WP/12/53

IMF Working Paper

From Stress to CoStress: Stress Testing Interconnected Banking Systems

Rodolfo Maino and Kalin Tintchev

INTERNATIONAL MONETARY FUND

 WP/12/53

IMF Working Paper

Monetary and Capital Markets Department

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Prepared by Rodolfo Maino and Kalin Tintchev[1]

Authorized for distribution by Dimitri Demekas

February 2012

Abstract

This paper presents an integrated framework for assessing systemic risk. The framework models banks' capital asset ratios as a function of future losses and credit growth using a generalized method of moments to calibrate shocks to credit quality and credit growth. The analysis is complemented by a simple measure of systemic risk, which captures tail risk comovement among banks in the system. The main contribution of this paper is to advance a simple framework to integrate systemic risk scenarios that assess the impact of aggregate and idiosyncratic factors. The analysis is based on CreditRisk+, which uses analytical techniques—similar to those applied in the insurance industry—to estimate banks' credit portfolio loss distributions, making no assumptions about the cause of default.

JEL Classification Numbers: G10, G20, G21

Keywords: Stress Testing, Credit Risk, Systemic Risk

Author's E-Mail Addresses: rmaino@imf.org; ktintchev@imf.org

[1]The authors would like to thank Li Lian Ong and Laura Kodres for their useful comments. All remaining mistakes are the responsibility of the authors.

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I. INTRODUCTION

As recently stressed by Schmieder et al (2011), stress tests need to fulfill three key conditions as management tools. First, the assumptions about the level of adverse shocks (scenarios) and their duration should be plausible but severe enough to appropriately assess the resilience of individual institutions and the system. Second, the framework used to assess the impact of adverse shocks on solvency (resilience) has to be sufficiently risk-sensitive, which requires changes of risk parameters to be based on economic measures of solvency, in addition to statutory ones, which are usually not sufficiently risk-sensitive. Third, the results of the tests should be easy to communicate to decision makers (for example, policy makers and senior bank managers) and market participants.

This paper presents an integrated framework, which examines risks from the macro environment and banks' interconnectedness and assesses the resilience of the banking system to aggregate and idiosyncratic shocks. In particular,

- a general setup is advanced to design the scope and methodology of stress tests based on hypothetical data;
- the stress test exercise assesses the resilience of the banks in the system both individually and in peer groups by size;
- in addition to various scenarios, a range of single-factor shocks are simulated, including deterioration of the quality of the entire portfolio and individual sectors, defaults of the largest obligors, interbank contagion, exchange rate and interest rate shocks, and a systemic deposit run;
- the framework discusses a macro-risk model based on banks' capital asset ratios as a function of expected losses and credit growth, using a generalized method of moments to calibrate shocks to credit quality and credit growth; and
- a series of statistical simulations are used to find the distributions of banks' credit losses and economic capital.

This analysis is complemented by an assessment of individual banks' contributions to systemic risk. Using quantile regressions, we estimate a simple measure of systemic risk, which captures tail risk comovement among banks in the system. The main contribution of this paper is to advance a simple framework to integrate systemic risk scenarios that assess the impact of aggregate and idiosyncratic factors. The analysis is based on CreditRisk+ to estimate banks' credit portfolio loss distributions, making no assumptions about the cause of default.

The paper is structured as follows. Section II advances a macro-risk stress testing model with simulations for portfolio loss distributions. Section III presents systemic (micro) risk stress tests using quantile regressions while Section IV discusses how to design sensitivity tests depending on the shocks at hand. Concluding thoughts are advanced in Section V.

II. Credit Risk Stress Testing

A. Related Literature

The purpose of system-focused stress testing is to identify common vulnerabilities across institutions that can lead to a systemic failure (Jones et al., 2004). As common vulnerabilities are often driven by banks' exposure to macroeconomic risks, such stress tests typically aim to understand how changes in macroeconomic variables impact the stability of the financial system.

Early applied stress testing frameworks, such as Čihák (2007), provide an Excel-based format to quantify the impact of credit, market and liquidity shocks on the banking system. Excel-based tests are relatively easy to implement but shocks are determined *ad hoc,* the link between banks' losses and the macro environment is not modeled explicitly and banks' assets do not change over the stress test horizon. Ong, Maino and Duma (2010) caution against the use of extreme *ad hoc* shocks in stress tests, as there is always a shock that is sufficiently large to break the banking system. Second-generation Excel-based frameworks such as Schmieder (2011) extend the approach to allow banks' risk weighted assets (RWA) to change under stress.

The link between credit quality and macro fundamentals has been investigated empirically. Among others, Sorge (2004), Chan-Lau (2006), Foglia (2009), Quagliariello (2009), and Borio et al (2012) provide overviews of existing models, which for the most part use a reduced-form "satellite" approach to map exogenous macro shocks into credit quality indicators. Foglia (2009) distinguishes between approaches that model banks' nonperforming loans (NPL) or loan-loss provisions (LLP), and models that focus on household and corporate default rates. Espinosa and Prasad (2010) and Nkusu (2011), among others, incorporate feedback effects from banks' credit quality to the real economy.

Other stress testing models focus on interdependencies among financial institutions. Segoviano and Goodhart (2009) view banking systems as portfolios of banks and model the system's portfolio multivariate density to derive banking stability measures that embed the distress dependencies among financial institutions. Gray and Jobst (2010), on the other hand, model the financial sector as a portfolio of individual contingent claims, which allows them to define their joint put option value as the multivariate density of each institution's individual marginal distribution of contingent liability. Other systemic risk indicators, such as CoVar (Adrian and Brunnermeier, 2009) and CoRisk (Chan-Lau, 2010), are derived using econometric methods and measure individual institutions' contributions to systemic risk.

The global crisis demonstrated that financial risks need to be assessed in a systemic perspective that considers potential spillovers across institutions and the interaction of multiple risk factors. The integrated approach to systemic risk stress testing is still developing. One early integrated framework developed by the Oesterreichische Nationalbank (Boss et al., 2006) combines satellite credit and market risk models with an interbank network model. The RAMSI model of Bank of England (Aikman et al., 2009), which is one of the most comprehensive frameworks, includes a vector autoregression that simulates macro scenarios, satellite models for credit risk, market risk, and net interest income, as well as embedded market liquidity shocks. In a recent paper, Barnhill Jr. and Schumacher (2011) model correlated systemic liquidity and solvency risks.

This paper aims to contribute to existing research along two dimensions. First, it advances a simple method to construct integrated systemic risk scenarios, which assess the marginal contributions to systemic risk of both macroeconomic and idiosyncratic factors.[2] Second, the paper derives a stylized theoretical model, which measures the impact of future credit losses, credit growth and net interest income on banks' capital to risk-weighted asset ratio (CAR). We model credit growth's direct effects on RWA and indirect effects on future credit losses, which, to our knowledge, have not been examined in prior research.

We study the linkages between credit risk and the real economy in a simple macro-financial framework, using econometric and statistical methods.[3] We use the framework to measure the impact of various scenarios on banks' solvency. In this section, we investigate the linkages between the macro environment and banks' credit quality and credit growth. In the next section, we design integrated scenarios that simulate simultaneous macro and micro shocks to credit quality.[4] The macro-financial stress testing framework involves the following modeling steps (Figure 1):

- First, we model econometrically banks' credit quality and credit growth as a function of a set of risk factors and use the regression estimates to project banks' NPL ratios and credit growth under various scenarios.

- Second, we use the regression projections to model banks' credit portfolio loss distributions in CreditRisk+ and measure their expected losses and economic capital.

