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STRESS TESTING CREDIT RISK: A SURVEY OF AUTHORITIES' APPROACHES

Antonella Foglia[*]

Abstract

This paper reviews the quantitative methods developed at selected authorities for stress testing credit risk, focusing in particular on the methods used to link macroeconomic drivers of stress with bank-specific measures of credit risk (macro stress test). Authorities with a mandate for financial stability are particularly interested in quantifying the macro-to-micro linkages and have developed specific modeling expertise in this field. Stress testing credit risk is also an essential element of the Basel II Framework. The paper highlights recent developments in macro stress testing and details a number of methodological challenges that may be useful for supervisors in their review process of banks' models as required by Basel II. It also contributes to the on-going macroprudential research efforts to integrate macroeconomic oversight and prudential supervision, for early detection of key vulnerabilities and assessment of macro-financial linkages.

JEL Classification: E32; E37; G21.

Keywords: Macro stress testing, financial stability, macro-prudential analysis, credit risk, probability of default.

Contents

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1. Introduction

This paper reviews the quantitative methods developed at selected central banks and supervisory authorities to assess the vulnerabilities of financial systems to credit risk, focusing in particular on the stress test methods used to link macroeconomic drivers of stress with bank-specific measures of credit risk. It is based on a number of recent papers and internal documentation provided by supervisors and central banks. The models included in this survey are listed in Table 1.

Financial sector stress tests provide information on a system's potential losses under exceptional but plausible shocks, helping policymakers to assess the significance of the system's vulnerabilities. The value added by system stress tests derives from a consultative process that combines a forward-looking macroeconomic perspective, a focus on the financial system as a whole, and a uniform approach to the assessment of risk exposures across institutions.[1] System stress tests can complement those of individual institutions, and provide a cross-check for other types of analysis.

For many authorities the practice of stress testing was introduced as part of the Financial Sector Assessment Programs (FSAPs) conducted by the IMF and the World Bank. The FSAP stress tests stimulated widespread research interest in developing new techniques and many additional studies are under way. The survey includes methodologies that were used during the FSAPs and other studies developed afterwards at the individual agencies.

The focus on credit risk and on the "macro-to-micro" models reflects a number of concerns: (i) stress testing credit risk is an essential element of the Basel II Framework (BCBS, 2005) and some stress testing requirements of Basel II – such as the IRB-cyclicality stress tests (par. 435-437) and the forward-looking stress testing in the ICAAP (par. 726) – are formulated by making explicit reference to the economic cycle (e.g. mild recession scenarios) and the macroeconomic background of a stress event; (ii) in this area, sound industry practices have not yet been established and the translation of a stress event defined in terms of macroeconomic variables into movements in bank micro-variables often represents a challenge for individual banks; (iii) both in the FSAP context and more generally for financial stability analysis, it is also one of the modeling areas most in need of further development.[2]

Because of their mandate for financial stability, central banks and supervisors are particularly interested in quantifying the macro-to-micro linkages and have developed specific modeling expertise. Such expertise can be a useful starting point to develop a common analytical background as, in this field, supervisors and banks often face the same methodological challenges. Sections 2-6 review the current stress testing practices across various supervision and financial stability authorities, comparing features and outlining the latest developments. Section 7 discusses a number of technical issues that may be relevant for supervisors in reviewing the Basel II stress testing requirements. As methods to better incorporate macro/system-wide conditions as drivers of default risk and macro-stress testing in general are among the main tools of supervisors with a "macroprudential" orientation, the

[1] See IMF and World Bank (2003).

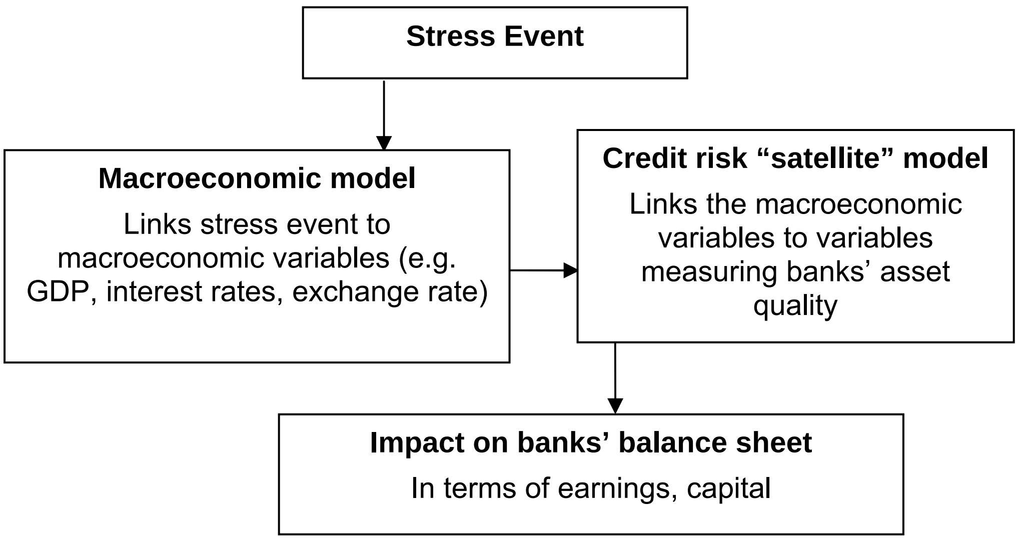
[2] See the discussion in Swinburne (2007).

discussion can also contribute to the on-going analytical efforts to integrate macroeconomic oversight and prudential supervision, as recently advocated by the Financial Stability Forum.[3] Section 8 concludes and sets out a research agenda.

