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Original Paper

Credit Risk Stress Testing of Commercial Banks in Tunisia

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Abstract

Stress tests of credit risk is greatly affected by data constraints in Tunisian banking system. Aiming to improve the assessment of credit risk in such conditions, we propose a model to conduct a macro stress test of credit risk for a sample of ten Tunisian commercial banks based on scenario analysis.

The approach consists first in explaining the credit risk for each bank in terms of macroeconomic and bank-specific variables through a static fixed effects model, second in a stress-testing exercise using the Monte Carlo Simulation for generating credit risk losses distributions in case of different scenarios and for determining unexpected losses for each bank.

The panel analysis applied suggests a robust negative relationship between the credit risk of bank loans and real GDP growth, with a lag response of four periods. In addition, return on assets ratio and bank size show significant negative effect on credit quality, while the net loans to total asset ratio is positively associated with it.

The credit risk stress testing results indicate that an adverse scenario of economic downturn produces increase of the frequency of the higher credit loss comparatively to the lower ones for all banks of the sample and that the estimated unexpected losses that would take place in a stress situation can be covered by available capital of these banks.

Keywords

stress testing, credit risk, panel, Monte Carlo simulation, scenario

1. Introduction

The universal financial turmoil that economies were bearing with the sub-prime crisis in the United States of America (US) in 2007-2008 has underlined the importance of financial soundness indicators to prevent banking exposure to credit risk impacts. Credit risk stress testing is a technique for quantifying banks vulnerabilities.

In Tunisia, the high level of nonperforming loans in the banking sector and the extent of losses supported on their loan portfolios have shown interest to understand the determinants of credit risk for banking institutions in order to manage this risk and maintain macroeconomic and financial stability.

According to the recommendations of the Financial Sector Assessment Program (FSAP) conducted in Tunisia by the World Bank and the IMF in 2012, the prudential supervision in Tunisian Central Bank should be backed up by new techniques based on the "risk model" with rating and stress testing that anticipates banking difficulties (BCT, 2015).

Within the framework, we intend to set up the specific relation between credit risk of Tunisian commercial banks on one side and bank specific factors and macroeconomic variables on another side. We seek subsequently to explore the impact of macroeconomic shocks on bank's credit risk.

For this aim, our study is based on a bank balance sheet database of ten Tunisian commercial banks for 2002-2016 period. It describes a model to perform credit risk stress testing for main banks in the Tunisian banking sector. The methodology consists first in identifying through panel data technique the bank-specific and macroeconomic determinants of credit risk of Tunisian commercial banks; second, in employing the results to construct macroeconomic stress scenarios and to simulate the impact on credit risk under two given scenarios (baseline and adverse scenarios); third in constructing an indicator to measure resilience of banks to macroeconomic shock. In the study, loan loss provisions ratio is used as a proxy of the bank loss rate for credit risk.

The outcomes of the study indicate that the deterioration of the economy growth and of some bank-specific indicators forces the banks to allocate higher loss provisions, and consequently increase the implied credit risk level. The results suggest also an increase of credit risk under the stress macroeconomic scenarios with an impact under the adverse scenario greater the baseline one. However, banks have resilience to macroeconomic shock.

Motivated by the scarcity of case studies on credit risk stress testing in Tunisian banking system, this paper focuses on ten Tunisian commercial banks that holds 71% of the total assets of the Tunisian banking system, in order to empirically investigate the bank-specific and macroeconomic determinants of credit risk in Tunisian banking system and to measure the risk exposure of banks and to find out their resilience to macroeconomic stress scenarios by using credit stress testing. Another interest of this study is providing recommendations that can be utilized by policymakers and regulators in identifying and dealing with adverse effect of credit risk on the banking sector and also, it may be integrated to allow the strengthening of bank supervision tools in Tunisia.

The remainder of this paper is organized as follows. Section 2 discusses the relevant literature. Section 3 provides a description of the methodology. Section 4 discusses the credit stress testing results. And finally, section 5 concludes by debating interpretations and possible future research.

2. Literature Review

Various studies about the credit risk stress testing tool have been carried out with the aim of helping policymakers and monetary authorities assess the consequences of eventual shocks on credit risk and therefore sustaining financial stability. Stress testing is defined in the RiskMetrics technical document (1994) as a part of a risk management process that uses scenarios to estimate risk in crisis conditions. Credit risk stress testing is a recent discipline related to credit risk modeling (Schuermann, 2014); it was mentioned in CreditMetrics (Gupton, Finger, & Bahtia, 1997) and CreditRisk+ (Wilde, 1997) credit portfolio models but was not really essential. In fact, it was only introduced as an essential element to the Basel II framework (Basel Committee on Banking Supervision, 2005). In this field, a review study is made by Foglia (2009) to analyze and discuss the assessment methods of macro-financial linkages between macroeconomic drivers of stress event and bank-specific measures of credit risk that aim to link prudential supervision to macroeconomy perspectives. He refers to macro stress testing experiences made in different central banks and supervisory authorities.

In the following and in order to adopt the model strategy that could be most applicable to the Tunisian banking system, we observe the different credit risk stress testing approaches applied by different countries to manage their financial stability and that have developed specific modeling expertise in this field. Kalirai and Scheicher (2002) perform a macro stress test for the Austrian banking system to help policymakers in prevailing financial stability. They present a linear regression to analyze the relation between loan loss provisions, which is considered in the study as an indicator of banks credit quality, and macroeconomic factors. Then, they examine if the simulation effect on LLP is beard by the Austrian banks capitalization. For this aim, they choose to define the adverse events by the historical scenarios and compare risks related to these scenarios on the risk bearing capacity of Austrian banks measured by the capital adequacy ratio. Virolainen (2004) employ Wilson's model for the Finnish corporate sector to analyze corporate credit risks conditional on current macroeconomic conditions and also apply the model to macro stress testing which is conducted by comparing the average result of a stressed scenario, where an artificial adverse macroeconomic development is introduced, with that of the average of a base scenario, where no adverse shock takes place. Estimated averages of the default rates for each sector corresponding to the stressed and base scenarios are obtained from simulating a large number of future default rates by applying a Monte Carlo method. Čihák (2004) proposes a number of extensions and modifications to the Czech FSAP (Financial Sector Assessment Program) to improve credit stress tests so as be suitable for the Czech National Bank and pertinent for use on corporate and household borrowers. He proposes to model bank by-bank increases in NPLs based on past data of NPLs and other macroeconomic variables and to improve statistical database on the financial situation in the real sector, both in the corporate sector and, in particular, in the household sector. He suggests also to include in the credit risk stress tests concentration risk in lending and sectoral risk. Sorge and Virolainen (2006) use the Wilson framework to estimate a macroeconomic credit risk model for Finland; they analyze the relationship between macro fundamentals (GDP, interest rate and corporate indebtedness) and corporate sector default rates. For macro stress-testing purposes, they simulate GDP and short term interest rate stress scenarios on credit risk of an aggregated Finnish credit portfolio as prevailing in the Finnish recession of the 90's. They find that the impact of the interest rate shock is temporary, whereas the GDP shock is more persistent. Čihák (2007) design a practical excel file to simplify the stress testing application, including credit stress testing, for new users of different countries within the IMF-FSAP (Financial Sector Assessment Program) and to enable users to see directly the impact of different stress testing scenarios and assumptions on the results. Wong, Choi and Fong (2008) perform Macro stress-testing to assess the Hong Kong retail banks' vulnerability and risk exposures by using an empirical model with a system of equations comprising a multiple regression model explaining the default probability and a set of autoregressive models describing the macroeconomic environment in order to have a joint evolution of economic performance, the associated default rates and their error terms. Then, a Monte Carlo method is applied to estimate the distribution of possible credit losses conditional on an artificially introduced shock. Girault (2008) construct a three-staged approach for performing macro stress testing the Argentine banking system's credit risk. He estimates a dynamic panel data model to explain credit risk proxy with bank-specific and macroeconomic variables. Then, he models the macroeconomic drivers of bank loan loss provisions with a Vector Autoregression (VAR). In the third step, a stress testing model of credit risk loss is performed by a deterministic approach and stochastic approach with Monte Carlo simulation. The results show that the Argentine financial system is adequately capitalized to absorb the prospective losses in a stress situation. However, Alfaro and Drehmann (2009) highlight the limits of stress testing models of underestimating the risks to the economy and they suggest three methods for sound stress testing practices; one way is to frame the results in confidence intervals; the second is to take account at most of judgments and of views across the organization; the third is a scenario design which requires supposing unusual assumptions and expecting the unexpected. Simons an Rolwes (2009) look for assessing which macroeconomic variables are related to the default behavior of Dutch firms through a macroeconomic-based model and to assess the default behavior by developing on the basis of Virolainen (2004) a framework for stress testing the credit exposure to macroeconomic shocks and precisely the effect in Dutch default behavior given two quarters of zero GDP growth. The default rate corresponding to the stress-test and base scenarios are obtained from simulating a large number of future default rates by applying a Monte Carlo method. They find that Dutch firms default rate has a convincing relationship with GDP growth and oil price and, to a lesser extent, the interest and exchange rate and that the applied stress-test scenario does not significantly influence the default rate. Huang, Zhou and Zhu (2009) propose a framework for measuring and stress testing the systemic risk of the banking sector, using vector auto regression (VAR) system and employing financial market variables to examine the dynamic linkages between the major US banks and the macroeconomy and to assess the resilience of the financial sector. They estimate the probability of default and the asset return correlation of a portfolio and introduce hypothetical shocks to simulate their future dynamic. They validate their model to measure and stress testing the systemic risk of the banking system and show its lack of resilience in perspective. Moretti, Stolz and Swinburne (2009) presented stress testing methodology and evolvement in the Financial Sector Assessment Program (FSAP) of the IMF. Credit risk is among the risks addressed by the FSAP in stress tests, a typical stress test in this category models NPLs or loan-loss provisions as a function of various macroeconomic variables. The methodologies applied in FSAPs are mainly an approach based on CreditRisk+ that has been complemented with models of PDs and LGDs with specific links to macro-financial factors and an approach using nonparametric techniques to addresses two major constraints faced by standard macro stress testing: short time series of risk variables and lack of default dependence information, this approach allows to better quantify the impact of macroeconomic shocks on individual banks. Havrylchyk (2010) construct a macroeconomic credit risk model for stress testing the South African banking sector at the different economic sectors and relying on the loan loss provisions as a dependent variable in each multivariate regression. She found that the credit risk in the South African banks is more sensitive to the interest rates and property prices than changes in GDP growth, exchange rate and commodity prices. The extreme scenarios applied to the model show that credit losses induced could be covered, referring to the capital-adequacy ratios. Rouabah and Theal (2010) perform a stress testing model for the Luxembourg banking sector, using loan loss provisions as an approximation for the aggregate probability of default related to a system of macroeconomic variables, through a seemingly unrelated regression (SUR) specification. Then, Monte Carlo simulation results reveal that banks capitalization could bear severe macroeconomic shocks.