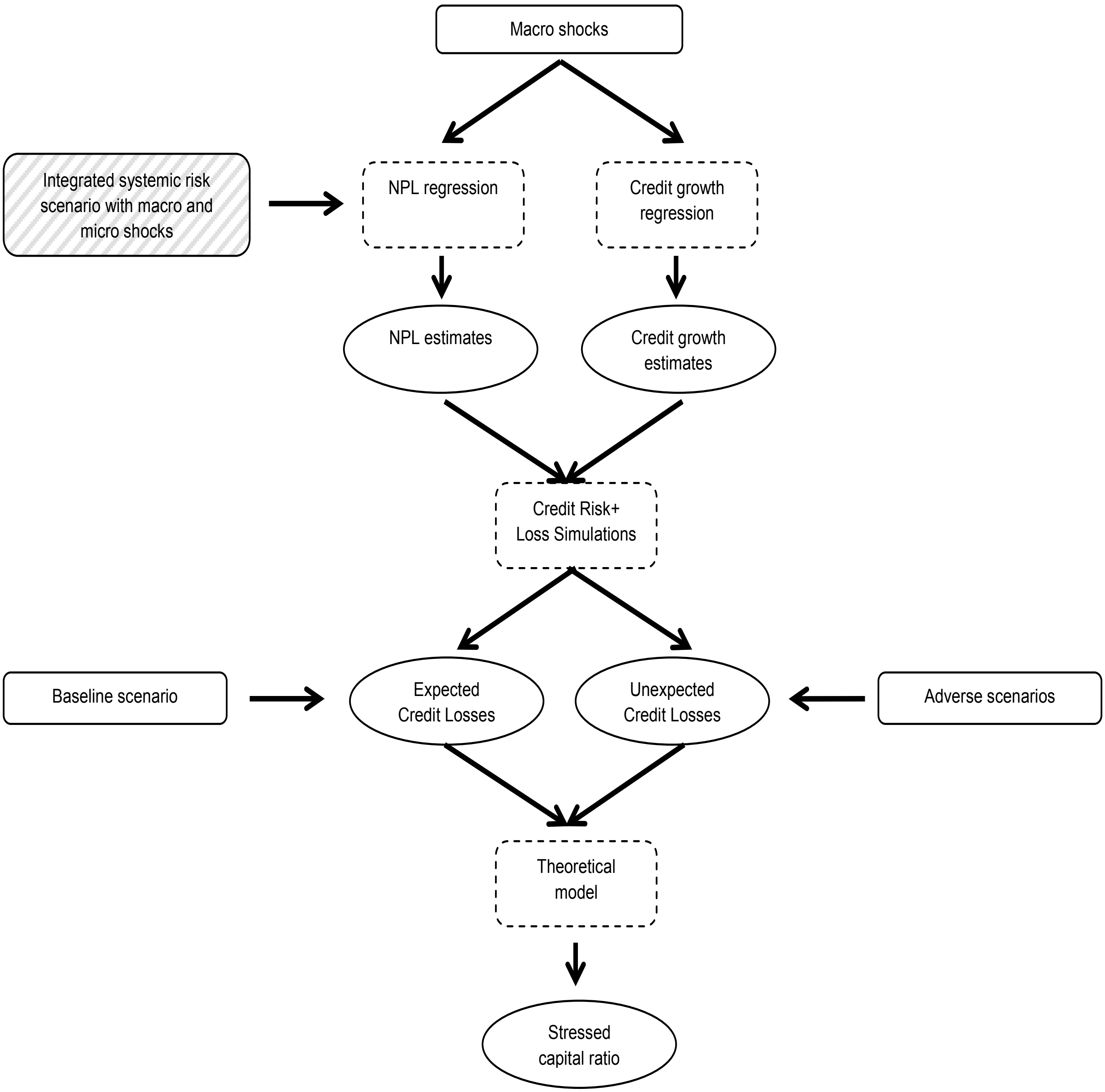
- Third, we derive a simple theoretical model, where banks' CARs are functions of future credit losses, credit growth and the credit spread. Incorporating the credit loss and credit growth projections into the theoretical model allows us to estimate the impact of the scenarios on banks' CARs.

[2] The approach does not require data on interbank exposures.

[3] The exercise that follows is based on fictional data generated with the sole purpose of presenting the scope and advantages of using the framework.

[4] Stein (2011) describes some limitations of scenario-based approaches as a sole mechanism for assessing portfolio risk.

Figure 1. Macro-Financial Stress Testing Framework



Source: Authors' estimates.

B. Theoretical Credit Risk Model

One common approach to credit risk stress testing assumes that banks' assets do not change over the stress test horizon. Thus, projections of future losses are deducted directly from banks' present CARs.[5] Although convenient for short modeling horizons, such an approach involves a high degree of simplification. Abstracting from credit growth effects may underestimate the buildup of risks during a credit boom. RWA may increase significantly over longer stress test horizons and banks would need additional capital to keep their CARs stable. Higher credit growth also implies higher exposures at default and thus higher credit losses when the boom goes bust. In this section we develop a stylized model that attempts to incorporate such effects.

We model banks' CAR as a function of future credit losses, credit growth and net interest income. Negative shocks in the model arise from banks' mispricing of credit risk. The approach is highly simplified and assumes a banking system that is engaged in traditional intermediation. Thus, banks rely solely on net interest income to cover their operating expenses and credit losses, accumulating the residual as capital.[6] Credit is fully weighted in RWA and operating expenses represent a fixed fraction of credit. Net interest income depends on credit growth and the spread of the lending rate over the deposit rate. Spreads are reset by the banks at the beginning of each period. Banks accumulate capital only internally and distribute dividends if this will not reduce their CARs. Under these assumptions, bank *i's* capital and RWA at time *t+1* evolve as follows:

$$\Delta Capital_{i,t+1} = Credit_{i,t+1} \times Spread_{i,t+1} - Oper.\ Expenses_{i,t+1} - Credit\ Loss_{i,t+1} \tag{1}$$

$$\Delta RWA_{i,t+1} = Credit_{i,t+1} - Credit_{i,t} - Credit\ Loss_{i,t+1} \tag{2}$$

$$Oper.\ Expenses_{i,t+1} = \theta Credit_{i,t+1} \tag{3}$$

$$Spread_{i,t+1} = Net\ Interest\ Income_{i,t+1} / Credit_{i,t+1} \tag{4}$$

Capital accumulation in (1) depends on future credit losses, credit growth and the credit spread. Accumulation of RWA in (2), on the other hand, is driven by future credit growth and credit losses. Thus, changes in banks' CARs depend on the trade-off between new capital and new RWA. If banks trade new capital for new RWA at a rate that is equal to their present CAR, their capital adequacy ratios will remain unchanged.

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[5]See for example Čihák (2007).

[6]Given our focus on credit risk, we consider only the banking book and abstract from other types of assets and sources of income, which however are relatively easy to incorporate and would not affect the basic results. Thus, we do not model changes to market valuations of banks' trading book, which would have a direct impact on their CARs, as well as non-interest sources of income (e.g., fees and commissions).

Baseline estimation: Since the baseline is the realization of the most likely outcome, we assume that banks are able to forecast correctly the actual shocks to credit quality and credit growth, based on the prevailing outlook, and choose a spread that would fully absorb the shocks, keeping their CARs constant. Thus, in the baseline, condition (5) holds and banks' CARs do not change:

$$CAR^{Baseline}_{i,t+1} \equiv \frac{\Delta Capital_{i,t+1}}{\Delta RWA_{i,t+1}} \equiv \frac{Capital_{i,t}}{RWA_{i,t}} \equiv CAR^{Baseline}_{i,t} \quad (5)$$

Equations (1), (2), and (5) define a system with three unknowns—credit losses, credit growth and the credit spread. We substitute (1) and (2) into (5) and solve for the baseline spread as a function of baseline credit losses and credit growth:

$$Spread^{*}_{i,t+1} = \theta + \frac{Credit\ Loss^{Baseline}_{i,t+1}}{Credit_{i,t}(1+Credit\ Growth^{Baseline}_{i,t+1})} \times (1-CAR_{i,t}) + \frac{Credit\ Growth^{Baseline}_{i,t+1}}{1+Credit\ Growth^{Baseline}_{i,t+1}} \times CAR_{i,t}$$

(6)

Expression (6) defines the condition under which the spread would fully absorb the shocks and keep CAR constant. The weights $(1\text{-}CAR_{i,t})$ and $CAR_{i,t}$ sum to one and depend on banks' initial condition. The more a bank is initially in distress, the bigger the weight placed on credit losses and the smaller the weight placed on credit growth. We use a macro-financial regression model to forecast the NPL ratios and credit growth and substitute the projections in CreditRisk+ to find the loss distribution. Credit losses in the baseline equal the mean of the distribution. Finally, we substitute in (6) the credit loss and credit growth projections to obtain the spread:

$$NPL^{Baseline}_{i,t+1} = f(Macro^{Outlook}_{i,t+1}) \quad (7)$$

$$Credit\ Growth^{Baseline}_{i,t+1} = f(Macro^{Outlook}_{i,t+1}) \quad (8)$$

$$Credit\ Loss^{Baseline}_{i,t+1} = Expected\ Credit\ Loss^{\ Outlook}_{\ CreditRisk+} \quad (9)$$

Adverse scenarios: Banks set their spreads in line with the baseline projections, which are the most likely outcome. Spreads can only be reset at the end of the period, after the realization of the shocks. Thus, deviations of the actual shocks from the baseline projections have an impact on CARs. We simulate adverse macro scenarios, where shocks diverge significantly from the baseline and credit losses correspond to the 99th percentile of the distribution:

$$NPL^{ScenarioA}_{i,t+1} = f(Macro^{ScenarioA}_{i,t+1}) \quad (10)$$

$$Credit\ Growth^{ScenarioA}_{i,t+1} = f(Macro^{ScenarioA}_{i,t+1}) \quad (11)$$

$$Credit\ Loss_{i,t+1}^{ScenarioA} = Credit\ Loss_{99\%\,CreditRisk+}^{ScenarioA} \tag{12}$$

We estimate the impact of adverse scenarios on banks' capital and RWA using the credit losses and credit growth projections under the scenario, while retaining the baseline spread:

$$\Delta Capital_{i,t+1}^{ScenarioA} = Credit_{i,t+1}^{ScenarioA} \times Spread*_{i,t+1} - Oper.\ Expenses_{i,t+1} - Credit\ Loss_{i,t+1}^{ScenarioA} \tag{13}$$

$$\Delta RWA_{i,t+1}^{ScenarioA} = Credit_{i,t+1}^{ScenarioA} - Credit_{i,t}^{ScenarioA} - Credit\ Loss_{i,t+1}^{ScenarioA} \tag{14}$$

Thus, banks' CARs become functions of the magnitudes of the credit quality and credit growth surprises under the scenario. Higher than expected credit losses and credit growth would reduce CARs. The model can be estimated for multiple periods, depending on the stress test horizon.