2. The stress testing process

In all the approaches surveyed, system-focused stress testing can be seen as a multi-stage process as shown in Figure 1.

Figure 1: Credit risk - a typical macro stress testing process[4]



Given the origin and purpose of FSAPs, the first step is to put together a coherent stress test scenario, typically using a macro-econometric model. The scenario or the model may include endogenous policy responses. Given that such models do not generally include financial sector variables, the stress testing framework usually includes "satellite" models: (i) to map macroeconomic variables to some "key" financial variables, such as asset prices (typically, housing prices) and credit growth and (ii) to map macroeconomic and financial variables into financial sector measures of asset quality and potential credit losses. Total bank losses are calculated by aggregating credit and market losses, in some cases including additional allowances for the impact on net interest income and on funding costs.[5] Losses are then compared to the buffers of profits and capital.

3 See Financial Stability Forum (2008).

4 This figure is adapted from Čihák (2007). For an overview of a typical stress testing process see also Jones, Hilbers, and Slack (2004).

5 In fact, many of today's macro-scenario stress tests also consider the effects of macroeconomic shocks on banks' earnings, taking into account factors such as growth in lending and credit conditions.

Table 1 summarizes the common stress testing framework of the various agencies and classifies the models used in the different stages of the process according to their methodologies and assumptions.

This approach has valuable strengths, but it also suffers from some important limitations. Generally, current models are weak in the treatment of key financial system interactions. For example, they only rarely model the impact of funding and market liquidity stresses or the correlation between credit, market and liquidity risks. Feedback effects are often absent or modeled in rudimentary fashion. Existing methods are generally unable to endogenously account for cross-border transmission channels for risk, including cross-border contagion between financial institutions. They often ignore potential non-linearities and structural breaks in estimated relationships. In addition, some approaches focus on a projected conditional mean stress scenario outcome and fail to consider the cross-sectional distribution of the losses that will be borne by individual financial institutions in a real-world stress situation.[6]

The market turmoil that began in mid-2007 in the US "subprime" mortgage market has highlighted the crucial importance of the links between credit risk, funding liquidity risk, market risk, and counterparty credit risk as well as other limitations of current stress tests. Addressing these limitations is therefore an important priority for both banks and financial stability authorities, as is shown by the recent initiatives undertaken by various international bodies.[7] Some of the enhancements designed to overcome specific problems of traditional stress testing techniques are addressed in the latest research projects initiated by the various agencies and are also reviewed in the following Sections.

3. The design of the macroeconomic stress scenario

In macro-scenario stress testing, the financial sector effects of multiple shocks to macroeconomic and financial variables are estimated using different models. The stress scenario's effects on macroeconomic conditions are typically measured using: (i) a structural econometric model, (ii) vector autoregressive methods, and (iii) pure statistical approaches.

Many stress testing approaches use an existing structural macroeconomic model (e.g. one used by the central bank for forecasts and policy analysis) to project the levels of key macroeconomic indicators under the stress conditions assumed. A set of initial shocks are taken as exogenous inputs, and their interactions with the other macroeconomic variables are projected over the scenario horizon. The simulations will produce a range of economic and financial variables as outputs, such as GDP, interest rates, the exchange rate, and other variables.[8]

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6 The strengths and limitations of traditional stress tests were examined extensively at the ECB conference on "Simulating Financial Instability", Frankfurt, 12-13 July 2007.

7 As for the work of the Basel Committee related on stress testing liquidity risk, see BCBS (2008).

8 Often macro models do not include key financial variables such as credit growth or asset price behaviour in their specification. However, these variables are typically found to be significant in explaining credit quality. An example of such "satellite" macro models is proposed by Norges Bank (Berge and Lindquist, 2007). Household credit is modelled as a function of housing prices, the interest rate, the turnover rate, demography, housing stock, income, and unemployment. Housing prices, in turn, are determined by housing credit, interest rates, unemployment, income, housing stock, and expectations.

The use of structural models imposes consistency across predicted values in the stress scenario. Moreover, they may allow for endogenous policy reactions to the initial shock. The feasibility of the approach for stress scenario analysis varies with modeling expertise and the type of macro model. Some considerations involved in using a macro structural model are discussed in Jones, Hilbers and Slack (2004), such as the choice of the baseline assumptions, the policy responses, the time horizon and which variables are assumed fixed and which are shocked. Another frequently mentioned concern is the inability of linear models to capture relationships between macroeconomic variables that may become non-linear at times of stress, as well as the difficulty in determining the likelihood of a specific macro-scenario.