Castrén et al. (2010) assess the impact of shocks that have national and international macro-financial origins on expected corporate sector credit quality in the Euro area. They use a Satellite-Global Vector Autoregressive (GVAR) model to take account of trade and financial transmission channels, then they construct a satellite equation linking the GVAR to the probability of default of the Euro area corporate sector. The results show that GDP, exchange rates, equity prices and oil prices shocks have significant impact on the aggregate credit quality in Euro area corporate sector. Rongjie and Yang (2011) construct a VAR model to view the effect of specific macroeconomic variables on the credit risk of Chinese commercial banks and used the Monte Carlo simulation to get the credit loss distribution in case of three exceptional scenarios. According to the results, severe scenarios lead to a worse impact in the long term on Chinese commercial banks credit risk. Ganbaatar and Selenge (2012) apply correlation analysis, regression analysis and transition matrix analysis in the credit stress testing approach of Mongolian commercial banks. They determine sensitivities of bank specific credit risk to macroeconomic and bank-specific factors. Then, they use micro stress testing, instead of macro stress testing, to provide more detailed information to see which banks were more vulnerable or more resistant to which kind of shocks and therefore to have more practical results to policy makers.

Schechtman and Gaglianone (2012) develop a framework for macro stress testing the credit granted in Brazilian's private financial system to the household sector. The analysis by the Wilson model and a quantile regression method suggests a significant relationship between NPL and key macroeconomic factors, including real GDP growth, credit volume growth, unemployment rate and lagged inflation rate. Stress testing results show that unemployment rate distress produces the most harmful effect, followed by GDP distress, while inflation and interest rate distress have higher impacts for longer periods. Vazquez et al. (2012) propose a model to conduct a macro stress test of credit risk for the Brazilian banking sector based on scenario analysis. The framework comprises: A macroeconomic model to estimate the relationship between selected macroeconomic variables and uses the results to simulate macroeconomic scenarios spanning two years. A microeconomic model using panel data econometrics to estimate the sensitivity of nonperforming loans (NPLs) to GDP growth and uses the results to simulate the evolution of credit quality for individual banks and credit types under distressed scenarios produced. And a credit VaR model to estimate the banks' capital needs to cover tail credit losses under the distressed scenarios. Buncic and Melecky (2013) develop credit risk stress testing methodology that can be used as a tractable macroprudential tool for policy makers in Eastern European banks. The methodology takes into account systemic and idiosyncratic economic risk to measure bank resilience to macroeconomic as well as bank specific shocks. Onder et al. (2016) use dynamic panel GMM (Generalized method of moments) to see effects of macro-economic scenarios on Turkish banking according to the Basel's standard and economic capital approaches. They apply Stress Testing Scenarios to the model to understand how the banking system in Turkey was affected by a baseline and an adverse scenario in two-year horizon.

On the basis of this review of literature, this paper comprises an empirical model that relates credit risk to a number of macroeconomic and microeconomic variables and a Monte Carlo simulation for estimating the impact of adverse macroeconomic conditions.

3. Methodology

3.1 Panel Data Model

The natural approach to estimate our panel data model is with the static fixed-effects estimator, it constitutes a reasonable assumption since we are working with commercial banks in the financial system. The equation of the panel data model to be estimated is expressed as:

$$y_{it} = \alpha_i + X_{it}\beta + Z_t w + \varepsilon_{it} \qquad i = 1, \dots N; t = 1, \dots T \qquad (1)$$

Where y_{it}, ε_{it} are N x 1 vectors, y_{it} is the dependent variable for bank i in period t and ε_{it} is the bank-specific disturbance in period t, X is N x k matrix that contains bank-specific time varying variables (observed heterogeneity) and a constant, Z has time varying macro variables, common to all the banks. β is k x 1 vector and α_i represents bank specific and time invariant (fixed) effects (unobserved heterogeneity). In panel data, the observations are indexed through N x T dimension. N is the number of banks (panels) and T is the dimension of a time series, therefore we have t=1, 2…, T of each i=1, 2,…., N cross-section observations in the sample. The common method used to estimate the parameters of this model is applying the OLS (ordinary least squares) to the model in deviation from time means:

$$y_{it} - \overline{y_i} = (X_{it} - \overline{X_i})\beta + (Z_t - \bar{Z})w + (\varepsilon_{it} - \overline{\varepsilon_i}) \quad (2)$$

However, an examination of the time pattern of the loan loss provision ratio leads to apply dynamic specification to model the dependent variable by including the lagged dependent variable as a regressor in the static fixed-effects model in order to account for the time persistence in the LLP structure. This dynamic fixed-effect specification or within estimator is given by:

$$y_{it} = \rho y_{it-1} + \alpha_i + X_{it}\beta + Z_t w + \varepsilon_{it} \quad (3)$$

which would be estimated by applying OLS to the model expressed in deviations from time means. However, this approach as above renders biased estimates: the within estimator is inconsistent for finite T and N→ ∞ (Nickell, 1981). The reason for this bias is the correlation between the transformed lagged dependent variable and the transformed current disturbance.

In order to remedy this latter limit, Anderson and Hsiao (1982) propose an instrumental-variable estimator (AH) which is consistent for T fixed and N→ ∞, this estimator is based on a differenced form of the original dynamic equation:

$$y_{it} = \rho(y_{it-1} - y_{it-2}) + (X_{it} - X_{it-1})\beta + (Z_t - Z_{t-1})w + \varepsilon_{it} - \varepsilon_{it-1} \quad (4)$$

which cancels out the fixed effects, that may be correlated with the exogenous variables. Anderson and Hsiao (1982) suggest instrumenting $(y_{it-1} - y_{it-2})$ with (y_{it-2}) or $(y_{it-2} - y_{it-3})$, which are expected to be uncorrelated with the differenced error term.

Although N-consistent, the AH estimator is not efficient since it does not use all the available moment conditions. Arellano and Bond (1991) propose a Generalized Method of Moments (GMM) estimator (AB), which is based on the first difference transformation of the static fixed effect model and the subsequent elimination of bank specific effects. This estimator poses the following model :

$$\Delta y_{it} = \rho \Delta y_{it-1} + \Delta X_{it}\beta + \Delta Z_t w + \Delta\varepsilon_{it} \quad (5)$$

where Δ is the first difference operator. But, in equation 5 the lagged depended variable, Δy_{it-1} is by construction correlated with the error term, $\Delta\varepsilon_{it}$, imposing a bias in the estimation of the model.

However, AB which utilizes the estimated residuals in order to construct a consistent variance–covariance matrix of the moment conditions, may impose a downward (upward) bias in standard errors (t-statistics) due to its dependence on the estimated residuals. This may lead to unreliable asymptotic statistical inference (Bond, 2002; Bond & Windmeijer, 2002; Windmeijer, 2005), especially in data samples with relatively small cross section dimension. Therefore, we also compute the system GMM estimator, developed in Blundell and Bond (1998), who exploit further moment conditions. The System GMM estimator is however not free from problems; for example, Hayakawa (2005) shows that when the variances of the individual effects and of the disturbances are unequal the bias of this estimator is fairly large.

3.2 Stress Testing

(A) Simulation method

In this paper, we stress test the losses for credit risk of the commercial banks. To this purpose, we use the toolkit developed in the previous section, then we suggest macroeconomic scenarios to perform a macroeconomic stress testing on the commercial banks' credit risk in Tunisia. It consists of assuming hypothetical changes of the macroeconomic risk factors in the aim of simulating each bank's credit loss in the extreme scenarios. We suppose the realization of a baseline and harmful macro scenarios. The scenario could be an historical macro occurrence, that is assumed to happen again, or a hypothetical macro realization.

We opt to consider two artificial macroeconomic scenarios, comprised of the following:

Scenario 1: baseline scenario: expected trend by the monetary authorities (BCT).

Scenario 2: extreme but plausible adverse scenario with levels similar to those of the year 2011.

In these two scenarios, the perturbations of the selected model were assumed to follow a normal distribution of zero mean and variance estimated by the empirical variance of the residuals.

The idea is to illustrate the model sensitivity to two scenarios considering current conditions and incorporating stressed forward-looking considerations. To anticipate this reaction, a Monte Carlo simulation is used to generate a stochastic scenario based on a random sample from a standard normal distribution. The distribution thus constructed is considered as the baseline scenario. In a similar manner, a Monte Carlo Simulation is used to generate an adverse scenario.

The incorporation of Monte Carlo simulated values of disturbance terms with the assumptions of the evolution of the macroeconomic variables in case of each scenario and the estimates obtained from the model make it possible to have a large number of simulated values of the dependent variable, which allows to estimate its distribution in each scenario. In addition, we assume that all explanatory bank-specific variables in the forecasting horizon of the stress exercise have been fixed.

(B) Unexpected loss

We consider also estimating the banks' capital needs to cover tail credit losses under the distressed scenarios. It's computed as the difference between the estimated LLP in the stressed scenario, and LLP as of the baseline scenario; For this purpose, we use the simulated distributions of LLP for each bank and for each scenario, assuming in one hand the real GDP growth considered according to the scenario and in the other hand that all other bank-specific factors are held fixed since the last observation of the sample.

In this exercise, our main interest lies on the right tails of the simulated distribution in case of the adverse scenario. In fact, we compute the Value-at-Risk corresponding to a 99.9% confidence level of adverse scenario distribution, we subtract the ratio of the expected LLP as of the baseline scenario, in the aim to have the potential downside credit risk that would result from an adverse scenario produced by a harmful worsening of economy growth, with a 99.9% confidence level. Finally, the resulting losses are compared to the available capital because the bank needs to have enough capital to absorb the increase in the ratio of LLP that would result from the stress event

Having examined how credit risk proxy for each bank of the sample will behave facing trend-based scenario or distressed scenario. We then use the model to forecast LLP ratio to estimate bank losses for credit risk during the first semester of 2019.

Knowing that the bank needs to have enough capital to absorb the increase in the ratio of LLP that would result from the stress event, we quantify the capital needed to cover the unexpected losses for credit risk. For this aim, we compute the Value-at-Risk corresponding to a 99.9% confidence level of the distribution of banks ratio of LLP in the stress scenario, then we subtract expected value of LLP ratio as estimated in the baseline scenario, both forecasted for the first semester of 2019. The result is the unexpected losses that would result from an adverse scenario produced by the risk factor (real GDP growth), with a 99.9% confidence level.