C. Empirical Credit Risk Model

The theoretical model is linked to a regression model, which investigates the linkages between credit risk and the macro environment. Exploiting quarterly bank-level data, we estimate two dynamic panel equations that model credit quality and credit growth as functions of exogenous macro risk factors. The empirical model has the following specification:

$$NPL_{it} = Y_{it}'\beta + \alpha_i + \varepsilon_{it} \tag{15}$$

$$Credit\ Growth_{it} = X_{it}'\gamma + \delta_i + \eta_{it} \tag{16}$$

where $NPL_{i,t}$ denotes the NPL ratio of bank i at time t; $Credit\ Growth_{i,t}$ stands for a year-on-year percentage change in total private sector credit of bank i at time t; Y_{it} and X_{it} denote vectors of endogenous and predetermined variables, including lag(s) of the dependent variables and the macro risk factors, $i=1,\dots,N$ is the cross-sectional dimension, $t=1,\dots,T$ is the time dimension, α_i and δ_i are time-invariant individual fixed effects; and ε_{it} and η_{it} are disturbances. We allow the independent variables to vary between the two equations and consider up to four lags to provide sufficient response time to the dependent variables.

It is well-known that dynamic specifications lead to inference problems in panel data models. The Ordinary Least Squares (OLS) levels estimator would produce inconsistent, upward-biased estimates since by construction there is a positive correlation between the lagged dependent variable and the unobserved individual fixed effects (Bond, 2002). Individual fixed effects can be removed using the Within Groups (WG) estimator, which uses the deviations of the observations from their individual means. However, WG estimation induces endogeneity in the transformed lagged dependent variable, which would be negatively correlated by construction with the transformed error term. Thus, the WG estimator would be biased downwards.

Generalized Method of Moments (GMM) estimators have been proposed for panels with endogenous regressors. GMM estimation offers inference that is asymptotically efficient, whilst relying on relatively weak statistical assumptions. The Arellano and Bond (1991) one-step "difference" GMM estimator transforms the panel data model in first differences to remove the individual effects and uses lagged levels of the variables as instruments for the endogenous differences. The estimator is based on all available orthogonality conditions that exist between the lagged endogenous variables and the disturbances and is the most efficient in the class of linear instrumental variables estimators. Arellano and Bover (1995) and Blundell and Bond (1998) develop an augmented version of the estimator, known as "system" GMM, which is based on extra moment conditions and has better finite sample properties. The conditions are derived from the model in levels and combined with moment conditions for the model in first differences. The "system" GMM estimator tends to outperform the "difference" estimator when series are highly autoregressive.

We exploit the "xtabond2" estimation procedure, discussed in Rodman (2006), which has been implemented in STATA (see Drukker, 2008). Since we have a small unbalanced panel, the forward orthogonal deviations transform, proposed by Arellano and Bover (1995), was used instead of first differencing. Rather than subtracting the previous observation, the orthogonal-deviations transform subtracts the average of all available future observations. The transform preserves the sample size in panels with gaps, where differencing would reduce the number of available observations. The robustness of the GMM estimates is influenced by the number of available data points. Since we have a small panel, we exploit also an alternative estimator due to Hausman and Taylor (1981), which fits a random effects model with lagged instruments. We also utilize the WG and Pooled OLS estimators, which would be biased downward and upward respectively, but still provide useful lower and upper bounds for the estimation.

The model is estimated with each of the estimators discussed above. The results suggest that banks' credit quality and credit growth are largely driven by real GDP growth and inflation (Table 1). The coefficients have the expected sign and appear robust to alternative specifications. NPL ratios are correlated negatively with GDP growth and positively with inflation. Lending to the private sector, on the other hand, is associated positively with GDP growth and negatively with inflation. It takes approximately three quarters for GDP growth to affect NPLs and credit growth, while inflation affects credit quality and credit growth in two quarters and one quarter, respectively. The large coefficients on the autoregressive terms indicate presence of strong inertia in the dependent variables.

D. Modeling Banks' Credit Portfolio Losses in CreditRisk+

Next, we use the NPL and credit growth projections to assess the impact of the scenarios on banks' credit portfolio losses. The baseline scenario assumes robust GDP and credit growth, and moderate inflation, the inflation scenario envisages a significant increase in inflation, while the slowdown scenario assumes a sharp economic slowdown. The regression estimates suggest that the system's average NPL ratio would increase by around 27 percent and growth of credit to the private sector would decelerate to around 14 percent in the inflation scenario. By contrast, the average NPL ratio increases by nearly 60 percent and credit growth decelerates to roughly 7 percent in the slowdown scenario.

We use the estimates to model banks' portfolio loss distributions in CreditRisk+. Knowledge of the loss distribution allows us to assess the economic capital that a bank has at risk by holding the credit portfolio. Losses on individual loans depend on the borrower's probability of default, banks' exposure at default and the recovery rate. To estimate the portfolio VaR at the 99 percent confidence level CreditRisk+ makes some distributional assumptions that are detailed in Box 1 and Appendix I. The data requirements for the simulations include data on banks' individual loans, their default probabilities and recovery rates. We focus on the large loans in banks' portfolios. As default probabilities are not directly observable, we use as a proxy the required provisioning rates, which reflect the expected impairment on loans in that classification (e.g. performing = 0.03; past due = 0.05; substandard = 0.25; doubtful = 0.5; and loss = 1). Alternatively, default probabilities may be available from banks' own internal risk management data systems or proxied by borrowers' credit risk ratings or loan classifications.

In order to simulate the macro scenario in CreditRisk+ we proceed as follows:

- initial loan default probabilities were shocked by using the projected increase in NPL ratios;

- exposure at default is found by multiplying the loan balances by the credit growth projections;

- a 25 percent recovery rate is assumed on all loans;

- under the previous assumptions, banks' credit portfolio loss distributions are generated before and after the shocks; and

- unexpected losses from the simulations and the credit growth projections from the regression analysis are fed into the theoretical model to gauge the impact of the scenario on banks' CARs.

Table 1. Macro Determinants of Credit Risk [1/]

(Estimation period: 2002Q3–2010Q1)

	Difference GMM [2/]		System GMM [3/]		Hausman-Taylor [4/]		Within Group [5/]		Pooled OLS	
Credit quality equation — Dependent variable: NPL ratio										
NPL ratio (t-1) [6/]	0.49	***	0.57	***	0.57	***	0.52	***	0.60	***
	0.00		*0.00*		*0.00*		*0.00*		*0.00*	
NPL ratio (t-2) [6/]	0.47	**	0.52	**	0.34	***	0.33		0.37	***
	0.03		*0.04*		*0.00*		*0.06*		*0.00*	
Real GDP growth (t-3) [7/]	-0.16	***	-0.13	***	-0.16	**	-0.16	***	-0.15	**
	0.00		*0.01*		*0.03*		*0.01*		*0.04*	
Inflation (t-2) [8/]	0.14	***	0.14	***	0.13	***	0.13	**	0.13	**
	0.01		*0.01*		*0.01*		*0.02*		*0.01*	
Constant	...		-0.54		1.36		1.18	*	0.52	
			0.45		*0.15*		*0.09*		*0.54*	
Number of observations	296		306		306		306		306	
R2	...		...		...		*0.61*		*0.61*	
Credit growth equation — Dependent variable: Private Sector Credit Growth										
Private Sector Credit Growth (t-1) [9/]	0.67	***	0.72	***	0.68	***	0.68	***	0.73	***
	0.00		*0.00*		*0.00*		*0.00*		*0.00*	
Real GDP growth (t-3)	0.61	**	0.61	**	0.60	**	0.61	*	0.59	**
	0.03		*0.03*		*0.04*		*0.08*		*0.04*	
Inflation (t-1)	-0.48	***	-0.49	***	-0.49	***	-0.48	***	-0.50	***
	0.01		*0.01*		*0.01*		*0.00*		*0.01*	
Fiscal balance to GDP (t-2)	0.27	*	0.24	*	0.26	*	0.27	*	0.23	
	0.07		*0.10*		*0.08*		*0.10*		*0.12*	
Constant	...		7.25	**	7.14	**	8.24	***	7.01	***
			0.02		*0.02*		*0.00*		*0.02*	
Number of observations	254		264		264		264		264	
R2	...		...		...		*0.60*		*0.60*	

Source: Authors' estimates.