In the context of the FSAP exercise, all the authorities used the domestic macroeconomic models developed for monetary policy purposes. However, since a domestic model does not provide all the information that is needed when shocks arise from international linkages, in some cases the models were extended to incorporate international effects.

If a well-developed macroeconomic model is not available or it is not considered feasible to generate consistent relevant shocks, a second possibility is vector autoregression (VAR) or vector error correction models (VECM). In these models, a set of macroeconomic variables are jointly affected by the initial shock, and the vector process is used to project the stress scenario's combined impact on this set of variables. VAR models have appeal because they are a flexible and relatively simple way of producing a set of mutually consistent shocks, although they do not include the economic structure that is incorporated in the macro modelling approach.[9] As detailed in Table 1, these models are used in the studies developed at the central banks of the UK (BoE), Japan (BoJ), Spain (BoS), the Netherlands (DNB), and at the ECB.

In its Financial System Report (2007), the BoJ estimates a VAR model comprised of five macroeconomic variables (GDP, inflation rate, bank loans outstanding, effective exchange rate, and the overnight call rate). Van den End, Hoeberichts, and Tabbae (2006, DNB) and Jiménez and Mencía (2007, BoS) use a VAR structure to model the response to a shock of the two macroeconomic factors included in an auxiliary credit risk model (see Section 4).[10] The model used by Castrén, Dées, and Zaher (2008, ECB) is a Global Vector Autoregressive (GVAR) model based on country- or region-specific VECM, where domestic and foreign variables interact simultaneously; the endogenous variables included in the country-specific models are real output, the rate of inflation, real equity prices, and short and long-term interest rates.[11] The BoE prototype model uses a two-country version of the GVAR

9 As noted by Åsberg and Shahnazarian (2008, Sveriges Riksbank), an important operational advantage of VAR models based on a few variables is that they do not require particularly substantial resources, and their results are easy to interpret.

10 Van den End, Hoeberichts, and Tabbae (2006, DNB) also use a well-developed macro model (Norkmon/Nigem) to simulate macro stress scenarios. The projected path of macro variables (GDP, interest rate) is subsequently used as input in a VAR model (see Section 4).

11 The GVAR is a set of 26 VAR(2,1) models specific to 25 countries and one specific to the euro area. Each model includes a set of domestic/regional macroeconomic variables (usually five or six) and a vector of foreign variables specific to the respective country/region. In addition to the usual macro-variables, the specification also includes the stock market return.

approach, modeling the UK and US economies only, with the same macroeconomic variables as in the ECB paper.[12]

In contrast to structural macro-econometric and VAR-VECM models, the Oesterreichische Nationalbank (OeNB), in its Systemic Risk Monitor (SRM) has developed a pure statistical approach to scenario design.[13] Macroeconomic and financial variables are modeled through a multivariate t-copula. The copula approach has two important advantages. First, the marginal distributions can be different from the multivariate distribution that characterizes the joint behavior of the variables. Second, the co-dependence between the macro-financial variables displays tail-dependence (i.e., "correlation" increases under stress scenarios). However, as a "purely" statistical approach, it is not as well suited for policy analysis, because the transmission mechanism from shocks to impact is not easy to interpret.

4. The credit risk models

Both the structural econometric and the VAR approaches require a method to map macroeconomic variables into indicators that can be used to estimate the implications of the stress scenario for banks' balance sheets. Macroeconomic models, in fact, typically do not include a measure of credit risk, so the second stage of a stress testing process usually involves estimating satellite or auxiliary models that link a measure of credit risk to the macroeconomic model variables, thus mapping external shocks onto bank's asset quality shocks.

In these credit-quality regression models, loan performance measures are typically related to measures of macroeconomic conditions. Blaschke, Jones, Majnoni and Martinez Peria (2001) report an example in which the non-performing loan ratio (NPL) is regressed against the nominal interest rate, the inflation rate, the change in real GDP, and the change in the terms of trade. The coefficients of the regression provide an estimate of the sensitivity of loan performance to those macroeconomic factors.

The assumption is that loan quality is sensitive to the economic cycle. The estimation strategy normally requires the selection of an initial set of macroeconomic and financial variables that, according to theory and empirical evidence, affect credit risk. Variables such as economic growth, unemployment, interest rates, equity prices and corporate bond spreads contribute to default risk. In particular, interest rates are a crucial variable as they represent the direct cost of borrowing. Among alternative specifications, the preferred one is selected on the basis of the consistency of macroeconomic variables with economic theory (that is, the variable's sign has to be "right", otherwise it is dropped), and on the specifications' goodness of fit.[14]

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12 In the BoE approach the GVAR is a set of two VAR(2,1) models, one for the UK and one for the US; the UK is treated as a small open economy and the US represents the rest of the world. The BoE approach (discussed in Haldane, Hall, and Pezzini, 2007) models income, market and credit risk jointly as well as some key feedbacks across banks, such as network and market liquidity externalities; a prototype version of the model is described in Alessandri, Gai, Kapadia, Mora, and Puhr (2007, BoE).