4. Results

4.1 The Data Set

The data is collected from financial statements of 10 Tunisian commercial banks (table 1) over 15 years as well as macroeconomic information. In order to have a complete series of the credit risk proxy, we opt for semi-annual data of a period ranging from January 2002 to June 2016. So, two hundred ninety (290) observations should be collected from these 10 banks. However, some financial statements are not available, especially during the year 2002. For this reason, the total number of observations reduced to 285. It's noteworthy that the sample is considered because it holds 71% of the total assets of the Tunisian banking system. The financial data was provided by the Financial Market Council website and semi-annual financial reports, and macroeconomic information which came from the Tunisian National Institute of Statistics and the International monetary fund (IMF). It should be noted that as data have semi-annual frequency, they may be subject to seasonal variations, that's why we proceed to seasonal adjustments for some variables, through moving average to smooth a data series. It should also be noted that fairly common accounting changes are encountered from one year to another in banks' financial statements.

Table 1. Sample Coverage of Tunisian Commercial Banks

Commercial bank code	Description	Bank ownership
BNA	Banque Nationale Agricole	Public
BIAT	Banque Internationale arabe de Tunisie	Private
STB	Société Tunisienne de Banque	Public
BH	Banque d'Habitat	Public
Attijari bank	Attijari bank	Private
ATB	Arab Tunisian Bank	Private
UIB	Union Internationale de banques	Private
BT	Banque de Tunisie	Private
UBCI	Union Bancaire pour le Commerce et l'Industrie	Private
Amen Bank	Amen Bank	Private

For the dependent variable, we rely on the ratio of loan loss provisions to total loans (LLP), as a proxy of the bank credit risk. There are a number of credit risk indicators that can be used as proxy for credit risk, for example non-performing loans (Louzis et al., 2012), but it was not possible to create a complete series of the NPLs variable as the information is not available over the entire period. The loan loss provisions to total loans measure is one of the most commonly used measures in stress testing (Moretti et al., 2009). It should be noted that in the computation of this ratio we include on-balance loans and provisions only. Therefore, loans completely written-off and removed to off-balance accounts have not been included in the computation of the LLP ratio.

The empirical literature identifies two broad sets of drivers that explain NPLs: the macroeconomic and the bank-specific factors. Table 2 presents the bank specific variables and macroeconomic variables used in the econometric analysis and their correspondence to the specific hypothesis.

Table 2. Description of Explanatory Variables

Variable	Definition	Hypothesis tested	References
Return on Assets	ROA= net profit/total assets	(-)	Boudriga et al. (2010)
Return on Equity	ROE= net profit/ total equity	(-)	Louzis, Vouldis, and Metaxas (2012) Klein (2013)
Leverage ratio	B_LR = Total liabilities/ total assets	(+)	Louzis et al. (2012)
Bank Revenue	B_R = the total of the bank operating income	(-)	
Capital to asset ratio	B_CAR= owned capital/ total assets	(-)	Salas and Saurina (2002) Makri et al. (2014)
Total loan to total deposit ratio	B_LD= total loans/total deposits	(+)	Ahmad and Ariff (2007)
Bank size	B_S= total assets	(+)	Chaibi and Ftiti (2015) Louzis et al. (2012)
Real gross domestic product	GDP	(-)	Ghosh (2015) Beck et al. (2015)
Inflation rate	we apply two measures of inflation rate, GDP deflator and consumer price index.	(+)	Louzis et al. (2012) Nkusu (2011) Skarica (2014)
Total loans granted to the economy	D	(+)	Keeton (1999)
Crude oil price	OIL	(+)	Simons and Rolwes (2009)
Real effective exchange rate	REER	(+)	Simons and Rolwes (2009)
Broad Money (M2)	M2	(+)	Fofack (2005)

Table 3 characterizes the banking system throughout the period of research. From this table, it may be concluded that there is a high disparity between banks at all the bank level data, in fact we observe a wide range between the minimum value and maximum value of the specific bank variables. Overall, state-owned banks displayed worse financial indicators than those of private banks during the sampled period.

Table 3. The Mean of the Banking System Financial Indicators throughout the Period of Research

	LLP ratio	Bank size (TND)	Bank Revenue (TND)	B_CAR	B_LR	ROA	ROE	B_LD
Amen Bank	10,12%	4 384 903 379	234 764 241	8,65%	91,16%	0,90%	8,87%	1,0314
ATB	9,74%	3 209 657 103	157 346 897	8,88%	91,12%	0,88%	8,84%	0,7293
Attijari Bank	7,94%	3 427 560 655	181 395 552	9,98%	92,80%	0,85%	6,01%	0,9077
BH	9,01%	4 608 366 372	221 590 892	7,32%	92,95%	0,69%	7,32%	1,2191
BIAT	7,77%	5 881 275 415	311 828 672	7,81%	92,19%	0,89%	8,37%	0,7808
BNA	14,73%	5 783 686 552	290 298 310	8,38%	91,62%	0,40%	4,04%	1,1323
BT	6,40%	2 710 748 724	154 152 621	15,72%	84,28%	1,94%	10,08%	1,1640
STB	19,42%	5 854 933 483	273 431 483	7,58%	92,65%	0,36%	5,83%	1,1465
UBCI	9,14%	1 906 392 828	123 241 000	10,99%	89,01%	1,01%	6,85%	1,0616
UIB	13,03%	2 590 544 724	137 535 552	8,17%	94,69%	0,16%	-22,78%	1,0083

the tendency of GDP growth and LLP ratio evolution during the estimation period shows in Figure 1 that is evident how the global financial crisis (2008) leads the Tunisian economy into recession caused by the Europe recession. Then after a short recovery in 2010 from the recession and in the aftermath of the January 2011 revolution, the GDP growth follow a downward trend until regaining slightly increase from 2012. However, there isn't a clear relationship between GDP growth and the evolution of LLPs to loans ratio. The ratio of loan loss provisions to overdue loans has not been constant. In fact, the LLP graph shows many peaks, one of the possible explanations for this is the requirements of the new measures for assessing provisioning on non-performing loans in circulars issued by the central bank of Tunisia during the period of the sample.

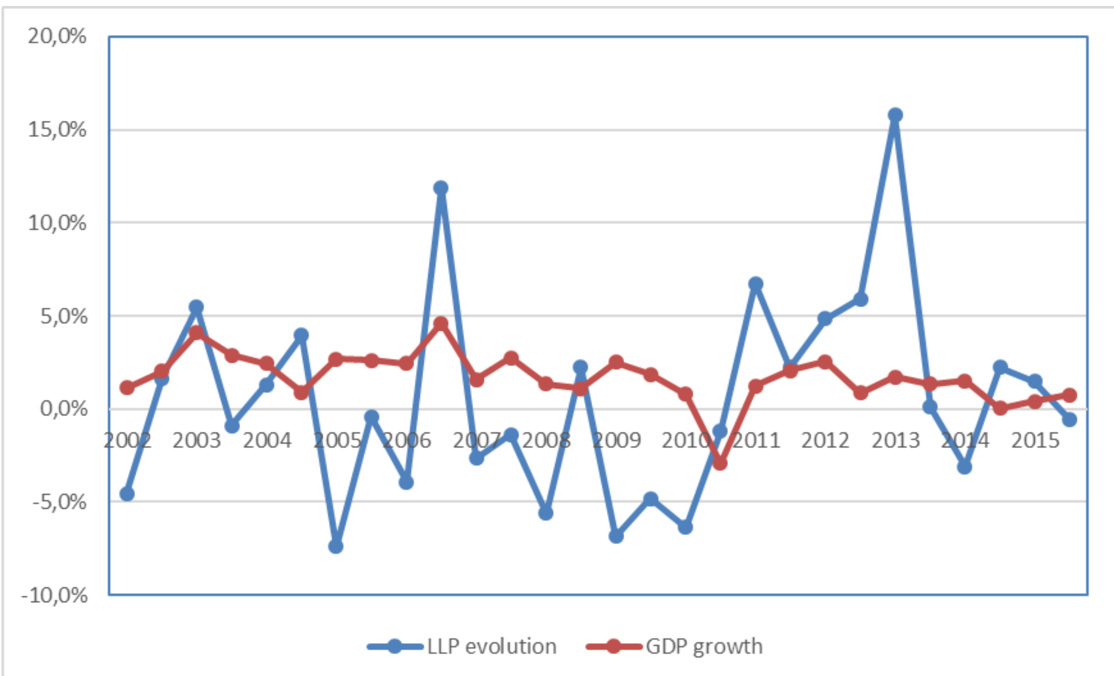

Figure 1. LLP Ratio and GDP Growth (2002-2012)

The evolution of LLP is diverse across banks types (Figure 2). Overall, state-owned banks displayed lower loan loss provisions ratio during 2002 to 2010. After this period and remarkably, state-owned banks experienced a sustained increase in LLP ratios after 2011, reflecting the impact of recent Tunisian Central bank's measures to cover risks that have not been sufficiently covered so far. The same figure suggests that LLP ratio may follow unit root process since most series display a negative trend before 2011 and hinting at a possible cointegrating relation with the other variables.