1/ P-values are in italic; * denotes significance at the 10 percent level; ** at the 5 percent level; *** at the 1 percent level.
2/ Arellano-Bond (1991) one-step "difference" Generalized Method of Moments estimator with forward orthogonal deviations transform; robust variance-covariance matrix.
3/ Blundell and Bond (1998) one-step "system" Generalized Method of Moments estimator with forward orthogonal deviations transform; robust variance-covariance matrix.
4/ Hausman-Taylor panel-data random-effects model with endogenous covariates.
5/ Fixed effects (within group) panel data estimator.
6/ Nonperforming loans include past-due loans.
7/ Year-on-year real GDP growth.
8/ Year-on-year percent change in the CPI index (2005=100).
9/ Year-on-year percent change in total loans.

Box 1. CreditRisk+

CreditRisk+ is a portfolio credit risk model, which can be used to generate estimates of the expected (average) and unexpected (extreme) losses in a bank's portfolio. The model was developed by Credit Suisse First Boston (CSFB) in 1997 and can be applied to any credit instrument, including loans, bonds and derivatives. We utilize a modified version of the model implemented at the IMF (see Avesani et al, 2006).

CreditRisk+ takes a portfolio approach to credit risk. The model is tractable and obtains, under some statistical assumptions, a closed-form solution for the distribution of portfolio losses, using analytical techniques similar to those applied in the insurance industry. The model treats credit risk as a sudden event rather than a continuous change. Since credit risk in the model represents a binary outcome—default or no default—CreditRisk+ has been characterized in the literature as a "default mode" model as opposed to other models (e.g. Credit Metrics) that are based on non-default migrations in credit quality (see Saunders and Allen, 2010).

Since the exact timing of default events and the exact total number of defaults cannot be predicted, default is modeled as a continuous random variable with a probability distribution. In contrast to structural models (e.g. Merton, 1974) CreditRisk+ makes no assumptions about the cause of default. Its theoretical underpinnings can be traced back to the insurance industry and are similar to intensity-based models. CreditRisk+ models the default process in a portfolio with a large number of loans with relatively small default probabilities, which are independent of one another. Under these assumptions, the frequency of default events can be closely approximated by the Poisson distribution, which is more appropriate than the normal distribution for estimating the probability that a given number of defaults will occur within a specific time period (see Appendix I).

E. Main Findings

The stress test results in Table 2 reveal banks' vulnerability to macroeconomic fluctuations. The system's CAR declines from 9.4 percent to 5.2 percent under the inflation scenario and to 4.5 percent under the slowdown scenarios. The two scenarios have a broadly similar impact on CARs. Although NPL ratios are higher in the slowdown scenario, their impact is mitigated by lower credit growth. By contrast, the increase in RWA in the inflation scenario partly offsets the impact of lower credit losses in that scenario. Higher credit growth also implies higher exposures at default and higher future losses, keeping everything else the same. Thus, abstracting from credit growth effects may underestimate the impact of the inflation scenario on banks' CARs.

Figure 2 shows the loss distribution of the average bank credit portfolio before and after the shock. The distribution was generated by averaging over individual portfolios and using the average loan balances and default probabilities in the CreditRisk+ estimation. The shock shifts the distribution to the right, with expected and 99th percentile losses increasing by 70 percent and 50 percent, respectively. The unexpected losses under the scenario, defined as the difference between the 99^{th} percentile loss and the mean of the distribution, exceed capital. Thus, the system's capital buffers would be insufficient to absorb an extreme shock to credit quality.

Table 2. Summary Stress Test Results

(In percent, unless indicated otherwise)

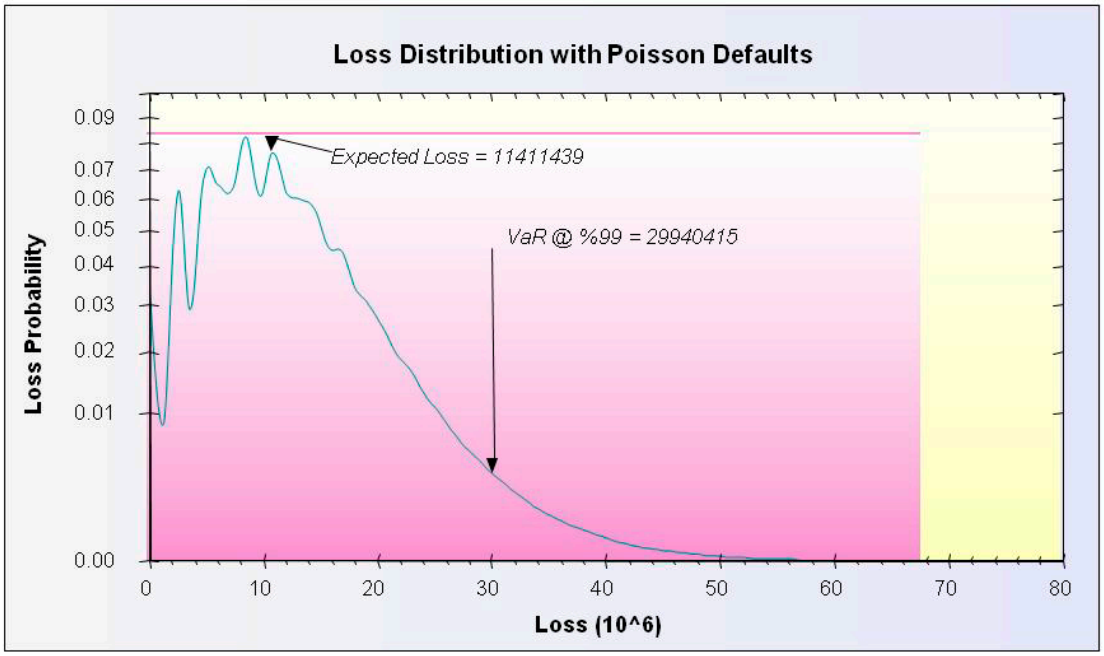
	Banking system		Large banks		Medium banks		Small banks	
	CAR	Tier 1 ratio	CAR	Tier 1 ratio	CAR	Tier 1 ratio	CAR	Tier 1 ratio
Reported capital adequacy ratio	16.3	12.9	15.2	11.3	16.6	13.8	65.9	65.9
Adj. capital adequacy ratio [1/]	9.4	4.9	11.8	6.2	2.9	0.5	53.2	53.1
A. Sensitivity Analysis								
Credit Risk								
Increase in NPLs by 40 percent [2/]	7.8	3.3	10.7	5.1	0.5	-1.9	47.2	47.2
Downgrade of 30 percent of standard loans to substandard [3/]	3.7	-1.0	6.1	0.1	-2.9	-5.4	51.7	51.7
Credit Concentration Risk								
Default of the single largest borrower	5.8	1.2	9.4	3.7	-2.9	-5.4	47.0	47.0
Default of the 2 largest borrowers	3.4	-1.2	8.0	2.2	-6.8	-9.2	36.6	36.6
Sectoral Credit Shocks to: [4/]								
Agriculture	8.7	4.2	11.0	5.3	2.5	0.2	52.4	52.4
Construction	6.7	2.2	9.1	3.5	0.2	-2.2	52.7	52.7
Manufacturing	6.5	2.1	9.3	3.6	-0.5	-2.9	50.1	50.0
Mining	7.1	2.6	9.4	3.8	0.8	-1.5	50.4	50.4
Trade	6.1	1.6	8.5	2.9	-0.4	-2.7	49.5	49.5
Exchange Rate Risk								
20 percent appreciation	9.2	4.8	11.7	6.1	2.7	0.4	51.4	51.4
25 percent depreciation	9.6	5.2	12.0	6.4	3.1	0.7	55.3	55.3
Interest Rate Risk								
Interest rates increase by 250 b.p.	9.8	5.3	12.2	6.6	3.3	0.9	55.1	55.1
Interest rates decrease by 300 b.p.	8.9	4.4	11.4	5.7	2.4	0.1	50.8	50.8
B. Scenario Analysis								
Interbank Contagion Risk								
First round [5/]	8.2	4.4	8.1	4.5	-0.2	-1.4	33.2	33.2
Second round [6/]	7.5	3.8	7.3	3.7	-0.4	-1.7	32.2	32.2
Macroeconomic scenarios:								
High inflation scenario	5.2	1.0	8.9	3.7	-3.1	-5.5	27.5	27.5
Slowdown scenario	4.5	-0.1	8.7	3.1	-4.8	-7.4	24.4	24.4

Source: Authors' estimates.

