US Bank Stress Test
Supervisory Capital Assessment Program

A Project Report
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1. Introduction

The Federal Reserve along with the Office of the Treasury, Office of Thrift Supervision (OTS) and the Federal Deposit Insurance Corporation (FDIC) (Jointly called Agencies hereafter) announced on February 10, 2009 that they would initialize a macro stress test on top US banks as a part of a Supervisory Capital Assistance Program (SCAP). Their stated goal was to ensure that US banking institutions remain appropriately capitalized in the face of ongoing financial crisis and have sufficient capital to continue to carry out their role critical to helping the economy overcome the recession. The assessment was conducted on 19 U.S. bank holding companies (BHC) with more than 100 billion in assets. The stress test was conducted under two economic scenarios; a baseline scenario that represented the average predicted values of housing price decline, rate of unemployment, and GDP growth; and an adverse scenario which envisioned enduring severe recession in the economy.

In the exercise, concluded in July, the Supervisors worked with BHCs to estimate the extent of their future credit loss and the way to acquire capital resources needed to absorb losses in case they materialized. SCAP included a plan to adjust (increase) capital bases of BHCs under those three adverse what-if scenarios for years 2009 and 2010. The exercise set the BHCs target capital cushion to be high enough to endure even the more adverse scenario. This one time exercise is supposed to bring back the public confidence in the banking sector.

A natural question is how the test was performed, or why US regulators considered it so important to do this solo exercise at this point. A major feature of US bank stress test is that the supervisory agencies would not shed light on the method they used to come up with the figures. 'Beyond housing, gross domestic product and unemployment projections, the Fed did not say how it tested particular assets'.[1] In the light of these questions, this paper attempts to explain what a conventional bank macro stress test is and, in line with the methodology /common practice adopted by major bank regulators particularly in Canada & Europe, the paper lays out a likely framework for US stress test.

2. Stress Test

Recent financial crises in major economies worldwide have underscored the need of stability in the financial system for better economic performance. To help cope with the increased complexities in supervising financial sector and identify exposures having considerable impact, brought by the diversification and innovation of financial instruments and increasing globalization of financial industry, the World Bank and the IMF helped many countries develop Financial Sector Assessment Program (FSAP).[2] FSAP employs stress test as a tool to judge the resilience of financial system to endure different shocks in the economy. It can be used to measure the extent of vulnerabilities of the bank's portfolio to the exposure to unusual but credible market/ economic shocks like extended recessions of say 1930s.[3] For example; Canada has participated in the FSAP program since 1999. As a part of 2007 FSAP update, Bank of Canada started the macro stress test for the Canadian banks. In fact Canada was the first G7 country to participate in IMF-World Bank FSAP stress test. Some consider this to be one of the reasons for the Canadian banks' stable performance during the current financial crisis.

According to IMF definition, 'Macro stress-testing refers to a range of techniques used to assess the vulnerability of a financial system to "exceptional but plausible" macroeconomic shocks'.[4] New Basel Capital Accord 2001 underlines its scope as 'Stress testing should involve indentifying possible events or future changes in economic conditions that could have unfavorable effects on a bank's credit exposures and assessment of bank's ability to withstand such changes'. As the definitions clearly point out, the major objective of stress testing exercise is to assess the resilience of a segment of a financial system in the happening of rare but plausible events that can create potential vulnerabilities. 'Precise specification of the key components, entity, performance indicators, and operating conditions, depends on the nature of the exercise and one's concerns'.[5]

The exercise should also benefit an individual institution. The knowledge of the possible vulnerabilities would give a bank an opportunity to assess its strength and weaknesses vis a vis its competitions. Unless a bank knows where it stands among competition, a particular exposure might not appear to be a matter of serious concern. Also individual institutions can use the aggregate stress tests results as a tool to crosscheck the results obtained using internal models designed under different settings or sources of information. This study models and estimates a macroeconomic credit risk model that links explicitly the set of macroeconomic factors, namely, unemployment rate, housing prices, and GDP growth to US banks' probability of credit loss based on the data over 81quarterly periods, from 1989Q1 to 2009Q1.

3. Methodology:

The main goal of our study is to develop a model for credit loss distribution for a bank. Fortunately, in the literature, there seems to have been a consensus that the loss distribution be ascertained using the following formula:

Expected Loss (EL) (%) = Probability of Default (PD_t) * Loss Given Default (LGD)
Expected Loss (EL) ($) = EL (%) * Size of Exposure (Ex)

Most of the literature only discusses on developing a model (models) for PD and assumes a certain arbitrary value for LGD to come up with expected losses. The rate seems to revolve around 50%. For example in a study done by Coletti, D. et. al. (2007) for Canadian Banks justifies its use of a fixed number in the in the following manner:
'There is very little information on losses given default in Canada. A very rough proxy can be obtained by looking at the ratio of estimated assets to liabilities at the time of bankruptcy……...
For the corporate sector, the average for the 1988–2006 period is 0.35, which would suggest an expected recovery rate of 35%, or losses given bankruptcy of 65%. Since bankruptcy is the last stage of distress, and most losses occur due to missed interest payments, we believe that this recovery rate might be somewhat low, and for the purpose of the FSAP exercise have agreed with the IMF to set the recovery rate at 50%,.