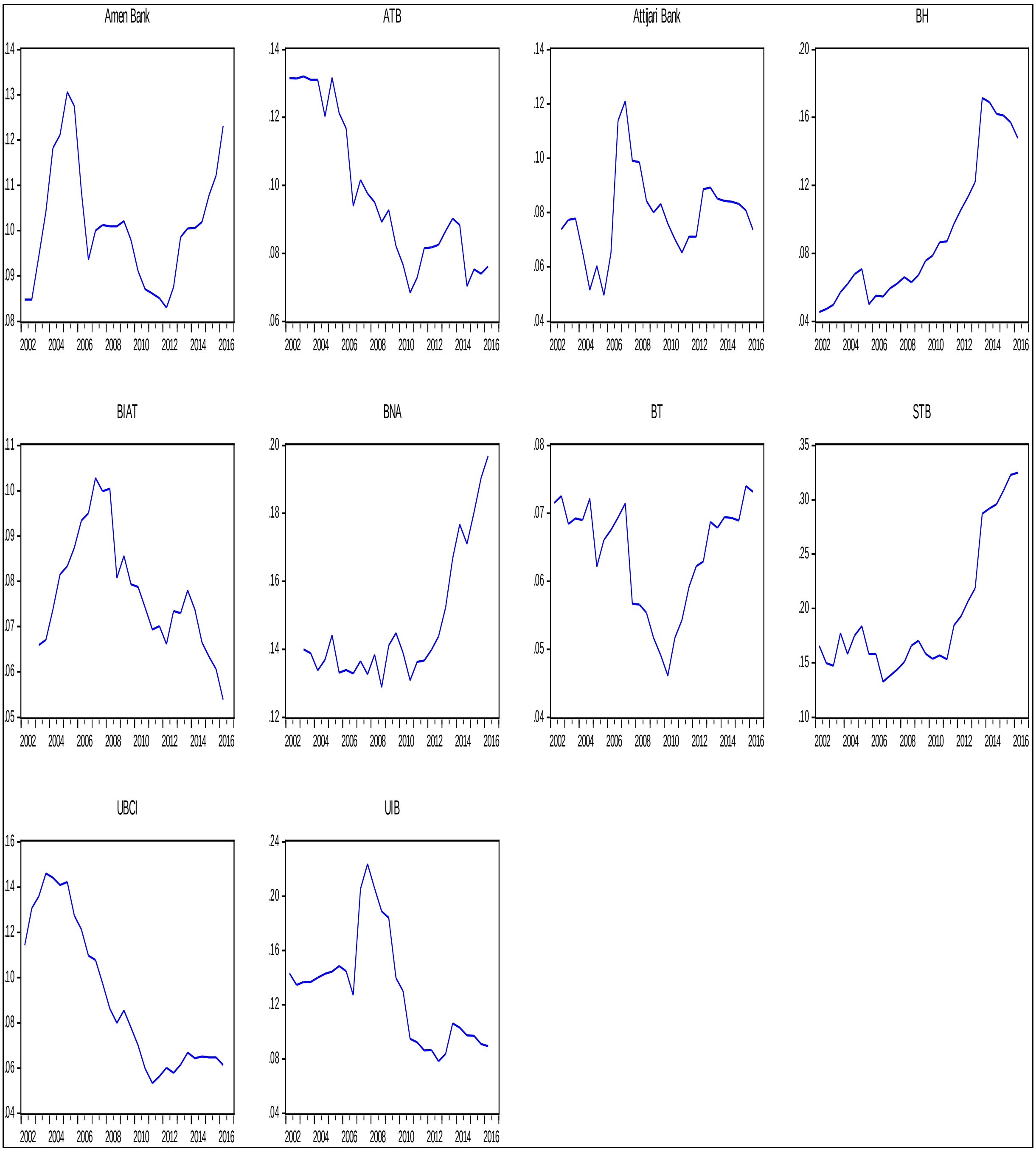

Figure 2. LLP Ratio across Commercial Banks of the Sample (2002-2016)

4.2 Panel Data Estimation

The data is analyzed using Stata 13 software. We start our empirical exercise by examining stationarity properties of loan loss provision ratio per bank applying Dicky Fuller unit root test. In fact, the stationarity status (the order of integration) of the variables helps to choose the appropriate model for estimating the coefficients. Table 4 presents the panel unit root results where the null hypothesis is of non-stationarity. The results from the table show variables that exhibit unit roots in their levels form were first-differenced to induce stationarity. The null hypothesis of the unit root presence cannot be rejected for the most of banks (ATB, BH, STB, UIB). Consequently, we considered the first difference of the explanatory and explained variables in the model in order to have unbiased estimators.

Table 4. Unit Root Test Results

Banks	t-statistic	Probability	Conclusion
Ame Bank	-2.546	0.0089	Stationarity is found
ATB	-1.314	0.6582	Unit root exists
Attijari Bank	-3.100	0.0024	Stationarity is found
BH	-2.593	0.2830	Unit root exists
BIAT	-6.675	0.0000	Stationarity is found
BNA	-5.205	0.0001	Stationarity is found
BT	-15.993	0.0000	Stationarity is found
STB	1.559	0.130	Unit root exists
UBCI	-12.271	0.0000	Stationarity is found
UIB	-3.077	0.1117	Unit root exists

As banks are not chosen randomly, the fixed effect is imposed in the estimations. Moreover, the specifications shown in the estimation methodology was applied after exploring the sensitivity of LLP to a combination of candidate macroeconomic and bank-level variables and after exploring them with various lag structures. The main criterion guiding model selection was the precision of the parameter estimates and the robustness of the results, reflecting the purpose of the exercise to simulate loan quality under alternative macroeconomic scenarios). In particular, the logit-transformed LLP which is expressed as log(LLP/(1−LLP)) ensures that the dependent variable spans over the interval [−∞; +∞] as opposed to between 0 and 1, and is distributed symmetrically. It also allows avoiding non-normality in the error term and accounts for nonlinearities in the sense that larger shocks to the explanatory variables may cause a large, nonlinear response in the transformed dependent variable (Wenzel et al., 2014). The explained variable Y_{it} is computed by taking the first difference to the logit of the loan loss provision ratio in a bank and the explanatory variables that are categorized as macroeconomic and specific variables, described in the previous paragraph, were introduced one by one into the specifications (or models) presented in the estimation methodology, then, they were selected after exploring the relationships between Y_{it} and the larger set of macroeconomic and microeconomic variables restricting the factors to those that were statistically more relevant to the panel specification, also yielding tighter error bands. Only the following variables presented a sufficient level of statistical significance :

- GDP growth lagged by 4 periods, defined by difference of order 4 of ($\log(GDP)_t - \log(GDP)_{t-1}$),
- the first difference to the ROA, defined by ($(ROA)_t - (ROA)_{t-1}$),
- the first difference to the bank leverage ratio, defined by ($(B\_LR)_t - (B\_LR)_{t-1}$),
- the first difference to the natural log of total assets of the commercial bank, defined by ($\log(B\_S)_t - \log(B\_S)_{t-1}$),

In Table 5, we report the estimated coefficients and their p-values of the static fixed-effects estimator, the dynamic fixed-effect specification Arellano-Bond estimation and the Blundell and Bond estimator. When treating LLP as endogenous for the panel variables, it appears that it is non-significant, that's why we don't consider a dynamic model (Table 4).

Table 5. Results of Exploratory Panel Regressions

	(1)	(2)	(3)	(4)
	Static fixed-effects model	Dynamic model		
Variables	**Within method**	**Within method**	**Arellano-Bond method**	**Blundell and Bond method**
LD.logitLLP	-	0.0657066	0.0378542	0.0202041
		(0.61)	(0.60)	(0.41)
Macroeconomic				
L4D.LGDP	-1.048004**	-1.012578**	-1.10311**	-0.9547359***
	(-3.11)	(-3.06)	(-2.13)	(-2.62)
Bank specific				
D1.ROA	-1.455067**	-1.601148*	-1.587491**	-1.067289
	(-2.44)	(-1.94)	(-2.03)	(-1.31)
D1.LB_S	-0.8445946***	-0.8344191***	-0.837614***	-0.8897977***
	(-3.36)	(-3.28)	(-5.21)	(-3.82)
D1.B_LR	2.372149**	2.342711**	2.346652***	2.649582***
	(2.72)	(2.76)	(4.38)	(2.87)
constant	0.0578622***	0.0567209***	0.05853***	0.0580021***
	(5.88)	(5.50)	(4.58)	(4.43)
σ_ε	0.09969792	0.09982348	-	-
R^2	0.2594	0.2609	-	-

T-statistics in parenthesis.

***, ** and * denote significance at 1%, 5% and 10%, respectively.

For estimating the variance of estimated parameters, we have considered robust estimators with respect to the hypothesis of homoscedasticity (robust method).

Consequently, on the basis of a comparison across estimation methods, we select the static fixed effects specification presented in column (1) of Table 5 as the preferred model. In fact, treating Y_{it} as an endogenous lagged dependent variable in columns (2), (3) and (4) indicate that estimates of the coefficients associated with Y_{it-1} are not significant in each latter specification.

In the following part, the first specification is retained since it provides a convergent estimator. The equation of this model specification is :

$y_{i,t}$=0.0578622 - 0.8445946 $dLBS_{i,t}$ - 1.455067 $dROA_{i,t}$ + 2.372149 $dB\_LR_{i,t}$- 1.048004 $dLGDP_{t-4}+u_i+\varepsilon_{i,t}$ (6)

Where

$y_{i,t} = logit(LLP_{i,t}) - logit(LLP_{i,t-1})$: is the dependent variable observed for individual i in time t.

$\begin{cases} dLBS_{i,t} = log(BS_{i,t}) - log(BS_{i,t-1}) \\ dROA_{i,t} = ROA_{i,t} - ROA_{i,t-1} \\ dB\_LRD_{i,t} = B\_LRD_{i,t} - B\_LRD_{i,t-1} \end{cases}$ are the time-variant bank-specific regressors.

$dLGDP_{t-4}$ is the difference of order 4 of $(log\,(GDP_t) - log\,(GDP_{t-1}))$: is the common macroeconomic regressor.

u_i: is the unobserved individual effect.

$\varepsilon_{i,t}$: is an idiosyncratic error term.

The R^2 in Table 6 for static fixed effect specification is about 25.9% with three bank specific variables and one macroeconomic factor having significant effects on credit risk at the 1% and 5% significance level. As expected, the lagged GDP growth variable is negatively correlated with the first difference of logit transformation of LLP ratio in commercial banks and significant for up to four lags. Hence, the LLP ratio is negatively affected in the short-run by a slowdown in Tunisian economic growth, a result that indicates the relative dependence of the Tunisian banks' ability to repay their loans on the phases of the economic cycle. Our result is in line with the results of other macro-studies on credit risk and with the results of De Bock and Demyanets (2012) and Nkusu (2011) and conforms to our initial hypothesis.

Considering microeconomic determinants, Table 6 shows, in the first specification, that loan loss provision ratio in Tunisian commercial banks is sensitive to bank-specific determinants. As expected, the coefficient on return on assets is significantly negative in relation to the LLP of Tunisian banks. These findings imply that the higher return on assets in a bank indicates a potentially lower credit risk, which is consistent with the "moral hazard hypothesis". Thus, a more profitable bank is engaged in more prudent lending and carefully originate its loans, implying a reduction in credit loss and hence a decrease in loan loss provisions ratio need to efficiently manage their resources when loans tend to be potentially impaired. This implies in a more profitable banking industry, banks are engaged in more prudent lending and carefully originate their loans, causing a reduction in NPLs. This result is consistent with the findings of Boudriga et al. (2010) and Ghosh (2015).

Proxied by the natural logarithm of total assets, bank size is significant but with unexpected negative sign. This suggests that greater size of commercial banks decreases credit risk. Our empirical evidence is not consistent with Chaibi and Ftiti (2015), which report a significantly positive relation between bank size and credit risk, but instead agrees with the findings of Salas and Saurina (2002); this result can be explained by the fact that size allows to benefit from the diversification opportunities.

On the other hand, the leverage ratio positively and significantly influences credit risk in commercial banks. This finding implies that the increase of leverage results in a higher ratio of loan loss provisions. This result is corroborated by the literature, as similar findings were recorded in the studies of Louzis et al. (2012).