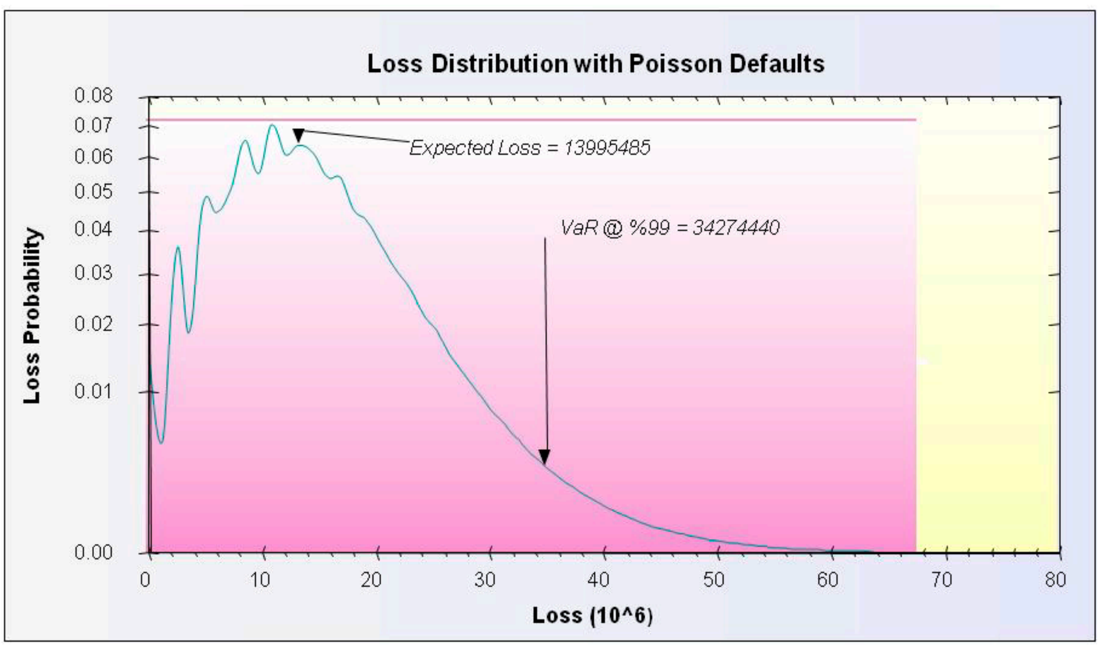
1/ Adjusted for underprovisioning.
2/ Past-due, substandard, doubtful and loss loans increase uniformly by 40 percent.
3/ 30 percent of standard (performing) loans are downgraded to substandard.
4/ 20 percent of the sectoral exposure is downgraded to loss.
5/ Assumes that five medium and small banks with lower CARs simultaneously default on their interbank exposures and the loss given default is 50 percent.
6/ Measures second-round effects.

Figure 2. Slowdown Scenario: Average Bank's Portfolio Loss Distribution

Prior to Shock



After Shock



Source: Authors' estimates.

III. SYSTEMIC RISK STRESS TESTS

A. Systemic Risk Drivers

Systemic risk can be viewed as a function of aggregate (macro) and idiosyncratic (micro) risk factors. Common shocks typically arise from the broader economy, whereas idiosyncratic shocks are institution-specific. In the previous section we modeled bank distress from a macro perspective as a reduced-form function of aggregate risk factors. Our approach implicitly assumes that idiosyncratic factors are independent of one another and thus would not have systemic implications. This assumption allowed us to quantify the default risk of individual banks in isolation from the default risk of the remaining banks in the system. However, in interconnected systems, the system's VaR is not a simple sum of the individual banks' VaRs since distress at an individual institution may affect other institutions. We define the risk of systemic spillovers in this framework as the risk that an idiosyncratic shock could have implications for the stability of the whole system. This section discusses a simple method to gauge individual banks' contributions to systemic risk.

We assess the risk of systemic spillovers using a simple indicator that measures the tail risk comovement among the banks in the system. The indicator, which we dub "CoStress", builds upon the insights in Adrian and Brunnermeier (2009) and Chan-Lau (2010). The systemic spillover risk measure for bank *i* is defined as the level of banking system stress conditional on bank *i* being in distress. Thus, the marginal contribution of bank *i* to systemic risk will be the difference between the level of systemic stress conditional on bank *i* being in distress and conditional on its "normal" or median state. In order to capture tail risk effects, we model the 90th percentile of the conditional quantile function of the banks' NPL ratios using quantile regression.

We use quantile regression, which is a modeling technique introduced by Koenker and Bassett (1978) that is especially useful for systemic risk analysis where extreme values are important. In contrast to ordinary least squares regression (OLS), which models the conditional mean function of a response variable Y given X=x, quantile regression models the conditional quantile function of Y given X=x. Since in systemic risk analysis the coefficients are likely to depend on the quantile, or the level of stress, quantile regression allows us to focus on the conditional distribution at the quantile of interest (e.g., the 90th percentile). Thus, quantile regression appears better suited to capture nonlinear effects, which are likely to be present at higher levels of stress (see Box 2).

The tail risk comovement among the banks in the system may be attributable to their financial linkages or common risk factors. In interconnected banking systems, distress at one institution could affect other institutions through the interbank market (see Lelyveld and Liedorp, 2006) or parent-subsidiary structures (see Arvai et al., 2009). Banks that are linked by interbank exposures or equity cross-holdings may be vulnerable to spillovers. Our systemic risk indicator is based on fundamental financial linkages among institutions.[7] Thus, the NPL ratios would respond to direct spillovers via counterparty exposures in the interbank market or ownership linkages. Another possibility is to use market-based variables that proxy overall bank distress such as credit default swap spreads (CDS), default probabilities, or equity prices, if available. Unlike NPL ratios, market-based indicators are forward-looking and would generally capture also indirect spillover effects. On the other hand, distress could be interrelated across banks because of their exposure to common risk factors. Banks may be simultaneously in distress if they lend to the same firms and sectors. For example, banks with large exposures to real estate would be jointly exposed to a housing price shock, whereas banks with large exposures to commodity producers—to a commodity price shock.

B. Empirical Model

We model the tail risk comovement among the banks in the system as a function of both common and idiosyncratic factors. We assume that are exposed to commodity price fluctuations with systemic implications. Thus, we include a year-on-year change in a monthly commodity price index as a common risk factor in the model. To model idiosyncratic shocks we use the NPL ratios of individual banks as another explanatory variable.[8] We utilize a logistic functional form put forward by Wilson (1997a, 1997b), which takes into account that NPL ratios are bounded between zero and one. The following quantile regression model was estimated using monthly data:

$$NPL_{\tau,t} = a_{\tau} + \beta_{\tau} NPL_{t-1} + \sum_{n}^{N} \beta_{\tau,n} CRF_{n,t} + \beta_{\tau,j} NPL_{j,t} + \varepsilon_{\tau,t} \tag{17}$$

where $NPL_{\tau,t}$ is the 90th percentile of the conditional quantile distribution $(\tau = 0.90)$ of the logit transformation of the pooled NPL ratios of the banks in the system, excluding bank j; NPL_{t-1} is the one-quarter lag of the dependent variable; CRF_n denotes the *n-th* common risk factor; NPL_j is the NPL ratio of the "explanatory bank" j, a_{τ} is a constant and $\varepsilon_{\tau,t}$ is the disturbance.

---

[7] Banks' NPL ratios in the data include interbank credit.

[8] A drawback of this approach is that to the extent that the common factor and the NPL ratio of the "explanatory" bank may be related, this would induce multicollinearity in the estimation. To avoid multicollinearity, one could use principle component analysis to extract common factors and use the common factors and the orthogonal component of the banks' distress indicator as explanatory variables (see for example Chan-Lau, 2010). However, this would complicate the interpretation of the common shocks since they cannot be linked directly to the macro environment.

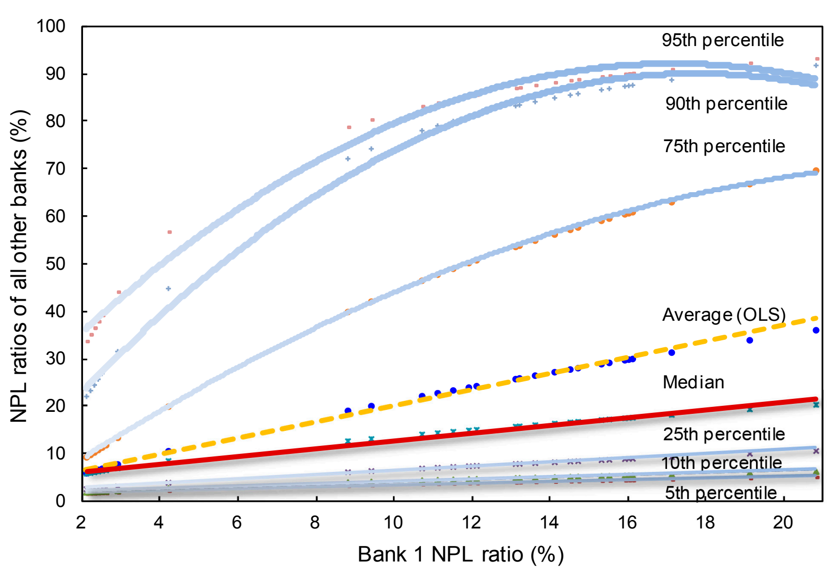
Box 2. Quantile Regression

The quantile regression method estimates the conditional quantile function by solving an optimization problem. While OLS regression minimizes the sum of squared residuals to obtain an estimate of the conditional mean function, quantile regressions minimize the sum of weighted absolute residuals to obtain an estimate of the conditional quantile function (further details on the minimization problem are presented in Appendix II).