The data we obtain from the Federal Reserve website allows us to directly model the percentage of expected credit losses (EL). Although, the theoretical framework of our study remains close to the traditional one, the $\mathbf{p_{j,t}}$ (probability of credit loss) value we obtain empirically with the help of the model we describe in the following paragraph would be regular PD multiplied by 50%, the arbitrary figure for the LGD. In this sense, our study is not force to make any assumption regarding LGD.

The expected loss distribution is ascertained for each sector / industry / category. Assuming there are J sectors in the economy to which a bank lends, the following logit function would be used to empirically estimate the relationship between PD and the macroeconomic variables.

$$p_{j,t} = \frac{1}{1+\exp(y_{j,t})}$$

where $\mathbf{p_{j,t}}$ measures the probability of credit loss for sector j at time t. $\mathbf{y_{j,t}}$ can be thought of as an index of economic environment in which the bank functions; $\mathbf{p_{j,t}}$ and $\mathbf{y_{j,t}}$ are negatively related, implying that a better economic environment would lead to a lower probability of loss. The use of the logit model ensures that the output of the model would take on positive values between zero and one. Using logit transformation of $\mathbf{p_{j,t}}$,

$$y_{j,t} = \ln\left(\frac{1-p_{j,t}}{p_{j,t}}\right)$$

a linear regression model is developed to estimate $y_{1,t}$.......$\mathbf{y_{j,t}}$, the sector specific macroeconomic indices. They are determined by using empirical relationships. Suppose, $\mathbf{Y_t} = (y_{1,t}; y_{2,t}; \ldots\ldots\ldots; y_{j,t})^T$, we can relate it with the macro environmental factors as (Hock-Yuen Wong, J. et. al. 2008):

$$\mathbf{y}_t = \mathbf{m} + \mathbf{A}_1\mathbf{x}_t + \cdots + \mathbf{A}_{1+s}\mathbf{x}_{t-s} + \mathbf{\Phi}_1\mathbf{y}_{t-1} + \cdots + \mathbf{\Phi}_k\mathbf{y}_{t-k} + \mathbf{v}_t$$

where **m** is a J×1 vectors of intercepts, $\mathbf{x_t}$ is M×1 vector of macroeconomic variable, A1, A2, …. A_{1+s} are each J×M coefficient matrix and ϕ1 to ϕk are each J×J coefficient matrix. $\mathbf{v_t}$ is J×1 vector of the error terms. If the nature of variable demanded non linearity, we could include the square terms, or cubic terms for that matter, with the effect of increasing the number of coefficients matrices (Misina, M. and Tessier, D. 2008).

Individual macro variables $\mathbf{x_t}$ can be modeled as:

$$\mathbf{x}_t = \mathbf{n} + \mathbf{B}_1\mathbf{x}_{t-1} + \cdots + \mathbf{B}_p\mathbf{x}_{t-p} + \mathbf{\Theta}_1\mathbf{y}_{t-1} + \cdots + \mathbf{\Theta}_q\mathbf{y}_{t-q} + \boldsymbol{\varepsilon}_t$$

where **n** and $\boldsymbol{\varepsilon_t}$ are M×1 vectors **B1, ….., Bp are** M×M & **Θ1, …., Θq** are M×J coefficient matrices. Here again we could have added squares or cubic terms as is the case for $\mathbf{y_t}$. Equations $\mathbf{y_t}$s and $\mathbf{x_t}$s define the system of equations that govern the probability of credit loss for each of the

J sectors with (j+i)×1 error terms, $\mathbf{E_t}$, and a (j+i) × (j+i) variance covariance matrix of error terms, commonly denoted by ∑. If we assume that $\mathbf{v_t}$ and $\boldsymbol{\varepsilon_t}$ are serially uncorrelated and normally distributed. Under the assumption the variance covariance structure can be specified as:

$$E = \binom{\upsilon}{\varepsilon} \sim N(0, \Sigma), \qquad \Sigma = \begin{bmatrix} \Sigma_{\upsilon} & \Sigma_{\upsilon,\varepsilon} \\ \Sigma_{\varepsilon\upsilon} & \Sigma_{\varepsilon} \end{bmatrix}$$