For the unobserved individual effect, the model yields the following results:

Table 6. Estimated Individual Effect

Banks	$\hat{u}_i$
STB	0.0216742
BIAT	-0.0179804
BH	0.0375269
AB	0.0105785
ATB	-0.0137046
BT	0.0006099
UIB	-0.0264036
UBCI	-0.0423207
BNA	0.0068168
Attijari Bank	0.0232411

With identical macroeconomic factors, unobserved individual-specific effect u_i, which has an effect on banks, is negative for banks with performance and positive for banks with less performance. Indeed, banks that have better profitability such as private banks BIAT and ATB have negative individual-specific effect, while banks that have less profitability and more indebtedness have positive individual effect, such as BNA and STB, which are public banks. Thus, we can argue that there is a structural difference between public banks and private banks.

Since the change of the variables may serve as warning indicators of future credit risk, the results have implications for decision makers at both macroeconomic and bank level. The results lead to recommend for the commercial banks to maintain optimal high credit standards to reduce credit loss while sustaining profits and maintaining them at a safety level, in fact, high profits will lead to more prudent lending. Efficient cost management constitutes a required passageway to reduce credit loss and improve the quality of banks' balance sheet. Moreover, results here provide that hypothesis of bigger size increase credit risk is rejected for the commercial banks in Tunisia.

In terms of regulation and policy implications, the estimation results indicate that structural reforms should be undertaken to improve economic health and to promote financial stability of banks. The significant role of specific bank factors in determining credit risk in commercial banks should incite regulatory authorities in Tunisia to encourage banks to manage less concentrated portfolios, to develop their activities and to gain market share through enhancing their professionalism, service quality and commitment of the teams, to maintain enough liquidity and to improve of effectiveness of their risk management systems, and in that way increasing the efficiency in credit risk analysis and debtors monitoring. On the other hand, analyzing profitability, bank size and indebtedness, supervisors could detect banks with potential for increase in credit risk.

4.3 Stress Testing

The exercises to assess stress testing credit risk are based on two macroeconomic scenarios, including a baseline that reflects the expected path of GDP growth by the Tunisian Central Bank and an adverse scenario considering stressed forward-looking.

The macroeconomic scenarios are used to assess the bank's vulnerability to exceptional macroeconomic scenarios. Indeed, the stress test consists of the comparison between the baseline and adverse scenario for the credit loss, which could highlight macroeconomic shocks leverage on the credit risk especially that the revolution of 2011 in Tunisia has shown fragility of the banking system in face of economic crisis.

The evolution of GDP growth under the two scenarios considered was determined as follows:

• Baseline scenario. This scenario is taken as reference and considers the expected evolution of economic activity as forecasted by the Tunisian Central Bank. Under this scenario, the GDP growth is projected to be 2.3% (BCT, 2017) in 2017.

• Adverse scenario. An artificial macroeconomic scenario is considered assuming a worsening of the GDP growth as a fall in Tunisia's real GDP by 2% in the first semester of 2017, comparable to the real GDP fall at the dawn of the revolution of 2011.

4.3.1 Scenario Analysis

We use in this section the results found in the estimated results above to stress test each bank's credit risk based on the scenarios. We first evaluate the model developed in methodology section (equation 6) with the bank individual effect.

$$\hat{y}_{i,t} = 0.0578622 - 0.8445946\, dLBS_{i,t} - 1.455067\, dROA_{i,t} + 2.372149\, dB\_LR_{i,t} - 1.048004\, dLGDP_{t-4} + \hat{u}_i + \hat{\varepsilon}_{i,t} \quad (7)$$

Where

$y_{i,t} = logit(LLP_t) - logit(LLP_{t-1})$: is the dependent variable observed for individual i in time t.

$dLBS_{i,t}$; $dROA_{i,t}$ and $dB\_LR_{i,t}$: are the time-variant bank-specific regressors.

$dLGDP_{t-4}$: is the common macroeconomic regressor.

u_i : is the unobserved individual effect.

$\varepsilon_{i,t}$: is the error term.

The simulations were analyzed for each bank of the sample, we estimate a credit loss distribution by performing Monte Carlo from a normal distribution. To that purpose, we take 10,000 random draws from the error terms involved in the model equation and which are supposed following normal distribution with zero mean and variance estimated by the model. These are then used to obtain LLP distribution for each bank and for each scenario, using the model considered above and supposing that bank specific factors remain unchanged relatively to the status in the first semester of 2016. It's noteworthy that we consider macro scenarios for the following semester (T=2017:1) and examine their consequences from that semester until two years ahead. The dependent factor in macroeconomic scenario S for bank i is then computed as:

$y^{S}_{i,2019:1}$=*0.0578622 - 0.8445946* $\widetilde{dLBS}_{i,2016:1}$ - *1.455067* $\widetilde{dROA}_{i,2016:1}$ + *2.372149* $\widetilde{dB\_LR}_{i,2016:1}$ - *1.048004dLGDP*$_{2017:1}$ +$\widehat{u_i}$+ε^{S}_{i}

(8)

Where

The term $y^{S}_{i,2019:1}$ captures changes in loan loss provisions due to changing macroeconomic conditions under the stress scenarios.

dLGDP$_{2017:1}$ is the supposed change in the real GDP growth depending on the scenario.

$\widetilde{dLBS}_{i,2016:1}$, $\widetilde{dROA}_{i,2016:1}$, $\widetilde{dB\_LR}_{i,2016:1}$ are bank specific variables fixed at the last observation of the panel.

$\widehat{u_i}$ is the estimated unobserved individual effect for each bank of the sample.

$\varepsilon^{S}_{i,2019:1}$ is the siulated error term for each bank.

For each bank, histograms derived from the baseline and adverse scenarios were produced. The graphic study of the credit loss distribution for the adverse scenario and for the baseline scenario shows following observations depending on the bank:

ATB: Figure 3 shows that introducing a GDP shock shifts the credit loss distribution in this bank to the right, indicating that the mean credit risk under the adverse scenario increases relative to the baseline scenario.

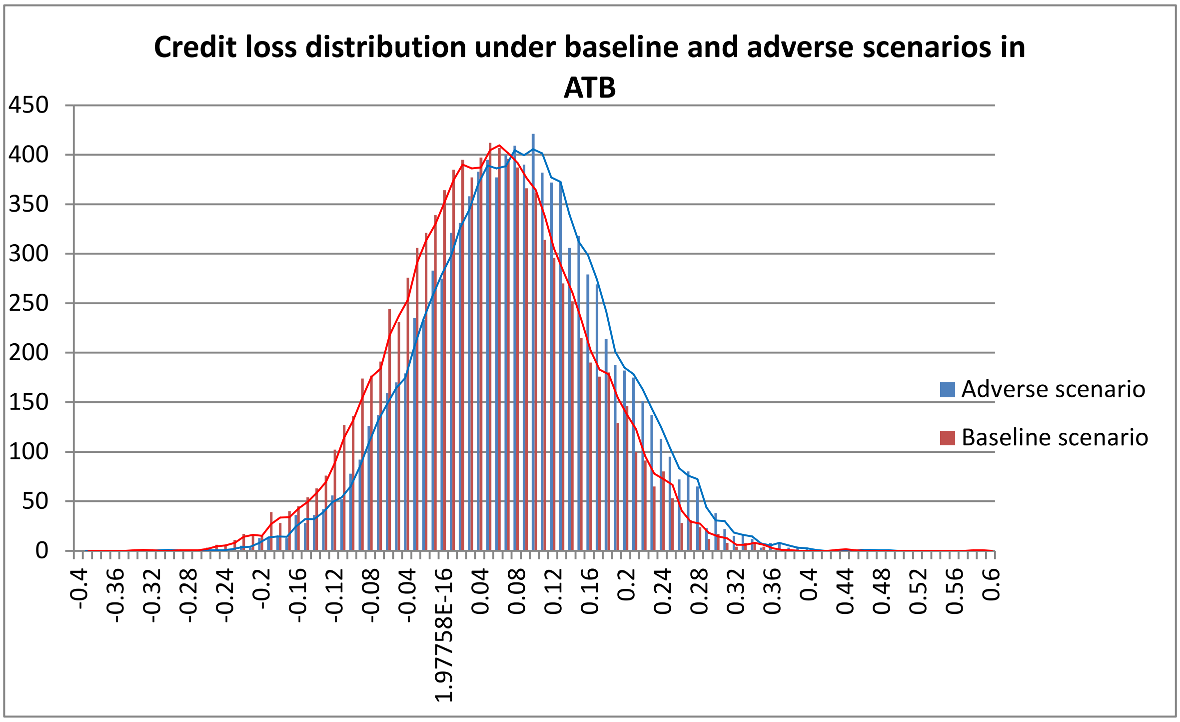

Figure 3. Baseline and Adverse Scenarios under Shock to Tunisian Real GDP Growth in ATB

Attijari bank: Figure 4 provides salient of credit losses in the case of the baseline scenario and of the real GDP stressed scenario. The histogram of the stressed distribution exhibits a shift to the right compared to that of the baseline distribution.

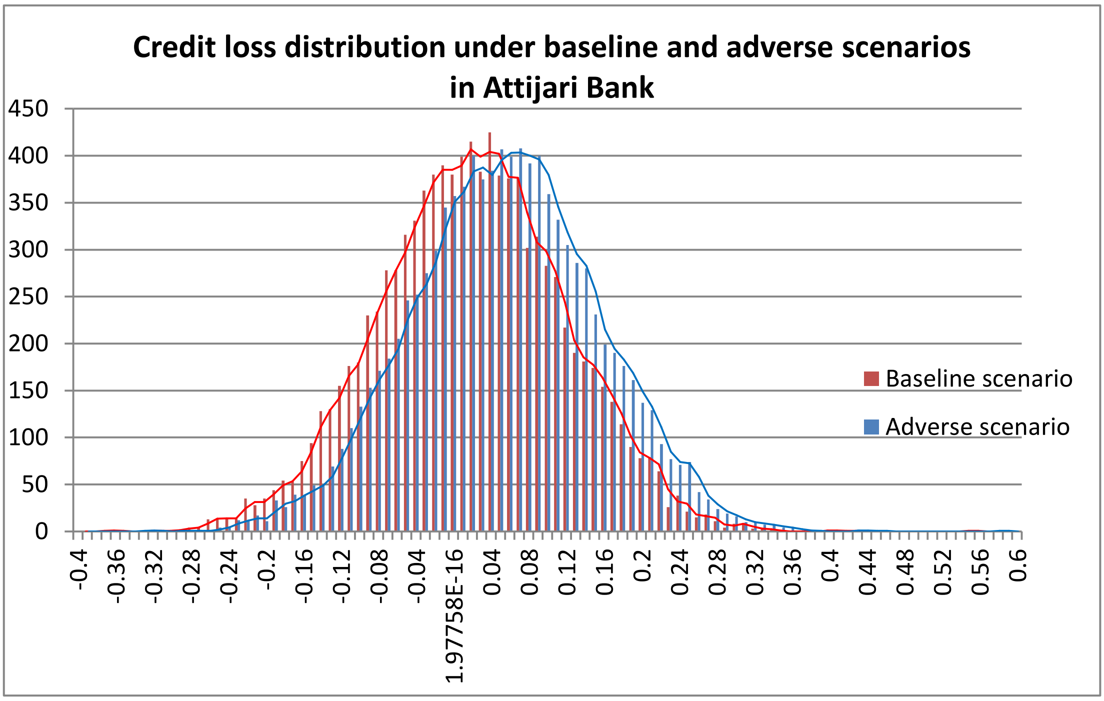

Figure 4. Baseline and Adverse Scenarios under Shock to Tunisian Real GDP Growth in Attijari Bank

BT: Frequency distribution of the baseline and stressed scenarios are simulated in Figure 5. It shows that, when introducing a GDP shock, the histogram exhibits a shift to the right of the stressed distribution relative to the baseline scenario, showing a small increase in the frequency of the higher credit loss percentages comparatively to the lower ones.