The use of quantile regression is justified by the properties of the data (Figure 3)**.** We fit the NPL ratio of one bank against the NPL ratios of the other banks using two alternative methods: quantile regression and OLS. Superimposed on the scatter plot are the fitted values of seven quantile regressions corresponding to the 0.05, 0.10, 0.25, 0.50, 0.75, 0.90, and 0.95 percentiles. The quantile regression estimate of the conditional median function is the red solid line, whereas the OLS estimate of the conditional mean function is the dashed yellow line. The two regression estimates diverge significantly due to asymmetry of the conditional density and sensitivity of OLS to outliers.

Quantile regressions are better suited to model heterogeneous conditional distributions (Koenker and Hallock, 2001). First, there is a tendency for the dispersion of the banks' NPL ratios to increase with the distress level of the "explanatory" bank. Second, the narrow spacing in the lower quantiles reveals higher density and shorter lower tail, while the wide spacing in the upper quantiles indicates lower density and longer upper tail. Finally, the spacing decreases sharply between the 90th and 95th percentiles since the upper tail fattens at the extreme end of the distribution.

Figure 3. Quantile Regression Lines



Source: Authors' estimates.

We estimate the model for each bank and refer to the prediction as the CoStress measure of bank *j*—the level of systemic stress conditional on distress at bank *j*. As in Adrian and Brunnermeier (2009), we define banks' marginal contribution to systemic risk (MCSR) as the percentage point difference between the systemic risk indicator (CoStress) conditional on an extreme shock to bank *j* and conditional on its median state:

$$MCSR = \beta_{\tau=0.9,j}(\hat{NPL}_{\tau=0.9,macro}{}^{\text{system}\,|\,\text{NPLj},\,\tau\,=\,0.9} - \hat{NPL}_{\tau=0.5,macro}{}^{\text{system}\,|\,\text{NPLj},\,\tau\,=\,0.5}), \qquad (18)$$

where MCSR is defined as the difference between the average fitted NPL ratio conditional on bank *j* being in distress ($NPL_{j,\tau} = 0.90$) and being in its median state ($NPL_{j,\tau} = 0.50$). The shocks are calibrated with historical data. Although CoStress is a function not only of idiosyncratic factors but also of the macro environment and the state of the banks in the previous period, in order to find the marginal contribution of bank *j* to systemic risk we need to keep the other factors constant. This estimation procedure enables us to rank the individual banks by their systemic importance, proxied by their MCSR.

C. Systemic Risk Scenarios

We expand the methodology to simulate scenarios, which assess the marginal contributions to systemic risk of both aggregate and idiosyncratic factors. Since we have two types of risk factors —aggregate and idiosyncratic—and shocks of two magnitudes—a median shock and an extreme shock (90^{th} percentile), we have four possible outcomes (see Figure 4): (i) *Scenario A*: median aggregate and idiosyncratic shocks; (ii) *Scenario B*: median aggregate shock and extreme idiosyncratic shock; (iii) *Scenario C*: extreme aggregate shock and median idiosyncratic shock; and (iv) *Scenario D*: extreme aggregate and idiosyncratic shocks. Using the quantile regression line, we project banks' NPL ratios under each scenario. "Shocked" variables assume their median historical value, if the shock is "normal", and the 90^{th} percentile of the historical distribution, if the shock is extreme. Scenario A, where both the macro economy and the bank are in their "normal" state, is the baseline scenario.

To calculate the marginal contributions of idiosyncratic and aggregate risk factors we take the difference between the fitted CoStress indicators in two scenarios. For example, the marginal contribution to systemic risk of an extreme idiosyncratic shock, when the aggregate risk factor is in "normal" state is equal to $\hat{NPL}_B - \hat{NPL}_A$, whereas the contribution of an extreme aggregate shock, when the idiosyncratic factor is in its "normal" state, is defined as $\hat{NPL}_C - \hat{NPL}_A$. Analogously, the marginal contribution of an extreme idiosyncratic shock, when the aggregate factor is in extreme state, is calculated as $\hat{NPL}_D - \hat{NPL}_C$. Finally, the marginal contribution to systemic risk of an extreme aggregate shock when the idiosyncratic factor is in extreme state is measured as $\hat{NPL}_D - \hat{NPL}_B$, where $\hat{NPL}$ are the CoStress fitted values and the subscripts indicate the respective scenarios.

Figure 4. Systemic Risk Scenarios

		Idiosyncratic risk factor	
		Normal (median) state	Tail event (90th percentile)
Aggregate risk factor	Normal (median) state	Scenario A	Scenario B
	Tail event (90th percentile)	Scenario C	Scenario D

Source: Authors' estimates.

D. Main Findings

We fit the CoStress measure under each scenario. Fitted CoStress values and MCSR of aggregate and idiosyncratic factors are shown in Table 3. The estimates suggest that in our data aggregate risk factors have a greater contribution to systemic risk. CoStress increases by around 75 percent following an extreme shock to commodity prices and the system's lagged NPLs. By contrast, individual banks contribute to systemic risk to a lesser degree, with CoStress increasing on average by around 10 percent. Naturally, scenario D, in which both the aggregate and idiosyncratic shocks are in extreme states, has the biggest impact on systemic risk.

Nevertheless, a simultaneous shock to several banks would be significant from a systemic perspective. For example, the impact of a simultaneous shock to 5 banks with the largest contributions to systemic risk is broadly similar to that of an extreme aggregate shock. Noticeably, we find that due to nonlinearities in the prediction the marginal impact of extreme shocks to one factor are bigger when applied in conjunction with extreme shocks to the other factor. For example, the impact of an extreme idiosyncratic shock is bigger when the aggregate factor is also in the extreme state.

Although the small sample complicates the formal analysis of the determinants of banks' systemic importance, we plot banks' MCSR against bank-specific factors such as banks' NPL ratios, share of the system's NPLs, share of the system's total assets, and interbank borrowing as a share of the total and of banks' capital. Albeit heavily influenced by outliers, the results suggest that banks' MCSRs are largely driven by their degree of interconnectedness, proxied by their dependence on the interbank market, as opposed to asset size. These results are broadly similar to other studies on systemic risk (e.g. Adrian and Brunnermeier, 2009), which find a loose cross-sectional relationship between absolute measures such as banks' unconditional VaRs and MCSR.

Finally, the regression estimates were used to model in CreditRisk+ individual banks' VaRs conditional on shocks to other banks in the system. Figure 5 shows a network structure, where banks' VaRs are conditional on a tail event at another bank. To estimate a bank's conditional VaRs we use the quantile regression line to project the bank's NPL ratio conditional on an extreme (90^{th} percentile) shock to the "explanatory" bank and simulate the bank's conditional credit portfolio loss distribution in CreditRisk+. Table 4 shows the conditional VaRs for the five banks with the largest MCSR as a percentage of their capital. Bank 2 emerges from this analysis as the biggest contributor to systemic risk within the group. CreditRisk+ could be also used to derive banks' VaRs conditional on integrated systemic risk scenarios, which may include not only shocks to individual banks, but also to aggregate risk factors and credit growth.

Table 3. Systemic Risk Scenarios [1/]

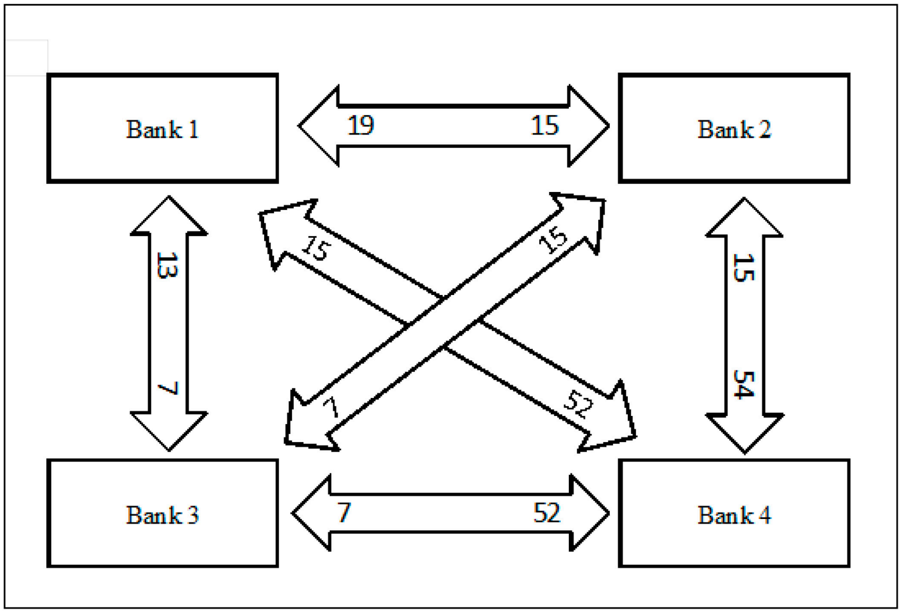
(In percent, unless indicated otherwise)