Since error terms in $\mathbf{v_t}$ and $\boldsymbol{\varepsilon_t}$ are correlated, we employ Seemingly Unrelated Regression (SUR) technique to solve the system of linear equations defined by $\mathbf{y_t}$s and $\mathbf{x_t}$s. Finally, we utilize the parameter estimates and the error terms with the systems of equations to simulate the future paths of joint default rates across J industries. Under the model we conduct the stress test by comparing probability distribution of credit losses under two hypothetical state of macroeconomic scenarios, baseline and adverse, as envisaged by recently concluded US stress test program. Estimated frequency distribution of period-end credit loss rate for each sector corresponding to baseline and adverse scenarios are obtained separately using future joint sector credit loss rates applying the Monte Carlo simulation method.

To simulate a vector of one-period-ahead values of sector specific credit loss rates, we simulate a random vector **r** from the multivariate normal distribution with mean being zero and variance-covariance matrix being the matrix of error terms, obtained as SUR output (SAS was used to solve the system of related regression equations $\mathbf{y_t}$s and $\mathbf{x_t}$s). This vector represents a realization of the vector of disturbances **E**. Given the estimated coefficients of the SUR system of equations and the historic values of macroeconomic variables, we determine the associated one-period-ahead values $\mathbf{y_{j,t+1}}$ and $\mathbf{x_{i,t+1}}$ for both baseline and adverse scenarios. Similarly, end of period two values ($\mathbf{y_{j,t+2}}$ and $\mathbf{x_{i,t+2}}$) can be calculated with another independently drawn **r** and the one-period ahead values previously calculated. The procedure is repeated for as many periods as needed. We simulate 1000 such paths to arrive at the distribution of credit loss. (Hock-Yuen Wong, J. et. al. 2008)

4. Variables and Data:

As already mentioned, this study attempts to mimic the stress test conducted by the US federal agencies on 19 BHCs. The macroeconomic variables/ scenarios for this study are the same as the ones used by the agencies for conducting their stress tests. The scenarios and the pairs of impact figures used by the agencies are produced in Table1.

Table-1

Year	2009			2010		
Scenarios	x1	x2	x3	x1	x2	x3
Baseline	135.7424	8.4	-2	130.3127	8.8	2.1
Adverse	123.1152	8.9	-3.3	114.4971	10.3	0.5

x1= Home price Index (2008 HPI figures adjusted for changes as per the agencies estimates)
x2 = Rate of Unemployment
x3 = Rage of growth (decline) in GDP

Charge-offs rate was used as the surrogate for the dependant variable, $\mathbf{p_{j,t}}$. Charge-offs rate is defined as "the value of loans removed from the books and charged against loss reserves measured net of recoveries as a percentage of average loans annualized". According to the data, we divide the US bank loans into six sectors; Real estate loan, Credit card loan, Other Consumer loans, Leases, Commercial & Industrial loans (C&I), and Agricultural loans. We prefer to model on charge-offs rate because we believe that charge-offs rate better represents the percentage of actual loan loss suffered by a typical US bank. GDP growth rate figures we use are expressed in current dollars as the charge-offs rates ($\mathbf{p_{j,t}}$)are all measured in current dollars.

Quarterly data for all the three macro-environment variables were also obtained from Federal Agencies' websites for years 1989 through 2009 and were adjusted to quarterly figures when necessary. After experimenting with various combinations of right-hand-side (RHS) terms developed under theoretical framework, we ended up using the following specified models for each of the loan categories:

$$y_{1,t} = b_{0,t} + b_{1,t}*x_{1,t} + b_{2,t}*x_{2,t} + b_{3,t}*x_{3,t} + b_{4,t}* y_{1,t-1} + b_{5,t} * y_{1,t-2}+ e_{1,t}$$

$$y_{2,t} = c_{0,t} + c_{1,t}*x_{1,t} + c_{2,t}*x_{2,t} + c_{3,t}*x_{3,t} + c_{4,t}* y_{2,t-1}+ c_{5,t} * y_{2,t-2} + e_{2,t}$$

$$y_{3,t} = d_{0,t} + d_{1,t}*x_{1,t} + d_{2,t}*x_{2,t}+ d_{3,t}*x_{3,t} + d_{4,t}* y_{3,t-1}+ d_{5,t} * y_{3,t-2} + e_{3,t}$$

$$y_{4,t} = f_{0,t} + f_{1,t}*x_{1,t} + f_{2,t}*x_{2,t} + f_{3,t}*x_{3,t}+ f_{4,t}* y_{4,t-1}+ f_{5,t} * y_{4,t-2} + e_{4,t}$$