13 SRM is a model developed by the Austrian central bank for systemic financial stability analysis and stress testing; the framework includes credit risk, market risk and interbank contagion risk. See Boss, Breuer, Elsinger, Jandacka, Krenn, Lehar, Puhr, and Summer (2006, OeNB).

14 A detailed description of such an estimation strategy is provided in Segoviano (2006).

A satellite model that treats the macroeconomic variables as exogenous ignores – by construction – the feedback effects from a situation of distress in the banking system to the macro-economy, which is one of the many limitations of traditional stress testing. Castrén, Dèes, and Zaher (2008, ECB) argue that there are several possible reasons for this approach, such as a lack of sufficiently long time-series data, more modeling flexibility, easiness of implementation and interpretation.[15]

Unlike the macroeconomic model, the credit risk satellite model can be estimated on data for individual banks and even individual borrowers. Various modeling techniques have been applied so far, mostly depending on data availability. Čihák (2007) divides approaches into two classes: one based on data on loan performance, such as NPLs, loan loss provisions (LLPs), and historical default rates; the other based on micro-level data related to the default risk of the household and/or the corporate sector. The same classification is used in this section, highlighting the distinct features of the different approaches. The capstone of many credit risk satellite models is the estimation of the credit portfolio loss distribution, which summarizes its overall risk profile and permits a thorough assessment of the impact of a shock (see Section 6).

4.1. Models based on loan performance

In this approach the key dependent variables are the NPL ratio, the LLP ratio, and historical default frequencies. As shown in Table 1, these models include various macroeconomic factors, ranging in a number from two to five depending on the country. In some cases variables more directly related to the creditworthiness of firms are added, such as measures of indebtedness; in other cases, market-based indicators of credit risk, such as equity prices and corporate bond spreads, are also used.[16]

As regards the level of aggregation, and depending on the availability of data, models based on loan performance data can be run at aggregate level, at industry level or even at the level of the individual banks.

Alessandri, Gai, Kapadia, Mora, and Puhr (2007, BoE) and Marcucci and Quagliariello (2005, Bank of Italy, BoI) model credit quality using observed default frequencies at household/corporate level of aggregation. Aggregate data allow Marcucci and Quagliariello to use a VAR approach to estimate the satellite credit risk model, whereas previously VAR models had been used in the first stage of the stress testing process.[17] Their model for the corporate sector includes the default rate and four macroeconomic variables (output gap, inflation, short-term interest rate and real exchange rate). In the identification scheme, the

[15] The analysis of feedback effects is a core concern for financial stability work, as the recent intensification of the financial crisis has aggravated the downside risks to growth. The typical econometric framework that allows for feedback effects between the financial sector and the real economy is the VAR methodology, in which a vector of endogenous variables includes both a measure of credit quality (or another proxy of financial distress) and aggregate economic variables associated with the state of the business cycle (see the discussion in Chan-Lau, 2006). Two studies reviewed in this section actually apply this methodology: Marcucci and Quagliariello (2005, BoI), who explicitly address this issue, and Åsberg and Shahnazarian (2008, Sveriges Riksbank) who, however, discuss only the sensitivity of credit risk to shocks to the macroeconomic variables.

[16] Introducing market variables such as interest rates, foreign exchange rates, equity and real estate price indices, into credit risk models is a way of explicitly integrating the analysis of market and credit risks.

[17] Åsberg and Shahnazarian (2008, Sveriges Riksbank) also use a similar approach, estimating a VECM model (see sub-section 4.2).

default rate is assumed to be contemporaneously exogenous to the output gap and all the other macroeconomic variables. The impulse response functions indicate significant impact of the various macroeconomic variables (except inflation) on the default rate.

The credit risk models of the German Bundesbank (DB), Lehmann and Manz (2006, SNB) and Van den End, Hoeberichts, and Tabbae (2006, DNB) use the LLP ratio to measure credit quality at the individual bank level, with static or dynamic panel data estimation. The panel estimation of individual banks' LLPs controls for individual bank characteristics that affect credit risk and captures the banks' different sensitivities to macroeconomic developments.

Fiori, Foglia and Iannotti (2008, BoI), Jiménez and Mencía (2007, BoS) and the OeNB's SRM all model historical default rates grouped by industry.[18] The sectoral breakdown allows the use of different macroeconomic variables to explain default frequencies in different industry sectors and the inclusion of sector-specific explanatory variables to improve the goodness-of-fit. For example, in the OeNB's SRM model, the number of statistically and economically most reasonable explanatory macroeconomic variables ranges from two to four depending on the sector, with some variables common to all the sectors.[19]

In such models, macroeconomic variables that are found to be significant for many sectors represent the systematic risk component; *inter-sectoral* default correlation is due to the common dependence on the systematic component. The idiosyncratic risk component is measured by potential sector-specific variables and by the residuals of the sectoral equations. When systematic risk is taken into account, default events should be independent, and the cross-equation residuals should be uncorrelated (conditional independence). If that is not the case, macroeconomic factors do not fully explain the default correlations across sectors; an important implication is that a portfolio's credit risk can be significantly underestimated (see discussion in Section 7).