	Predicted Co-Stress indicator conditional on an extreme shock to bank j (j=1,2,...,12) [1/]												
	System Average	**Bank 1**	**Bank 2**	**Bank 3**	**Bank 4**	**Bank 5**	**Bank 6**	**Bank 7**	**Bank 8**	**Bank 9**	**Bank 10**	**Bank 11**	**Bank 12**
I. Systemic risk scenarios													
A. Median idiosyncraticshock and median aggregate shock	26.7	28.3	28.5	26.3	26.9	26.6	26.0	25.0	26.3	26.3	26.7	26.9	26.6
B. Extreme idiosyncratic shock and median aggregate shock	29.2	29.6	31.3	27.6	30.3	28.6	29.1	31.3	26.7	28.2	28.9	27.6	31.7
C. Median idiosyncratic shock and extreme aggregate shock	46.3	47.1	48.5	45.5	46.6	44.4	45.4	45.3	46.3	45.9	45.5	45.9	49.3
D. Extreme idiosyncratic shock and extreme aggregate shock	49.4	48.7	51.9	47.1	50.7	46.9	49.2	53.1	46.8	48.4	48.3	46.7	55.4
II. Marginal contributions (MC) of aggregate and idiosyncratic factors													
MC of extreme idiosyncratic shock when aggregate risk is in the median state (transition from scenario A to B)	2.5	1.3	2.8	1.3	3.3	2.0	3.1	6.3	0.4	2.0	2.2	0.7	5.1
MC of extreme idiosyncratic shock when aggregate risk is in the extreme state (transition from scenario C to D)	3.1	1.6	3.4	1.6	4.1	2.5	3.9	7.8	0.5	2.5	2.7	0.8	6.2
MC of extreme aggregate shock when idiosyncratic risk is in the median state (transition from scenario A to C)	19.6	18.8	20.0	19.2	19.7	17.8	19.4	20.3	19.9	19.7	18.8	18.9	22.7
MC of extreme aggregate shock when idiosyncratic risk is in the extreme state (transition from scenario B to D)	20.2	19.1	20.5	19.5	20.4	18.3	20.1	21.8	20.1	20.2	19.4	19.1	23.7

Source: Authors' estimates.

1/ The Co-Stress measure is defined as the 90th percentile of the' NPL ratios of the banks in the system. Exteme shocks are defined as the 90th percentile of the variables, while median shocks as the 50th percentile.

Figure 5. CoVaR Network Structure 1/



Source: Authors' estimate.

1/ After Adrian and Brunnermeier (2009).The figure shows the VaR levels of banks at the end of the arrow conditional on distress at the banks at the origin.

Table 4. Conditional Value-at-Risk (VaR) to Capital 1/

(In percent, unless indicated otherwise)

	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Unconditional VAR to capital (1)	Cumulative conditional VAR to capital (2) 2/	Percentage point difference (1)-(2)
Bank 1	12	***18***	12	14	12	12	21	9
Bank 2	135	129	135	***136***	134	129	154	25
Bank 3	28	***31***	27	29	28	27	33	6
Bank 4	269	***283***	268	254	266	254	325	71
Bank 5	27	***28***	27	28	26	26	32	6

Source: Authors' estimates.

1/ 90 percent VaR of the bank in the row conditional on a shock to the bank in the column. The maximum VaR of each bank is bold and in italic.

2/ Cumulative impact of the VARs conditional on shocks to the other banks, which are assumed to be independent.

IV. Sensitivity Analysis

The scenario analysis was complemented by single-factor sensitivity tests, which assessed banks' resilience to credit, interest rate, foreign exchange (FX), liquidity and interbank contagion risk. The sensitivity tests gauged the impact of various risks in the system on banks' current CARs, using a relatively standard set of techniques (see Čihák, 2007). This section discusses key assumptions and findings.

A. Shocks

A number of sensitivity tests focused on credit and concentration risks, given their importance for the banking system. The following shocks were used in the exercise: (i) a 40 percent uniform increase in adversely classified loans across loan categories (past due, substandard, doubtful, and loss); (ii) a 30 percent downgrade of performing loans to substandard; (iii) a simultaneous default of the single largest and two largest obligors; and (iv) a 20 percent default rate on banks' lending to the agriculture, mining, construction, trade and manufacturing sectors. The tests for market, liquidity and interbank contagion risk applied the following shocks: (i) a 25 percent (20 percent) simultaneous depreciation (appreciation) against all currencies; (ii) a parallel upward (downward) shift in the yield curve of 250 basis points (300 basis points); (iii) a five day systemic deposit run resulting in a cumulative outflow of 20 percent of total deposits in domestic currency; and (iv) a simultaneous default on interbank exposures by five banks with lowest CARs.

B. Methodology and Assumptions

Credit risk

The credit risk stress tests simulated downgrades of various magnitudes to the loan rating transition matrix. The impact on banks' CARs was gauged by deducting the resulting increase in required provisions from capital. In addition, banks' default risk was assessed using Z-scores derived from accounting data. The Z-score measures the banks' distance to default in standard deviations of the asset return. A lower Z-score implies higher default risk. The index was estimated over a 3-year rolling window using the following formula:

$$Z\text{-}score = \frac{(ROA + Capital / assets)}{\sigma_{ROA}} \tag{19}$$

Market risk

Banks' sensitivity to interest rate risk was assessed in a re-pricing gap model, which measured the impact of interest rate shocks on the cumulative gap between interest-earning assets and liabilities, whereas banks' sensitivity to FX risk was gauged by conducting sensitivity analysis on the net open FX position in all currencies.

Liquidity risk and interbank contagion risk

The liquidity risk stress tests simulated a five day systemic deposit run leading to a cumulative outflow of around 20 percent of deposits in domestic currency. It was further assumed that banks have at their disposal 70 percent of their liquid assets in domestic currency readily available to meet daily withdrawals. Interbank contagion risk was assessed by performing sensitivity analysis on the matrix of net interbank exposures. The test assumed that five banks with low capital buffers would default simultaneously on their interbank obligations and measured their systemic impact, including second-round effects.

C. Main Findings

Credit risk emerged as a major vulnerability in the system. A number of banks with weak capital buffers and high NPL ratios are vulnerable even to moderate credit quality shocks. Vulnerability to credit risk is exacerbated by large single obligor and sectoral concentrations. In particular:

- A 40 percent increase in adversely classified loans would erode the capital buffers of banks accounting for around 15 percent of the system's assets (Table 5). Severe shocks to loan quality, such as a downgrade of 30 percent of performing loans to substandard, or a simultaneous default of the two largest obligors, would practically deplete the system's Tier 1 capital.

- A simultaneous default of five banks with weak capital buffers on interbank exposures would undermine the solvency of two other banks, including a systemically important one.

- Z-scores indicates that default risk still remains high, particularly for medium and small banks, which have Z-scores that are well below pre-crisis levels (Table 6).

Banks' exposure to direct FX and interest rate risks is small. More banks would suffer moderate losses if the domestic currency appreciates due to their prevailing long net open FX positions. A 20 percent simultaneous appreciation against all currencies will have only a modest impact on banks' capital adequacy. Asset-liability mismatches, measured by the re-pricing gap model, are small, thus net interest income sensitivity to interest rate shocks is generally low. However, FX and interest rate risk may indirectly contribute to credit risk by weakening the repayment capacity of borrowers.

Recent trends show improvements in bank liquidity. The system as a whole can withstand a hypothetical five day deposit run, albeit liquid assets will fall to around 7 percent of total assets. Medium-sized banks appear particularly vulnerable to the shock, and two banks that account for roughly 5 percent of the system's assets will require liquidity assistance.