$$y_{5,t} = g_{0,t} + g_{1,t}*x_{1,t} + g_{2,t}*x_{2,t} + g_{3,t}*x_{3,t} + g_{4,t}* y5_{,t-1}+ g_{5,t} * y5_{,t-1} + e_{5,t}$$

$$y_{6,t} = h_{0,t} + h_{1,t}*x_{1,t} + h_{2,t}*x_{2,t} + h_{3,t}*x_{3,t} + h_{4,t}* y_{6,t-1} + h_{5,t} * y_{6,t-2} + e_{6,t}$$

$$x_{1,t} = k_{0,t} + k_{1,t} * x_{1,t-1} + k_{2,t}*x_{1,t-2} + k_{3,t}*(x_{1,t-1})^2+ k_{4,t}*(x_{1,t-2})^2 + e_{7,t}$$

$x_{2,t} = m_{0,t} + m_{1,t} * x_{2,t-1} + m_{2,t} * x_{2,t-2} + k_{3,t} * (x_{2,t-1})^2 + k_{4,t} * (x2_{t-2})^2 + e_{7,t}$

$x_{3,t} = k_{0,t} + k_{1,t} * x_{1,t-1} + k_{2,t} * x_{1,t-2} + k_{3,t} * (x_{3,t-1})^2 + k_{4,t} * (x_{3,t-2})^2 + e_{7,t}$

where y_1 denotes 'logit transformation of real estate charge-off rates'. Similarly, y_2 through y_6 denote similar logit transformations of the charge-offs rates for Credit Card Loan, Other Consumer Loan, Leases, C&I loans, and Agricultural Loans respectively. Variables x_1, x_2, and x_3 represent 'HPI', 'Unemployment rate', and 'GDP growth rate' respectively. Likewise, $x_{1,t-1}$ represents 1st lag of x1 & $x_{1,t-2}$ the 2nd lag of x_1. $(x_{1,t-1})$ ^2 represents 1st lag of x_1 squared and $(x_{1,t-2})$^2 denotes 2nd lag of x_1 squared and so on. The right-hand side (RHS) coefficients with zero superscript denote intercepts and all coefficients having subscripts one through five denote the regression slope coefficients or weights. We expect x_1 and x_3 to have negative relation with $\mathbf{p}_{j,t}$ credit loss rate (hence positive relation with y_t) and x_2 to have positive relation with $\mathbf{p}_{j,t}$ (negative relation with y_t).

5. Results:

The first set of results reported in this section is based on the regression models given in section 4. The second set (Table-3 & Figure-1 to Figure-4) reports the mean and VaR values of loss distributions for each of the six economic sectors, generated according to the procedure outlined in section 3.

Table-2 SUR Output:

	Regresand	Constant	Regresor				
Model	y1		x1	x2	x3	y1t1	y1t2
Fitted Values		-0.70293	0.00099	-0.0767	0.015808	0.822865	0.246192
Pr > |t|		0.1414	0.0761	0.0573	0.3217	<.0001	0.0177
Model	y2		x1	x2	x3	y2t1	y2t2
Fitted Values		0.21407	0.000018	-0.00806	0.021763	0.672988	0.201499
Pr > |t|		0.2903	0.9251	0.4502	<.0001	<.0001	0.0326
Model	y3		x1	x2	x3	y3t1	y3t2
Fitted Values		0.93795	0.00073	-0.0265	0.027289	0.371432	0.394383
Pr > |t|		0.0089	0.0178	0.0593	0.0002	0.0002	0.0001
Model	y4		x1	x2	x3	y4t1	y4t2
Fitted Values		0.049176	0.000343	-0.05025	0.051626	0.672146	0.207028

Pr > |t|		0.9314	0.617	0.2204	0.0099	<.0001	0.0349
Model	y5		x1	x2	x3	y5t1	y5t2
Fitted							
Values		-0.45888	0.000185	-0.05949	0.047235	0.794377	0.173969
Pr > |t|		0.1286	0.6368	0.0151	0.0001	<.0001	0.0915
Model	y6		x1	x2	x3	y6t1	y6t2
Fitted							
Values		0.799372	0.000849	-0.0053	0.061787	0.539615	0.242077
Pr > |t|		0.2216	0.3925	0.9204	0.0212	<.0001	0.0133
Model	x1		x1t1	x1t2	x1t12	x1t22	
Fitted							
Values		-15.5019	0.73425	0.40589	0.001289	-0.00155	
Pr > |t|		0.0003	0.1247	0.4125	0.0573	0.0301	
Model	x2		x2t1	x2t2	x2t12	x2t22	
Fitted							
Values		0.043692	1.73202	-0.70677	0.003179	-0.00825	
Pr > |t|		0.9279	<.0001	0.0532	0.9172	0.7831	
Model	x3		x3t1	x3t2	x3t12	x3t22	
Fitted							
Values		1.2597	0.600638	0.408295	-0.03084	-0.01725	
Pr > |t|		0.3046	0.0009	0.3775	0.1094	0.6824	