Fiori, Foglia and Iannotti (2008, BoI) and Jiménez and Mencía (2007, BoS) argue that micro-contagion effects between sectors create an additional channel of default correlation. Using a different estimation strategy, both papers allow sectoral default frequencies to depend on macroeconomic conditions as well as on latent factors that can capture contagion effects. Accordingly, they are able to distinguish "cyclical" sectors (those highly sensitive to systematic risk) from those more dependent on idiosyncratic risk. Both studies find significant micro-contagion effects and similarly identify agriculture, manufacturing, construction, and trade as "cyclical" sectors, mining and quarrying and utilities as "idiosyncratic".[20]

The use of loan performance data to measure credit quality raises some important questions. Loan performance is a lagged or "retrospective" indicator of asset quality, in that it reflects past defaults. Loan loss provisioning rules may vary across jurisdictions and legal

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18 In addition to ten industry equations, Jiménez and Mencía (2007, BoS) model one mortgage sector and a sector of consumer loans.

19 GDP or industrial production, the unemployment rate, investment in equipment, and the price of oil are significant in more than one sector; see Boss (2003), pp. 64-82 for an explanation of the model selection procedure.

20 Latent factors are orthogonal to the observable macroeconomic conditions. Jiménez and Mencía (2007, BoS) use a Kalman filter to deal with the unobserved factors; Fiori, Foglia and Iannotti (2008, BoI) use factor analysis to identify the latent factors that account for the contagion component. Moreover, while Jiménez and Mencía (2007, BoS) find only pure cross-sector contagion effects, Fiori, Foglia and Iannotti (2008, BoI) find two latent variables, one accounting for pure contagion and one representing a diversification effect.

protocols may determine whether or not institutions actually write off non-performing loans or keep them on their financial statements with appropriate provisioning; variations in LLPs, in addition, may be only partly driven by changes in credit risk; other bank-specific factors, such as income-smoothing policies, might also come into play.

Another frequent problem in interpreting macroeconomic models of credit risk concerns the use of linear statistical models: the linear approximation may be reasonable when shocks are small, but when they are large, non-linearities are likely to be important. In fact, almost all the studies reviewed here, following Wilson (1997), have used non-linear specifications, such as the logit and probit transformation, to model the default rate. As Van den End, Hoeberichts, and Tabbae (2006, DNB) argue, non-linear transformations of the default rate extend the domain of the dependent variable to negative values and take into account the possible non-linear relationships between macroeconomic variables and the default rate that are likely in stress situations.

4.2. Models based on data for individual borrowers

In this approach the credit risk satellite model is estimated on individual borrower data. In this case, the model specification may also include macro-financial data as explanatory variables. When no macroeconomic variables are included, an additional satellite model may be used to link the macro-financial variables to borrower-specific data.

Using a database of yearly accounting data for all limited liability companies in Norway, Eklund, Larsen and Berhardsen (2001, Norges Bank) relate the probability of default to borrower characteristics such as firm age, size, industry and to accounting variables measuring corporate earnings, liquidity, and financial strength. In this model, the projected figures for the main macroeconomic variables are used to estimate the future income statement and balance sheet of each company and on this basis to calculate individual probabilities of default (PDs). These PDs are then aggregated to produce an estimate of the banking sector's total loan loss.

Individual measures of credit quality can be exploited to estimate a direct relationship with macroeconomic variables. Åsberg and Shahnazarian (2008, Sveriges Riksbank) and Castren, Fitzpatrick and Sydow (2008, ECB) use Moody's KMV EDFs to model the average credit quality of listed companies. The EDF is a forward-looking, market-based measure of credit risk that gauges a firm's probability of defaulting within a year, based on the volatility of its share price.

In the paper by Åsberg and Shahnazarian (2008, Sveriges Riksbank), the median EDF of all Swedish non-financial listed companies proxies for the probability of default. The authors estimate a vector error-correction model (VECM) for this aggregate EDF and three macroeconomic variables (industrial production index, consumer price index and short-term interest rate). Assuming a long-term correlation between variables, a VECM can discern shared trends between series as well as short-term fluctuations. The results indicate that the macroeconomic variable with the strongest positive impact on EDF is the interest rate; a fall in manufacturing output and an increase in inflation also lead to a higher EDF.[21]

[21] Åsberg and Shahnazarian (2008, Sveriges Riksbank) observe that higher inflation implies higher factor prices that lead to increased costs and tend to impair credit quality. Moreover, high inflation is usually considered a signal of macroeconomic mismanagement and a source of uncertainty. Thus the relation between the default rate and the inflation

The model by Castren, Fitzpatrick and Sydow (2008, ECB) also measures credit risk by the median EDF of euro area companies, but at sector level (eight economic sectors). The model relates the credit quality of European companies to five macroeconomic variables, including real equity prices, measured for the whole euro area; the parameters are statistically significant and with the expected sign for real equity prices and, in four of the eight sectors, for GDP.[22]

In contrast to the use of market-based measures of credit risk, the French Banking Commission (FBC) and the BoJ use internal data-sets of individual non-financial company ratings, whose evolution over time is summarized by transition matrices.[23] Both models estimate the sensitivity of a non-linear transformation of the probability that borrowers will migrate to a different rating class with respect to a limited number of macroeconomic variables.[24] In the FBC model, the macroeconomic variables are GDP and short-term and long-term interest rates. In the BoJ model, a system of five equations (one for each rating class) is estimated by Seemingly Unrelated Regression to take account of possible correlation between error terms. Explanatory variables are GDP growth rate and a leverage ratio as proxies of profit and liability conditions. GDP is significant in all but the lowest rating class; the results for the debt ratio are more mixed.