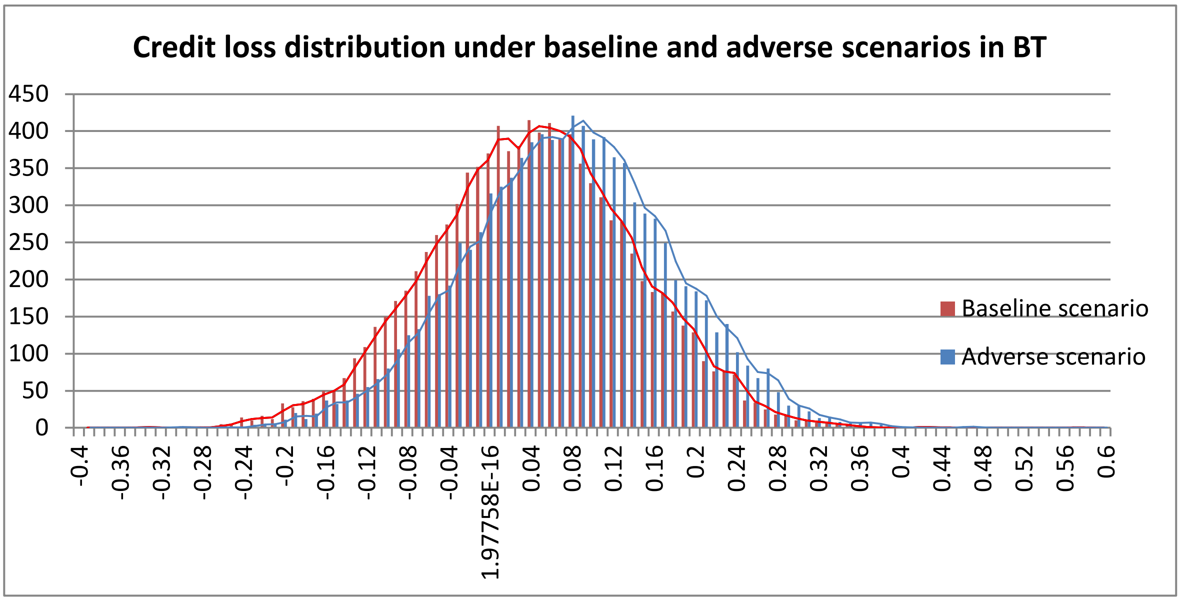

Figure 5. Baseline and Adverse Scenarios under Shock to Tunisian Real GDP Growth in BT

BNA: Figure 6 shows, as in BNA chart, that the distribution of losses after introducing a GDP shock shifts to the right compared to the baseline scenario, suggesting that a GDP shock has resulted in an increase of the expected credit losses proportion.

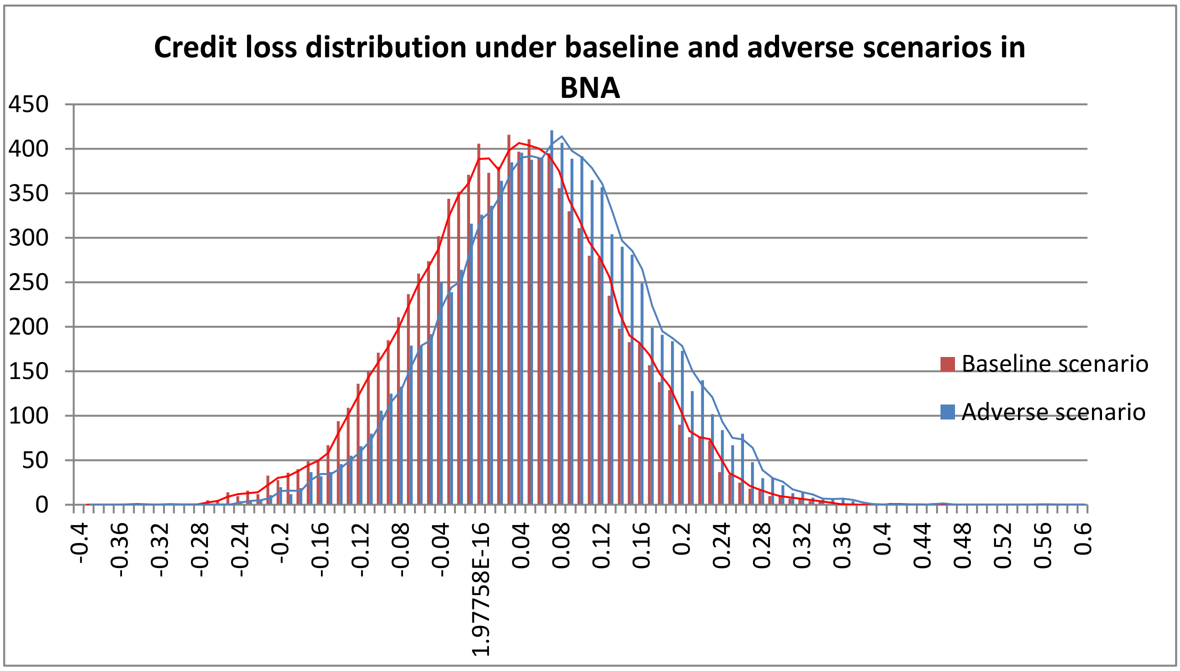

Figure 6. Baseline and Adverse Scenarios under Shock to Tunisian Real GDP Growth in BNA

STB: Under the adverse scenario applied to fundamental macroeconomic variable real GDP growth, the histogram shows a characteristic shift to the right of the stressed distribution (Figure 7) showing an increase in the frequency of the higher credit loss percentages comparatively to the lower ones.

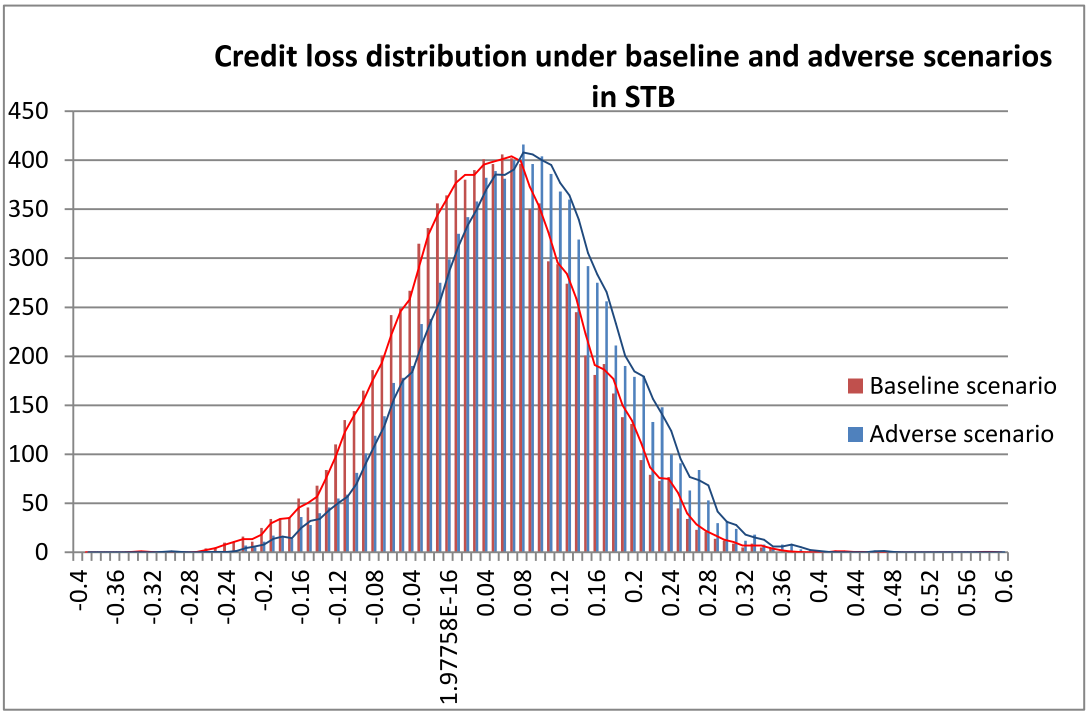

Figure 7. Baseline and Adverse Scenarios under Shock to Tunisian Real GDP Growth in STB

Amen Bank: Under the shock to the real GDP growth, the distribution of credit loss of the adverse scenario shifts to the right compared to the baseline scenario. The simulated frequency distributions of the baseline and stressed scenarios are depicted in Figure 8.