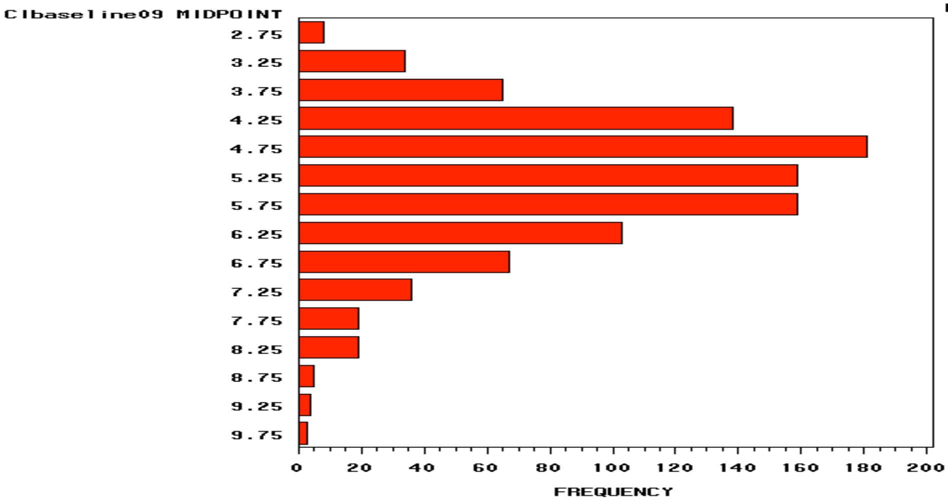
SUR Output: The SUR estimation results are presented in Table2. Both, for probability of loss models (y_js) as well as for macroeconomic variable models (x_js), the results shown in the table are obtained by removing the insignificant variables from the more general specification laid out in section 3. According to Table 2, the impact of macroeconomic variables on credit loss probabilities is intuitively plausible and fairly consistent across sectors. The results mean that the credit loss would become higher if GDP growth deteriorates or housing price declines and would be lower if the unemployment level rises; and vice versa.

However the degree and the significance of the impact of the macro economic variables on each of sector credit loss (default rate) is different. The results show that a change in GDP will have the largest impact on agricultural sector credit losses on the one hand while change in GDP is expected to have least significant impact on the change of real estate loan on the other. Increase in unemployment rate is accompanied by significant decrease in credit loss probability only for C&I loans and to some extent for real estate and other consumer loans. Unemployment rate weakly explains the variation in credit losses of Credit Cards, Lease, and Agricultural loans. The effect of variation in housing prices is significant only for ‘Other Consumer Loan’ losses. Our results show that the choice of HPI as a macro economic factor to explain loan losses is poor. All the coefficients of both 1st and 2nd lags of y_js (logit transformed values of sectoral loan loss rate) are positive and significant for all the sectors. This points to the fact that there exists a positive autocorrelation in default rates, meaning a macroeconomic shock can produce a prolonged impact on the credit loss rates. This phenomenon is also reflected in Monte Carlo stress test results for most of the sectors. It indicates the possibility of development of the default rate over a time horizon that is longer than the duration of the macro-environmental shock contributing to the longer term impact of the stress.

We modeled the macroeconomic variables as AR(2) process. While linear model seems to explain the path of the 'Unemployment rate' and quadratic AR(1) is found to be more appropriate for explaining the path of GDP growth; neither linear non quadratic AR(2) models seem to be suitably explain the movement of 'HPI'. This might be one reason for HPI's poor explanation of various sectoral credit loss rates, including real estate.