In sum, the survey shows a wide array of approaches to credit risk modeling in terms of measures of credit quality, level of aggregation, and estimation methodology. Methods that use current financial market data to predict bankruptcies (as contrasted with modeling LLPs or NPLs) within a given time horizon may be able to detect problems in the loan portfolio earlier than those based on loan classification data. Such methods, however, are restricted to listed companies and so may not be readily applicable in some countries. A common feature is that the macroeconomic variables used as explanatory variables are not numerous. As for the level of aggregation, models based on individual data can in principle lead to more accurate results; if these data are not available, there can still be benefits associated with parsimonious models using more aggregate data, as noted by Åsberg and Shahnazarian (2008, Sveriges Riksbank).

5. Stress test implementation

In the third stage of a typical stress testing process the macroeconomic models (structural, vector auto-regressive, or purely statistical) are used to project the values of the macroeconomic variables under stress conditions and then apply an auxiliary model of credit risk to estimate credit quality under stress.

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rate should be positive. However, higher inflation also implies higher product prices, which can boost earnings and a lower debt burden in real terms, thereby improving creditworthiness.

22 The fact that the interest rate is not significant may seem to be a counter-intuitive result in view of its importance as a driver of corporate credit quality. Castrén, Dèes, and Zaher (2008, ECB) explain by reference to the characteristics of the dependent variable: the main drivers of EDFs are the value of asset/equity (market capitalization) and the default point (which is a function of liabilities), so it is not surprising that the econometric analysis confirm the role of equity prices and not of interest rates.

23 See Commission Bancaire (2007) and Bank of Japan (2007).

24 In the BoJ model, the banks' borrower classification data available at the central bank were supplemented with credit scores provided by a Japanese rating agency.

As noted, all the authorities reviewed used a macro-econometric structural model for the FSAP exercises. In the Italian FSAP, one macroeconomic scenario involved a shock to oil and share prices. The effects on domestic macroeconomic variables were simulated using the BoI quarterly macro-econometric model to generate deviations from a baseline projection over several time horizons. The macroeconomic projections for output gap and short-term interest rate were used in the credit risk model to calculate an after-shock PD; the result was an estimated increase of 83 percent.

In such an approach, however, the structural macroeconomic model generates point estimates associated with a single future path, the conditional mean path under the stress scenario, with no probabilistic interpretation.

The VAR/VECM framework can generate stress scenarios that do allow for probabilistic interpretations. Shock sizes are specified in terms of the unconditional standard deviation of the innovation in an autoregressive series, and under a normality assumption they can be given a probabilistic interpretation. Thus scenarios do not follow from the economic reasoning behind a structural macro-model but are based only on a probabilistic method. Tail outcomes of such simulations present extreme scenarios.

Pesaran, Schuermann, Treutler and Weiner (2006) were the first to present a VAR model to generate a probabilistic scenario for credit risk analysis. Impulse response functions are used to examine how an isolated shock to one macroeconomic variable affects all the others. Impulse response functions assume that the other variables are displaced according to their historical covariances with the variable being shocked, so that the correlations across shocks are accounted for in an appropriate manner. The authors examine the impact on a hypothetical corporate loan portfolio and its exposure to a range of macroeconomic shocks. For example, they find that a 2.33-standard-deviation drop in real US equity prices causes an expected loss of 80 bp over four quarters. This approach is particularly valuable in addressing specific risk-management questions and, in particular, producing a rank order of the possible shock scenarios.

Examples of scenarios generated by this probabilistic method are given in the stress exercises conducted at the BoJ and in Jiménez and Mencía (2007, BoS) and Castren, Fitzpatrick and Sydow (2008, ECB). In the BoJ model, the stress test assesses the impact of a negative GDP shock of a size that has a one percent probability. Jiménez and Mencía (2007, BoS) apply a 3-standard-deviation shock to the GDP and interest rate variables; similarly, Castren, Fitzpatrick and Sydow (2008, ECB) use a 5-standard-deviation shock for one macroeconomic variable of the GVAR model.

The OeNB's SRM multivariate t-copula approach is used to draw risk factor changes randomly according to their estimated multivariate distribution. One or more of the simulated risk factor changes are set to a fixed value according to the given shock; changes for all other (non-stressed) risk factors are drawn from the conditional distribution given the stress scenario. For example, the SRM model documentation evaluates the impact of a drop in GDP or of a rise in interest rates; the t-copula approach ensures consistency with the overall dependency structure between risk factors.[25]

[25] The model can also simulate the effect of one single-factor shock (unconditional simulation). See Boss, Breuer, Elsinger, Jandacka, Krenn, Lehar, Puhr, and Summer (2006, OeNB).