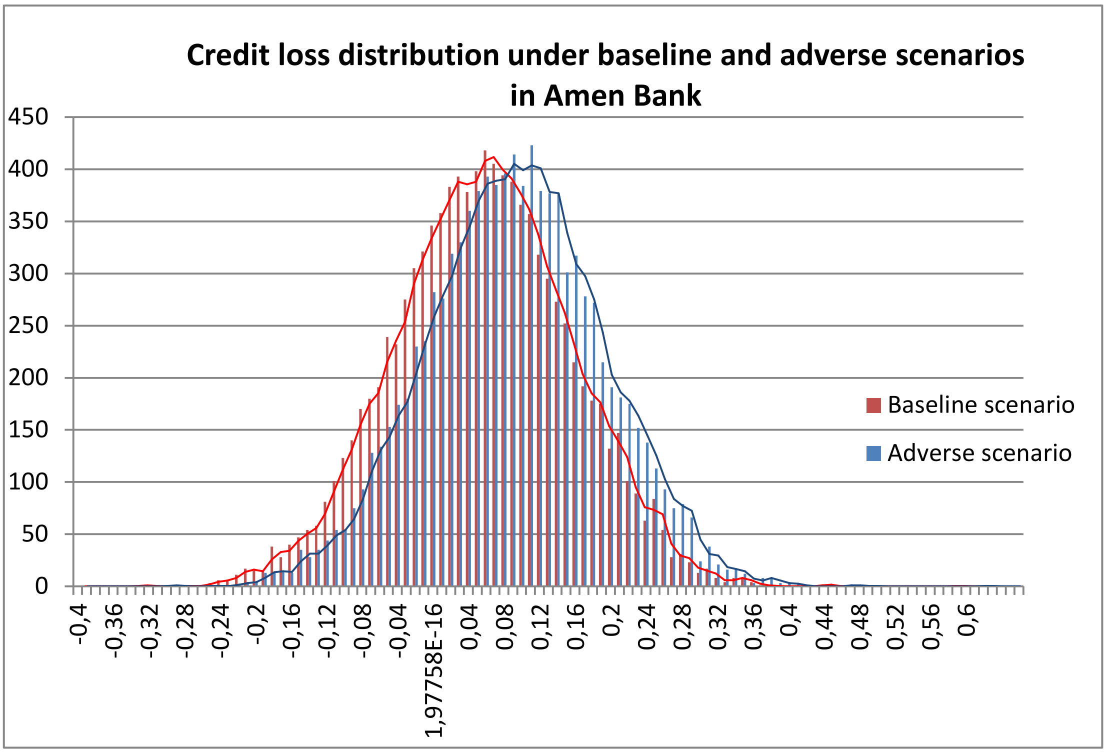

Figure 8. Baseline and Adverse Scenarios under Shock to Tunisian Real GDP Growth in Amen Bank

BH: The results of the two scenarios depicted in Figure 9 show that the adverse scenario generated by GDP shock produces a shift to the right of the loss distribution.

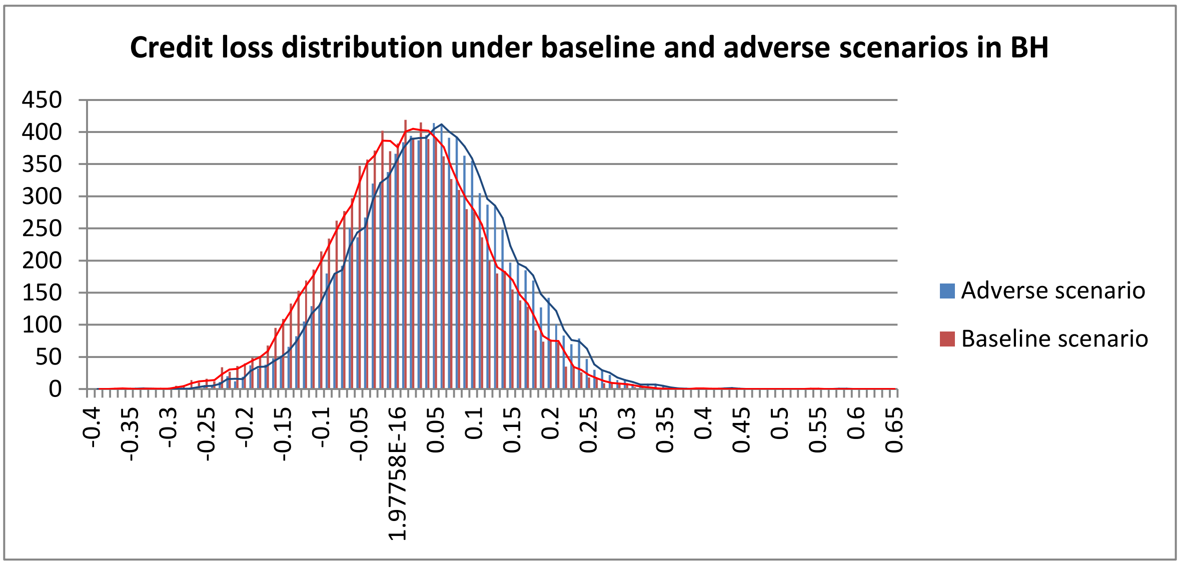

Figure 9. Baseline and Adverse Scenarios under Shock to Tunisian Real GDP Growth in BH

BIAT: The simulated frequency distributions in the two scenarios considered are depicted in Figure 10. It indicates that introducing the GDP shock leads to a shift to the right of the frequency distribution.

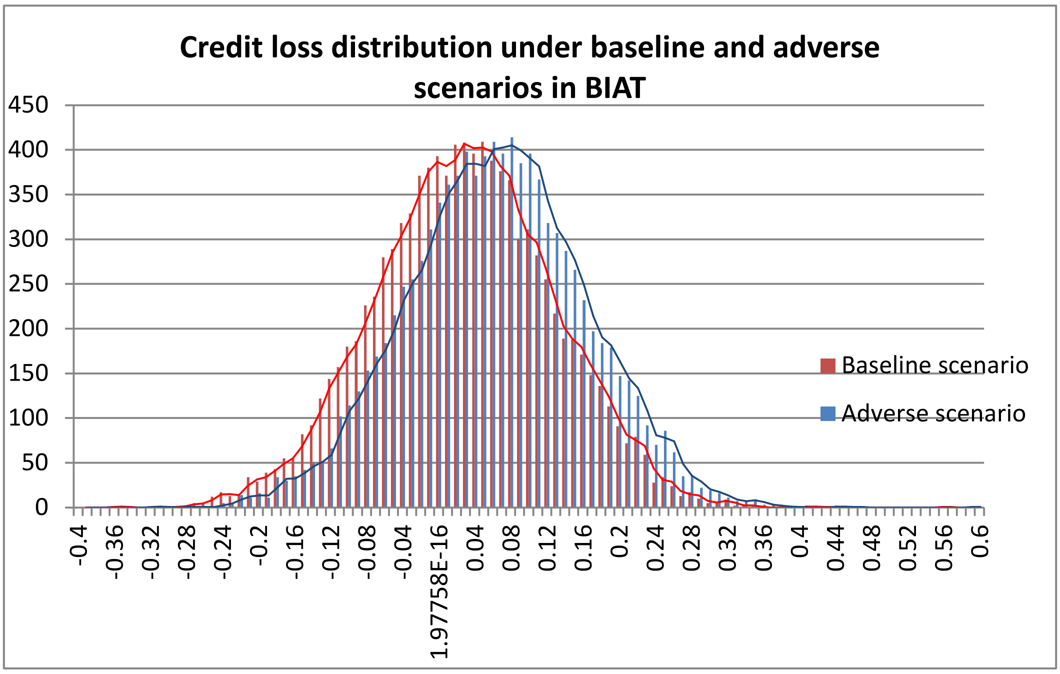

Figure 10. Baseline and Adverse Scenarios under Shocks to Tunisian Real GDP Growth in BIAT

UBCI: Figure 11 shows that introducing a GDP shock shifts the credit loss distribution in this bank to the right, indicating that the mean credit risk under the adverse scenario increases relative to the baseline scenario.

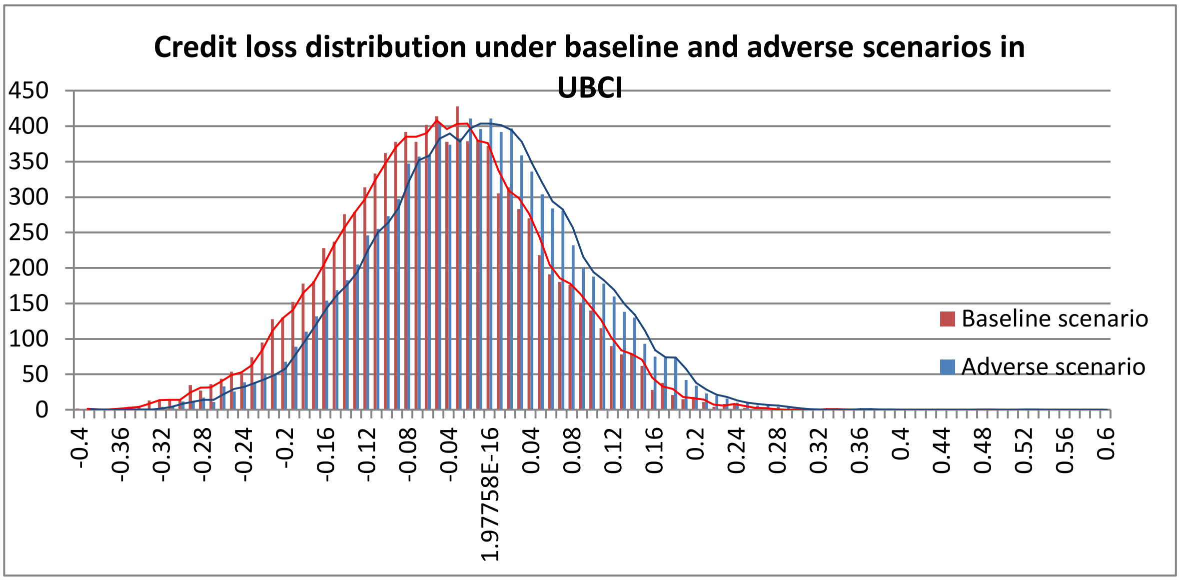

Figure 11. Baseline and Adverse Scenarios under Shock to Tunisian Real GDP Growth in UBCI

UIB: Frequency distribution of the baseline and stressed scenarios are simulated in Figure 12. It shows that introducing a GDP shock leads to a shift to the right of the stressed distribution relative to the baseline scenario, showing a small increase in the frequency of the higher credit loss percentages comparatively to the lower ones.