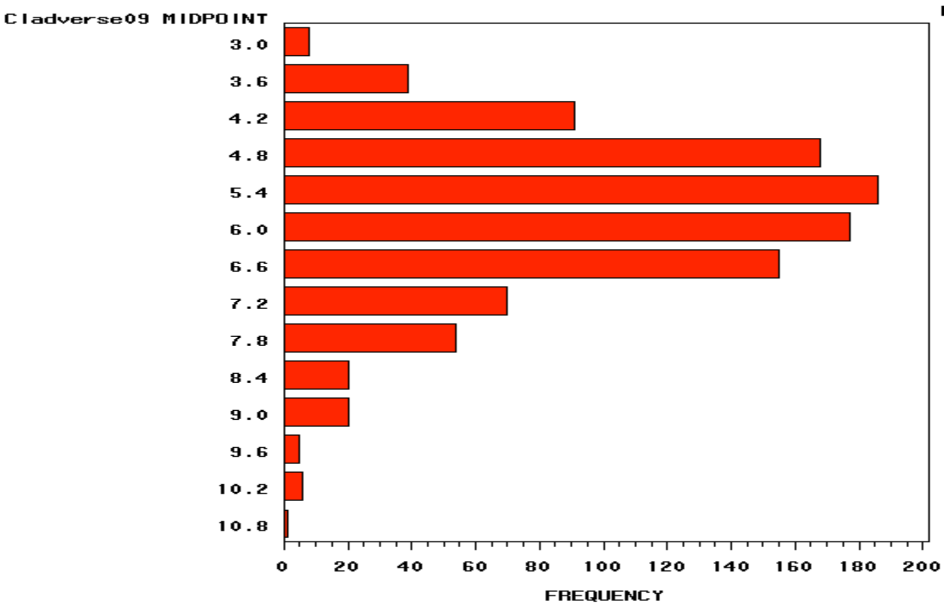
Monte Carlo Simulation and stress test Output: We now analyze the simulated paths of future credit loss rates based on the SUR estimates and describe the associated distributions thereof. In the interest of the length of our study, we only considered the effect of a combined macro-economic scenarios rather than modeling each scenario one at a time. The Monte Carlo simulation we present here depicts the total effect of a simultaneous decrease in housing prices, decrease in GDP growth, and increase in rate of unemployment on each of the six sectors. In each case, the magnitudes of the shocks are the same as in those scenarios specified by the agencies (Table1). Since we only consider the worst-case scenarios; the result should give insight into the maximum range of loss that is likely to occur. As an example, we depict the impact of the combined scenario on C&I loan losses in figures 1 through 4. Figures 1&2 show the results for baseline and adverse scenarios for 2009 and figures 4&5 show the corresponding scenarios results for 2010. All the figures have their expected heavy tail. As we add more shock in the second year (2010), the tail gets heavier. The 95th percentile of the VaR jumps up by more than 10% for baseline case and by more than 11% for more adverse scenario as we move from 2009 to 2010.

Figure1



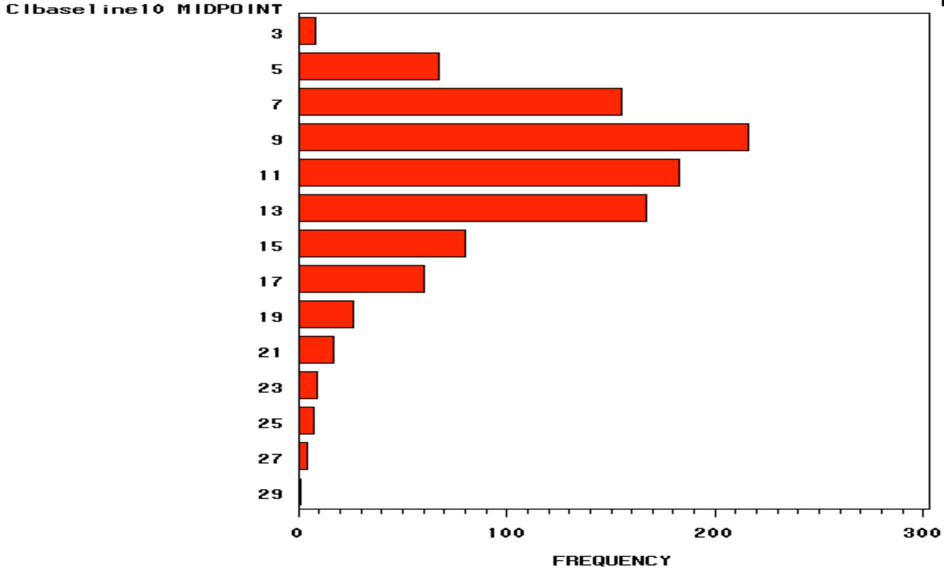
Clbaseline09 MIDPOINT	FREQ.	CUM. FREQ.	PCT.	CUM. PCT.
2.75	8	8	0.8	0.8
3.25	34	42	3.4	4.2
3.75	65	107	6.5	10.7
4.25	138	245	13.8	24.5
4.75	181	426	18.1	42.6
5.25	159	585	15.9	58.5
5.75	159	744	15.9	74.4
6.25	103	847	10.3	84.7
6.75	67	914	6.7	91.4
7.25	36	950	3.6	95.0
7.75	19	969	1.9	96.9
8.25	19	988	1.9	98.8
8.75	5	993	0.5	99.3
9.25	4	997	0.4	99.7
9.75	3	1000	0.3	100.0