Van den End, Hoeberichts, and Tabbae (2006, DNB) propose an alternative method that accounts for simultaneous changes in the macroeconomic variables and their interactions as typically present in the macro scenarios derived from structural macro-models. To simulate the hypothetical stress scenario, the projected values of the macroeconomic factors are included to re-estimate a VAR model including GDP and interest rate. Re-estimating a VAR that includes stressed values for the macroeconomic factors can take into account changes in the correlations, and overcome the objection that stress-testing models posit constant statistical relationships, which might not be the case in stress situations.

A similar procedure is applied in the paper by Åsberg and Shahnazarian (2008, Sveriges Riksbank): they use the impulse responses of the Riksbank's macro-econometric model to a given shock (e.g. a supply shock) to estimate stressed values for the three macroeconomic variables of a VEC-model that also include EDFs (see Section 4.2). The VEC-model is then used to forecast the stressed EDFs conditional on the stressed values of the macroeconomic variables.

6. Impact measures

The final step in the stress testing process is evaluating the impact on the banks' loan portfolio and judging whether banks can withstand the shock assumed. This means comparing the loss with an appropriate benchmark.

Depending on the credit risk model used, the results of the simulation can be expressed in terms of either provisions or projected default rates. In the latter case, given a (usually ad-hoc) figure for the recovery rate, one can estimate banks' expected losses, which determines the volume of loss provisions. As observed in Čihák (2007), in a normal situation ("baseline scenario"), banks would typically be profitable. When carrying out stress tests, it is important to evaluate impacts against such a baseline, as banks would exhaust profits before undergoing reductions in their balance-sheet or regulatory capital position. Expressing shocks only in terms of capital may result in overestimating the actual impacts if banks remain profitable in the baseline scenario. However, to accomodate the view that it is prudent to disregard profits one can measure losses directly against capital or capitalization (capital or equity to assets, or capital to risk-weighted assets). The effects on capital adequacy ratios are obviously particularly important for agencies with supervisory responsibilities.

An important extension focuses specifically on the impact measure. Instead of producing accounting measures of distress as point estimates under the assumed stress scenarios, more recent work has sought to derive a profit and loss distribution for the loan portfolio of the banking system as a whole, extending to system-wide scale the risk management framework adopted at a micro-level by many financial institutions in their risk management systems. The loss distribution shows the probability of loan losses of various sizes – from no losses occurring to the loss of the entire loan portfolio. The expected loss – the mean of the distribution – is normally covered by earnings; banks need to hold a capital buffer to cover losses above those expected (unexpected loss or value-at-risk).[26] The

[26] The shape of the loss distribution of a given portfolio is to a large extent determined by the presence of name concentration and/or correlations between the different exposures/sectors. In the setting described in this paper, correlation is determined by the common dependence on the various macroeconomic factors (multi-factor portfolio credit

estimation of a loss distribution for the banking system's loan portfolio makes it possible to calculate the size of the aggregate capital buffer given a tolerance level (the economic capital).

In the context of a loan loss distribution, the stress exercise can be couched in terms of deterministic shifts in the parameters, such as the PD and the loss-given-default (LGD). See, for instance, the sensitivity analyses reported in Sveriges Riksbank (2006). Alternatively, macro stress scenarios like those discussed in Section 3 can be used to simulate adverse macroeconomic conditions that – using the satellite models described in Section 4 – generate a stressed aggregate PD or a set of stressed sectoral PDs. Via this link, the stress test has a clear economic interpretation.

The idea of measuring the impact of credit shocks in terms of an overall system-wide credit loss distribution – as opposed to banks' expected losses – was first discussed in Sorge and Virolainen (2005) and applied in the OeNB's SRM stress test model.[27] Research projects along these lines are planned or under way at many authorities with a view to improving the existing framework.

In a first approach, used in Alessandri, Gai, Kapadia, Mora, and Puhr (2007, BoE), Jiménez and Mencía (2007, BoS), and Van den End, Hoeberichts, and Tabbae (2006, DNB), the portfolio loss distribution is estimated using Monte Carlo simulation techniques, taking random draws of the innovations in the macroeconomic factors (GDP, interest rates, etc.).[28] The estimation can be performed at aggregate level for the banking system or for individual banks.

In a second approach, used by Castren, Fitzpatrick and Sydow (2008, ECB), in the OeNB's SRM, and by the Sveriges Riksbank (2006), the simulation of random innovations in the macroeconomic factors is supplemented with a readily-available portfolio model, such as Credit Risk Plus. The use of a full-blown portfolio model can combine predictions on default frequencies with more granular information on the credit quality of individual borrowers.

The OeNB's SRM calculates a loss distribution using a modified version of Credit Risk Plus. Sectoral default frequencies from the model are combined with individual borrowers' default probabilities from the central credit register by adapting the latter according to the difference with the model-predicted default frequencies. If, for example, the model-predicted default frequency doubles due to changes in macroeconomic variables, this will result in a doubling of default probabilities of individual borrowers, which is then used to calculate the overall credit loss distribution using Credit Risk Plus.

