning of the Tunisian Revolution.

Figure 8 Time Series Plot of FSI vs. WVaR
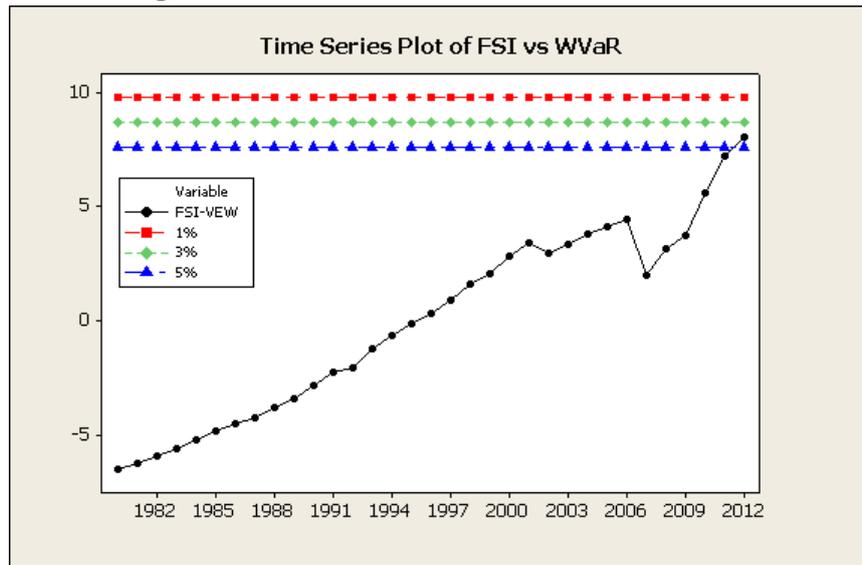
The regression equation for CR and GDP at 1% is

$$Gap = -39.8 - 18.1\,GDP\,Growth + 46.2\,CR$$

GDP Growth explains the absence of stress while the import/export CR explains its presence.

Table 10 gives the most extreme scenarios for CR and GDP Growth that correspond to the positive Gap for 1%, 3% and 5% plausibility levels.

For 1% level, the worst scenario is relative to a negative GDP growth, which makes sense since GDP Growth had a negative effect on credit stress. As for CR, scenarios are relative to a level that should be greater than 89.39% in 2010, 87.29% in 2011 and 89.02% in 2012.

Regression analysis estimates for the second combination IR versus IFR are summarized in Table 11 for 1%, 3% and 5% plausibility levels.

The regression equation for IR and IFR at 1% is

$$Gap = 1.30 - 93.8\,IR - 73.7\,IFR$$

Table 12 gives the most extreme scenarios for IR and IFR that correspond to the positive Gap from 2010 to 2012. We notice that worst case scenarios are relative to negative levels of IR and IFR. Same result was found at 3% level.

The regression equation for CR and GDP at 3% is

$$Gap = -38.7 + 46.2\,CR - 18.1\,GDP\ growth$$

For 3% level and 5%, the worst scenario is relative to a negative GDP growth. As for CR, scenarios are relative to a level that should be greater than 87.01% in 2010, 84.01% in 2011 and 86.64% in 2012. They are greater than 84.68% in 2010, 82.57% in 2011 and 84.31% for 5% level. So far, none of those levels were reached for the studied period.

However, some changes happened in IR versus IFR scenarios at 5% level. In fact, the worst scenarios reached when IR <0.28% in 2010 and less than 0.99% in 2011. While the IFR worst scenario is less than 0.65% in 2011. Those levels are not reached yet, so we can say that Tunisian banks remain on the "safe zone".

5.   Conclusion

Financial institutions should seek for a tradeoff between the severity and the plausibility of stress scenarios. FST provides information about changes in the risk profile of the system over time. An important shortcoming of FST is the danger to ignore harmful but plausible scenarios. This can create an "illusion of safety". A way to overcome this disadvantage is to search systematically for worst case macro scenarios in some plausible domain. In this paper, we propose a reverse reasoning for stress testing. After Tunisian Revolution, civil unrest and subsequent regime change in Tunisia had substantial economic costs for the country. We apply a new RST framework on banks which are the core for financial stability; more specifically we focus on credit risk RST. We choose the upper bound for VaR in order to identify worst case value with a probability of realization *a*. Our proposed RST relies on the regression of the financial stress index output gap versus macroeconomic risk factors in order to search for scenarios at 1%, 3% and 5% levels of plausibility. Results indicate that Tunisian deposit banks reached the worst case in 2012, one year after the Tunisian revolution. One can criticize the use of the regression model to search for scenarios; we are motivated to it because it is easy to use since we want to propose a useful and practical method for risk managers thus the application to real world stress testing problems is straightforward and does not raise complicated implementation issues. Empirical results show that Tunisian banks have likely to reach the WVaR in 2012 at 5% level. Besides the more extreme the scenarios which are considered the less plausible they become. Our reverse FST is a complement, and never a substitute for risk manager and what matters most is the mindset of those employing it.

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