Table 5. Distribution of Stress Test Results

(In percent, unless indicated otherwise)

	Distribution of banks by CAR (number of banks)			Distribution of banks by CAR (in percent of total assets)			Recapitalization need [1/]
	<4%	4%-14%	>14%	<4%	4%-14%	>14%	in % of GDP
Reported capital adequacy ratio	0	4	10	0.0	34.4	65.6	0.1
Adj. capital adequacy ratio [2/]	3	5	6	5.2	58.0	36.9	2.3
A. Sensitivity Analysis							
Credit Risk							
Increase in NPLs by 40 percent [3/]	5	4	5	15.2	76.8	8.0	2.7
Downgrade of 30 percent of standard loans to substandard [4/]	6	4	4	39.4	56.4	4.2	4.1
Credit Concentration Risk							
Default of the single largest borrower	5	5	4	15.2	80.6	4.2	3.4
Default of the 2 largest borrowers	6	4	4	39.4	56.4	4.2	4.1
Sectoral Credit Shocks to: [5/]							
Agriculture	3	6	5	5.2	86.9	8.0	2.5
Construction	5	5	4	15.2	80.6	4.2	3.0
Manufacturing	5	5	4	15.2	80.6	4.2	3.1
Mining	4	6	4	13.5	82.4	4.2	3.3
Trade	5	4	5	15.2	76.8	8.0	3.2
Exchange Rate Risk							
20 percent appreciation	4	5	5	6.9	85.1	8.0	2.3
25 percent depreciation	3	5	6	5.2	58.0	36.9	2.3
Interest Rate Risk							
Interest rates increase by 250 b.p.	2	6	6	4.6	58.5	36.9	2.2
Interest rates decrease by 300 b.p.	4	5	5	6.9	85.1	8.0	2.4
B. Macro Scenarios							
High inflation scenario	5	5	4	15.2	80.6	4.2	3.8
Slowdown scenario	5	5	4	15.2	80.6	4.2	3.9

Source: Authors' estimates.

1/ Additional capital needed by banks to reach CAR of 14 percent; in percent of 2010 GDP.
2/ Adjusted for underprovisioning.
3/ Past-due, substandard, doubtful and loss loans increase uniformly by 40 percent.
4/ 30 percent of standard (performing) loans are downgraded to substandard.
5/ 20 percent of sectoral exposure is downgraded to loss.

Table 6. Liquidity and Z-Score Stress Test Results
(In percent, unless indicated otherwise)

	Banking system 1/	Large banks	Medium banks	Small banks
Initial Position				
Liquid assets to total assets 1/	18.6	20.8	13.0	21.4
Liquid assets to total deposits 1/	42.5	45.0	33.8	111.2
Liquidity Scenario 2/				
Liquid assets to total assets	7.2	8.2	4.4	15.4
Liquid assets to total deposits	19.2	20.7	13.1	86.0
Z-Score Index 3/				
Dec-07	37.1	20.8	71.8	48.6
Dec-09	7.7	15.2	3.4	2.9
Jun-10	10.1	19.1	5.0	4.5

Source: Authors' estimates.

1/ Liquid assets in domestic currency.
2/ 5-day deposit run resulting in a total outflow of 22.5 percent of deposits in domestic currency.
3/ Financial fragility index defined as the sum of ROA and the capital to asset ratio divided by the standard deviation of ROA. Lower Z-score implies higher default risk.

V. Conclusion

An integrated framework for systemic risk analysis needs to consider risks from both the macroeconomic environment and banks' interconnectedness. This paper uses a general setup to present a simple framework to assess the resilience of a banking system to aggregate and idiosyncratic shocks, advancing a toolbox that can be used in financial sector risk assessments. In this framework:

- banks' CARs are modeled in a format that considers the simultaneous impact of future credit losses, credit growth, and the credit spread;
- the analysis focuses on economic measures of solvency and uses a generalized method of moments to calibrate the shocks to NPLs and credit growth;
- uncertainty about banks' future losses is modeled in CreditRisk+, which relies on analytical techniques to find the banks' credit portfolio loss distributions;
- a simple systemic risk indicator is proposed to measure tail risk comovements among the banks in the system; and
- quantile regressions and CreditRisk+ are used to model banks' conditional VaRs.

Appendix I. Default Risk Modeling in CreditRisk+[9]

CreditRik+ derives banks' portfolio loss distributions in a two-stage process. The first stage estimates the frequency of defaults and the severity of losses, while the second stage derives the loss distribution. While the frequency of defaults in a time period, within a loan portfolio of obligors with different probabilities, can be approximated by a Poisson distribution, the loss distribution depends both on the frequency of default occurrence and on the severity of the loss and would not be Poisson in general. The amount lost in a given default would be equal to the exposure to the obligor less a recovery amount.

Since it is difficult to estimate the severity of the loss on an individual loan-by-loan basis, the exposures, net of recoveries, are grouped into discrete loan bands, and the exposure level for each band is approximated by a common average. Loss distributions are derived for each exposure band, which are accumulated across bands to generate an overall distribution. Given its simplicity, the model has parsimonious data requirements. The inputs required for the estimation of the basic model are the loan exposures, their default rates and mean recovery rates. Default rates can be approximated by mapping obligors' credit ratings or using other proxies such as NPLs, required provisioning rates, etc.

The basic statistical theory behind the default event process in CreditRisk+ is as follows. The model assumes that in a portfolio with N obligors each exposure has a known probability of default over a one-year time horizon. Let p_A denote the annual probability of default for obligor A. To examine the portfolio loss distribution, the model introduces a probability generating function, which is defined using an auxiliary variable z:

$$F(z) = \sum_{n=0}^{\infty} p(n\ defaults) z^n \tag{20}$$

Since for an individual obligor there are two states of the world—default or no default—the probability generating function for a single obligor can be defined as:

$$F_A(z) = 1 - p_A + p_A z = 1 + p_A(z-1) \tag{21}$$

The individual default events are assumed to be independent and the probability generating function for the whole portfolio can be computed as the product of the individual probability generating functions. Thus:

$$F(z) = \prod_A F_A(z) = \prod_A (1 + p_A(z-1)) \tag{22}$$

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[9]The discussion in the appendix follows the methodology in Credit Suisse First Boston (1997).

$$\log F(z) = \sum_A \log(1 + p_A(z-1)) \tag{23}$$

Since the individual default probabilities are assumed to be small, the logarithms can be replaced using the expression:

$$\log(1 + p_A(z-1)) = p_A(z-1) \tag{24}$$

In the limit, equation (23) simplifies to:

$$F(z) = e^{\sum_A p_A(z-1)} = e^{\mu(z-1)}, \tag{25}$$

where the expected number of defaults in the portfolio is given by:

$$\mu = \sum_A p_A \tag{26}$$

The distribution corresponding to the probability generating function is found by a Taylor expansion:

$$F(z) = e^{\mu(z-1)} = e^{-\mu(z-1)} e^{\mu z} = \sum_{n=0}^{\infty} \frac{e^{-\mu} \mu^n}{n!} z^n \tag{27}$$

If the individual default probabilities are small, the probability of having *n* default events in the portfolio in one year would be equal to:

$$\Pr(n\ defaults) \frac{e^{-\mu} \mu^n}{n!} \tag{28}$$

Equation (28) is the well-known Poisson distribution for the probability of *n* defaults, which does not depend on the number of exposures or individual default probabilities.. The distribution's only parameter is the expected number of defaults μ**.** The default probabilities have to be uniformly small albeit not the same. The Poisson process assumed by the basic model implies that the mean of the distribution equals its variance. Since the variance of the default rate was found to be significantly higher in historical data, especially for lower quality exposures, it appears that the Poisson assumption would underestimate the actual default probabilities. To capture the fatter tails of observed loss distributions CSFB extend the basic model to allow for pair-wise default correlations among obligors.

Appendix II. Quantile Regression

The minimization problem reduces to solving the following expression:

$$\min_{\beta} \sum \rho_{\tau}(y_i - \xi(x_i, \beta)), \tag{29}$$

where y is the dependent variable, $\xi(x_i, \beta)$ is a linear parametric function of the explanatory variable x_i , and ρ_{τ} (.) is a weighting function for each observation, such as:

$$\rho_{\tau}(k) = k(\tau - I(k < 0)),\ 0 < \tau < 1, \tag{30}$$

where *I(.)* denotes the indicator function. The weights depend on the quantile of interest. To fit the median quantile the minimization equates the number of positive and negative residuals, while the residuals are weighted asymmetrically to yield other quantiles. The minimization leads to a linear program, which can be solved by the simplex method.

Quantile regression (QR) has certain advantages for modeling systemic risk over other methods such as OLS and extreme value theory (EVT):

- First, QR captures the differential impact of the covariates at various distributional quantiles and is thus better suited to modeling heterogeneous distributions (Chen, 2005). QR can fit the data better in the upper quantiles, where the estimated regression lines exhibit a steeper slope and a nonlinear relationship.

- Second, albeit the conditional quantiles could be modeled by fitting OLS regressions on sub-samples that correspond to various quantiles, the slopes of the fitted quantile curve and mean curve in this case will remain the same since the change will represent merely a locational shift in the conditional NPL distribution, which will not affect its scale and shape. Fitting regressions on sub-samples of the data could create small-sample problems in the upper and lower tails of the distribution, which are often encountered by EVT modeling techniques. Given their focus on the extreme tail of the credit loss distribution, standard EVT techniques have been found not very suitable for credit risk analysis (see Lucas et al., 2002).

- Third, the quantile method is based on less rigid distributional assumptions than OLS and is more robust to large outliers. While OLS assume that errors are normally distributed, QR makes no distributional assumptions regarding the error term since the covariance matrices are estimated using bootstrap methods, which do not require residuals and explanatory variables to be independent.

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