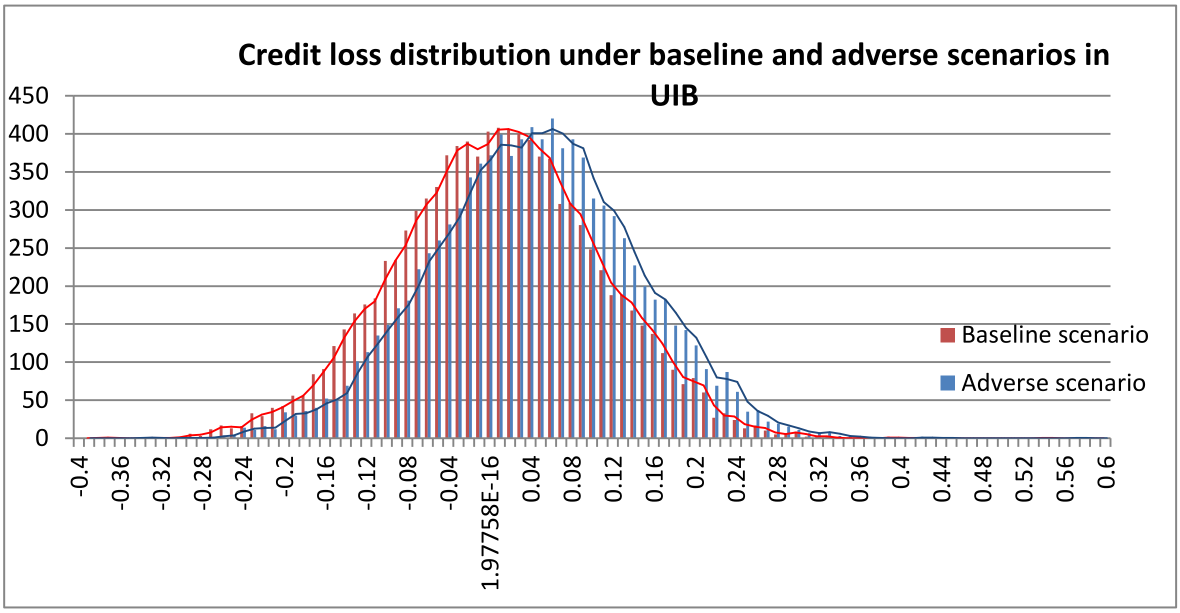

Figure 12. Baseline and Adverse Scenarios under Shock to Tunisian Real GDP Growth in UIB

We could note, for all scenarios, that the histograms exhibit a characteristic shift to the right of the stressed distribution, indicating that the average probability of default under the adverse scenario increases relative to the baseline scenario.

As a summary, the variation intensity of expected default probability is notably recorded in all banks.

So, we conclude that all banks are almost affected similarly, when facing the adverse scenario. It could be explained by the similarity between banks in loan distribution, in risk management.

4.3.2 Unexpected Loss

The bank unexpected loss results for the ten banks in the system are summarized in Table 7. Knowing that we have sorted the banks according to the size, so that the largest bank is STB and the smallest bank is UBCI.

According to the Monte Carlo application on LLP in two cases of scenarios and with a 99.9% confidence level, banks unexpected losses would escalate to a range between 1.67% to 8.07% of the loans. Therefore, banks have enough capital to absorb the credit risk losses that would arise from a sharp decrease of real GDP growth by 2% in the first semester of 2017 comparable with that of post-revolution period.

Otherwise, the results of the stress scenario indicate also that the unexpected loss may vary between banks. More specifically, the three public banks have higher unexpected loss compared to the private ones and especially for STB which presents the highest level of unexpected loss and could then be considered a problem bank in the system and may require attention of the prudential supervisor. Among the remaining seven private banks, there is also difference between them in term of unexpected loss, in fact, for Amen Bank, the unexpected loss is substantially higher, exceeding all other private banks and indicating that it's the most vulnerable among them. While, the most resilient bank is the smallest bank in the sample (UBCI); Under the Stress scenario, the magnitude of the unexpected loss of the latter bank is around 1.7% of its total gross loans.

Table 7. Unexpected Loss Results per Bank

Banks	Expected LLP (baseline scenario)	LLP at 99,9% (adverse scenario)	Unexpected Loss	Available Capital
STB	37.99%	46.06%	8.07%	9.07%
BIAT	6.19%	8.42%	2.23%	10.48%
BNA	22.55%	28.87%	6.32%	7.69%
BH	15.46%	20.31%	4.85%	7.14%
AB	16.18%	21.20%	5.02%	10.02%
Attijari Bank	8.06%	10.89%	2.83%	10.83%
ATB	9.63%	12.93%	3.30%	14.43%
BT	9.06%	12.19%	3.13%	17.21%
UIB	9.15%	12.31%	3.16%	7.60%
UBCI	4.51%	6.18%	1.67%	10.27%

Hence, the results indicate the resilience of the Tunisian banking sector to extreme but plausible adverse shocks. However, the presented results point to the importance of developing by supervisory authorities a bank-specific adjustment program suitable to the individual risk profile for the most vulnerable banks to increase their resilience to the credit risk.

5. Conclusion

This paper attempts to conceive a framework for macro stress-testing on credit risk in commercial banks in Tunisia. To this aim, a two-stage approach is used to investigate the impact of a macroeconomic distressed scenario on the credit risk of 10 commercial banks in Tunisia. We proceed by applying a static fixed effect method to examine loan loss provisions ratios of the banks sample, as proxy of credit risk loss, in terms of two types of determinants; specific bank indicators and macroeconomic variables. Return on assets (ROA), return on equity (ROE), net loans to total asset ratio (B_LR), bank revenue (B_R), capital to asset ratio (B_CAR), total loan to total deposit ratio (B_LD) and the bank size are specific indicators depicted in each bank. While, real GDP, oil price, real effective exchange rate (REER), inflation rate (INF), total loans granted to the economy (D) and broad money supply (M2) are macroeconomic variables.

The stress-testing exercises of this paper focus on assessing stress impact of a real GDP growth sharp decrease on credit risk level of a sample of commercial banks in Tunisia and their resilience for that kind of shock. Therefore, we simulate the distribution of each bank loss rate for credit risk by the

Monte Carlo method in case of two scenarios; first the baseline scenario taking into account the actual macroeconomic conditions; and second designed adverse scenarios, in this scenario, we create stress event by anticipating an extreme change of real GDP growth comparable to that in the first semester of 2011. This shock applied to the macroeconomic variable allow us to detect the commercial banks' vulnerability to macroeconomic instability.

The outcomes of the static fixed effect model analysis indicate a significant effect of the changes in bank-specific variables and macroeconomic variables on the credit risk proxy. More precisely, we find that the four-lagged real GDP growth rate has a strong negative effect on the level of LLP, as the only macroeconomic factor. Moreover, return on assets and bank size have an additional negative effect on LLP, while net loans to total assets ratio possesses positive explanatory power in the model. These results confirm our expectations, excepting for the bank size where bigger size doesn't imply credit risk increase in the case of Tunisian commercial banks and hence, a Tunisian policy concern to an eventual excessive risk taking due to bank big size is not necessary. These risk factors should also be monitored by banks' decision makers level in the aim of optimizing credit standards level while sustaining profits at a safety level.

In regards to stress-testing, we note that each bank is affected differently, when facing the adverse scenario. This is due to the difference between banks in their relative specificities. In fact, UBCI which has, on average, better specific indicators (higher return on assets and lower net loans to total assets ratio) is more resistant to GDP shock. Also, BIAT which has the biggest size and a relatively good ROA is resistant to GDP shock. The most vulnerable bank under the GDP shock is STB, it has a relatively low return on assets and a high net loans to total assets ratio.

the results from all the scenario analyses indicate that bank capital is sufficient to cover unexpected losses for credit risk in the stress event applied. The level of LLP ratio increases from a range between 4.51% to 37.99% under baseline conditions to a range from 6.18% to 46.06% under adverse conditions. Hence, stress test yields unexpected losses that range between 1.67% and 8.07% of loans, below available bank capital, meaning that the credit risk loss would be covered and that commercial banks would be resilient to the macroeconomic shock. But, the Tunisian banking supervisor should carefully consider whether this is enough to weather a prolonged crisis period.

Otherwise, it's noteworthy that the stress impact is dispersed across banks showing, in term of unexpected loss, more harmful effect in two public banks (STB and BNA) and in Amen Bank as a private bank. So, this kind of banks with problems requires special attention from the supervisory authority.

Financial regulatory authorities should consider probable impact of real GDP growth on the stability of the banking sector to deal with likely adverse macroeconomic developments. This would enable assessment of the ability of the commercial banks to resist unexpected macroeconomic risks, in order to introduce monetary policies and financial stability policies. It would also enable assessment of probable impact on these financial institutions when they are faced with macroeconomic instability.

The main contribution of this paper to the literature is that the model and the methodology have not been analyzed before for Tunisia and are applied at a bank level. Also, a particular combination of bank balance sheet data and macroeconomic factors are chosen to model the system in function of loan-loss provisions, the credit risk proxy in our model. It would be appropriate to allow each bank, drawing on its own stress indicator, to conduct stress testing on themselves and to have independence to decide on the simulation assumptions, with the aim of preparing banks well to assess their vulnerabilities facing major macroeconomic challenges.

Another interest of this study is the design of a macroprudential tool consisting of stress testing the financial system of an emerging economy such as "Tunisia" in order to guide Tunisian supervisory institutions to timely and efficient supervisory measures and to contribute to the financial sector's stability. This approach has an enormous relevance in banking supervision and monitoring to give useful and well-timed information.

Otherwise, the proposed approach is also useful, in an aggregate form, for monitoring and assessing banking-sector wide credit risk via macroeconomic indicators under the two macroeconomic scenarios that are analyzed. And also, useful, in an individual form, for identifying bank problems and developing individual adjustment programs for the least resilient banks to reduce their credit risk under a suitable supervisory mechanism.

In this direction, a number of recommendations are outlined that would be of benefit to policy makers :

- Well-capitalised banking system, some banks are less vulnerable to slowdown in economy that could result in higher credit risk, capital buffers should then be encouraged.
- Encourage diversified asset-bases for banks, authorities should promote and incentivize prudent risk-taking in lending to the real economy.
- The estimation is expected to give more insight on the credit risk management of commercial banks. The banks of the sample differ in terms of profitability, activity, capitalization, leverage, liquidity and size. Therefore, policy makers should encourage banks to focus on their managerial performance.
- The change of the variables may serve as warning indicators of future loan losses, then the decision makers should take account of the nature of estimated variables at both macroeconomic and bank level. In fact, the key issue is using the estimated results to monitoring credit risk and planning preventive actions before causing a harmful damage to the bank and without delimiting, in the same time, the role of banks as financial intermediaries.

Further studies should extend this approach with the aim of adjusting bank financial soundness indicators to macroeconomic risks within the macroprudential policy and to design a dynamic stress test allowing banking sector and policy makers to assess the response functions of the bank specific indicators to macroeconomic shocks. The direction of future research should also focus on highlighting the bank level granularity in any macroeconomic credit risk model that contains only aggregate factors of the banking system to ensure the practical usefulness of such approach on an individual bank.

The model presented in this paper represents an improvement over existing literature but is still subject to some limitations. First, using LLP as a proxy of default rates is a contested approximation. Second, the size of our sample is quite small which may decrease the reliability of the shock results. Finally, such a model doesn't consider contagion and feedback channels in the financial system.

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