Figure2



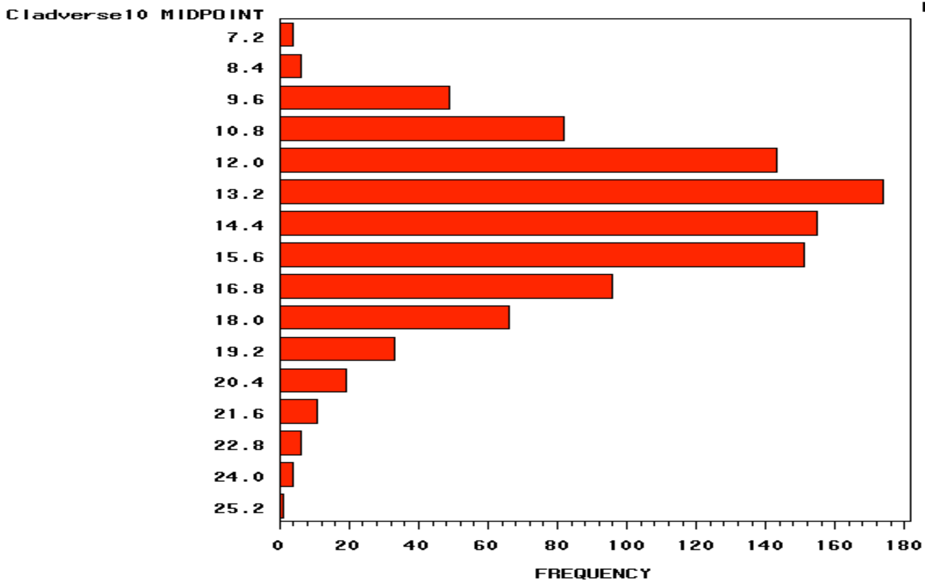
Cladverse09 MIDPOINT	FREQ.	CUM. FREQ.	PCT.	CUM. PCT.
3.0	8	8	0.8	0.8
3.6	39	47	3.9	4.7
4.2	91	138	9.1	13.8
4.8	168	306	16.8	30.6
5.4	186	492	18.6	49.2
6.0	177	669	17.7	66.9
6.6	155	824	15.5	82.4
7.2	70	894	7.0	89.4
7.8	54	948	5.4	94.8
8.4	20	968	2.0	96.8
9.0	20	988	2.0	98.8
9.6	5	993	0.5	99.3
10.2	6	999	0.6	99.9
10.8	1	1000	0.1	100.0

Figure3



FREQ.	CUM. FREQ.	PCT.	CUM. PCT.
8	8	0.8	0.8
67	75	6.7	7.5
155	230	15.5	23.0
216	446	21.6	44.6
183	629	18.3	62.9
167	796	16.7	79.6
80	876	8.0	87.6
60	936	6.0	93.6
26	962	2.6	96.2
17	979	1.7	97.9
9	988	0.9	98.8
7	995	0.7	99.5
4	999	0.4	99.9
1	1000	0.1	100.0

Figure4



FREQ.	CUM. FREQ.	PCT.	CUM. PCT.
4	4	0.4	0.4
6	10	0.6	1.0
49	59	4.9	5.9
82	141	8.2	14.1
143	284	14.3	28.4
174	458	17.4	45.8
155	613	15.5	61.3
151	764	15.1	76.4
96	860	9.6	86.0
66	926	6.6	92.6
33	959	3.3	95.9
19	978	1.9	97.8
11	989	1.1	98.9
6	995	0.6	99.5
4	999	0.4	99.9
1	1000	0.1	100.0

Table3 summarizes the results of Monte Carlo simulation to credit loss distribution under stress for all sectors over the two year period. On average, VaR figures for 2010 are much higher than those in 2009 across all the sectors. Also, as the last column of table3 reports, the Real estate sector has the highest risk of deviation in credit loss followed by industrial and commercial loan sector. Because of the random nature of the simulation, both of those deviations take place under 2010 baseline scenario rather than under more adverse one. In the following paragraph, we discuss some other interesting aspects of the stress test results.

Table3

		Mean	95% VaR	99% VaR	Mean–99% VaR
Real Estate	Baseline09	3.8	5.8	7.7	3.9
	Adverse09	4.1	7.0	8.1	4.0
	Baseline10	7.5	19.0	24.0	16.5
	Adverse10	10.0	16.0	18.6	8.6
Credit Cards	Baseline09	2.2	2.7	3.0	0.8
	Adverse09	2.3	2.75	3.2	0.9
	Baseline10	2.65	3.7	4.2	1.55
	Adverse10	7.3	8.65	9.2	1.9
Other Consumer Loan	Baseline09	2.93	3.7	4.0	1.07
	Adverse09	3.1	3.75	4.2	1.1
	Baseline10	2.7	3.5	4.2	1.5
	Adverse10	3.18	4.05	4.73	1.55
Leases	Baseline09	2.1	3.6	5.25	3.15
	Adverse09	3.58	5.97	8.7	5.12
	Baseline10	6.1	10.3	12.3	6.2
	Adverse10	6.2	13.4	18	11.8
Commercial & Industrial Loan	Baseline09	5.0	6.65	8.65	3.65
	Adverse09	5.45	7.85	9.3	3.85
	Baseline10	9.65	17.95	23.5	13.85
	Adverse10	13.65	19.0	21.8	8.15
Agriculture Loan	Baseline09	.48	1.33	1.87	1.39
	Adverse09	.50	1.23	2.08	1.58
	Baseline10	.70	3.0	4.75	4.05
	Adverse10	.58	1.6	2.1	1.52

Agricultural sector seems to be relatively immune to the shock with the maximum stress of about five percent of credit loss. This is consistent with the regression results which show that sensitivity of agricultural sector credit loss is highly insignificant with two out of three microeconomic variables. It is interesting to note that the maximum on agricultural loan loss occurs at baseline scenarios not with the adverse ones, which means more loans to the agricultural sector can play an insurance role if the worst case scenario materialized. Interestingly, consumer loans which include credit card and other consumer loan segments, also seems to be fairly immune to stress compared other categories despite high unemployment shocks in successive periods. Particularly, other consumer loan loss level remains the same irrespective of stress severity or duration.

6. Summary & Conclusion:

The macroeconomic credit risk models are suitable for macro stress testing purposes because they establish explicit links between default rates and macro factors. We have estimated a macroeconomic credit risk model for the US banking sector to gauge the impact of economic scenarios on the credit risk of US banks' sectoral credit portfolios. A distinctive aspect of this study is that it is constrained; it utilizes only those three macro-economic variables which were used by US agencies for administrating stress test to 19 US BHCs. We have basically attempted to test the quality and the magnitude of shock (macro-environmental variables) employed by the Federal Agencies.

The empirical regression results suggest that, except for the real estate sector, there is a significant and fairly robust relationship between credit loss rates and the GDP growth across all credit sectors. However, the unemployment rate effect is not equally strong across all sectors. Unemployment appears to play no significant role in explaining credit losses of the credit card, lease loans and agricultural sectors and only plays a marginal role in explaining real estate and consumer loan credit losses. The results suggest that movement in HPI is the poorest predictor of the credit losses for US banking sectors across all the sectors studied except for the losses in 'Other Consumer Loan' category. It explains only marginally the variation in the credit loss of even the real estate investment.

The results of the stress scenario analyses suggest that the current credit risks stemming from various loan sectors are fairly high; ranging from the lowest in the agricultural sector to the highest in the real estate sector. A major reason for the severe stress test results on real estate could be the effect of current housing market crash and resultant huge default in sub-prime mortgage market. The model's prediction of relatively lower probability of credit loss in agricultural sector under severe economic environment is consistent with the economic assumption of low correlation of farming cash flow with that of other sectors in the economy. On the middle of the risk spectrum close to real estate lie the C&I and Lease loans. The level of stress on credit card as well as other consumers' loan sector seems to be mild. Given the state of economy, the results seem fairly consistent.

Some aspects of our macroeconomic credit risk factors would certainly require further elaboration. First, it is unfortunate that we cannot find a major role played by the housing price index. This outcome is consistent with the fact that AR(2) modeling of housing prices both in the form of linear and quadratic is not suitable in explaining its path. A more consistent picture could be obtained by using other variables like interest rates, public default policy and so on. This is beyond the scope of the study because we confined our study only to three macro economic variables used by the federal agencies. It should also be noted down that this study did not include the mortgage loan sector in its analysis. Actually we only modeled six instead of 12 sectors and subsectors included in the US bank regulators' recently concluded stress test. This omission/aggregation might have resulted in poor explanatory power of the macro variables, particularly the housing price index. It should further be noted that despite the risk of oversimplification, we used charged-offs rate in our analysis because of the easy availability of data and simplification of our analysis. Hence the results might have just reflected a relatively crude approximation. Moreover, attempting to detect indications of potential crises in macro stress testing exercises needs sufficiently long time horizons. However, extending the time horizon poses a number of new challenges from the modeling point of view.

An assessment of financial system stability and potential vulnerabilities is a complex exercise, because of the nature of the entities comprising the financial system and the wide range of possible scenarios that may result in abnormal operating conditions. The study is limited by its focus on a relatively aggregated set of loan sectors US banks' lends and restricted set of macroeconomic variables that might have significant bearing on the credit losses. However, the tools underlying the analysis in this paper are general and can be easily extended to apply large number of sectors and scenarios.

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