A similar but simpler procedure is used by Castren, Fitzpatrick and Sydow (2008, ECB) and by the Riksbank. Instead of using individual default probabilities, both studies make assumptions about the creditworthiness of borrowers and classify loan portfolios into three

risk model). The shape is typically skewed and has a relatively fat right tail, indicating that, although losses less than or around the expected value are most frequent, more extreme outcomes may also occur.

[27] A similar analysis is conducted also in Pesaran, Schuermann, Treutler and Weiner (2006).

[28] In the paper by Jiménez and Mencía (2007, BoS), the simulation also includes random draws of the innovations in the latent factors; the BoE's model combines various sources of risk (see foot-note 12) and the corresponding output is a distribution of total banks' assets rather than pure credit losses.

quality classes; aggregate Moody's KMV EDFs of the lower and higher credit quality portions of the portfolio are adjusted accordingly.

Moving from a baseline to a stress scenario is likely to produce a shift in the conditional loss distribution and in the corresponding value-at-risk measure; accordingly, the stressed value-at-risk will measure the economic capital to be held in order to cover unexpected credit losses; in order to assess whether the banking system can withstand the assumed shock it should then be compared with a measure of actual capital held for credit risk by the banking system.

As is noted by Bonti, Kalkbrener, Lotz and Stahl (2006), stress tests performed within a portfolio credit risk model enable one to assess the outcomes of a stress scenario consistently with the quantitative framework used in a normal, non-stressed situation, because the stress scenario is translated into movements of "internal" risk drivers (the macroeconomic risk factors). The risk measures of the model (expected loss, value-at-risk) can be studied relative to the baseline simulation derived from the unconditional (non-stressed) risk factor distribution. Using the same quantitative framework for normal and stressed situations implies that the relationships between non-stressed risk factors remain intact and the experience gained in the day-to-day use of the model can be used to interpret the results from stress testing.[29]

Finally, depending on the availability of micro data, it is important that central banks and supervision authorities calculate the impact at the individual bank level and not only for an aggregate system-wide portfolio. In fact, seeing the distribution throughout the system is essential to assessing the threat of contagion and the possible impact of confidence effects on stability.

7. Discussion and evaluations

This section discusses the main findings of the survey, highlighting a number of methodological issues that may be relevant to supervisors in reviewing stress testing requirements under Basel II. From a financial stability perspective, it contributes to the on-going macroprudential research efforts to integrate macroeconomic oversight and prudential supervision by facilitating early detection of key vulnerabilities and the assessment of macro-financial linkages.

7.1. Characteristics of the credit risk models

One application of the macro credit risk models is the calculation of IRB capital requirements in stress scenarios: the impact of a macro stress scenario on regulatory capital can be evaluated by recalculating the Basel II formula with the stressed PDs from the credit risk model. The models surveyed here differ significantly in such areas as the measure of credit quality chosen, the level of aggregation, and the estimation methodology.

a) Borrower credit quality is modeled either on the basis of loan performance data, requiring time series data on different proxies for default rates (such as NPLs or LLPs), or on the

[29] Consistency is one of the desirable properties of stress testing mentioned also in a Basel Committee study on credit risk concentration (BCBS, 2006).

basis of market-based indicators (such as Moody's KMV EDFs). The use of different variables raises several issues that must be considered in interpreting the results. For example, loan performance is a "retrospective" indicator of asset quality: loan loss provisioning rules or policies may affect the financial statement data that are used. Market-based indicators, on the other hand, are fully reliable only for listed firms. Moreover, the magnitude and statistical significance of the relevant macroeconomic variables' estimated coefficients may differ with the indicator of credit quality.

b) The studies reviewed here use different levels of aggregation for the dependent variable. Whenever possible, disaggregated data are essential to capture the differing response of sectors/banks/portfolios to stress scenarios. One major shortcoming of econometric models based on aggregate data is that the conditional means may conceal significant variation at portfolio or bank level. More specifically, this procedure fails to detect uncertainty about (variations in) the actual defaults at the level of the single sector, bank, or individual obligor. Thus, the loss distribution obtained (see below) is more concentrated than the underlying overall loss distribution and so misses information about the extreme tails.

c) The survey shows the importance of the model development stage, i.e. the statistical model-building technique. Generally the first step in the selection of variables is to cull an initial set of macroeconomic and financial variables that theory and empirical evidence suggest affect credit risk. The second step selects the "preferred" specification of the model such that it is consistent with economic theory and satisfies a set of statistical selection criteria. In sum, a parsimonious selection of uncorrelated or weakly correlated, statistically significant, and intuitively understandable variables makes the model more attractive for stress testing. In particular, economic plausibility is a key requirement in all the models: the economic meaning of the macroeconomic factors used must be clear, with no counter-intuitive relationships with the dependent variable.

d) The most important aspect in assessing the model specification process is overall performance, in-sample and out-of-sample. A common feature of macro-econometric-based models of credit risk is that macroeconomic variables alone tend to explain a fairly small part of the variation of the dependent variable, especially when only one or two macroeconomic variables are considered (omitted variables). The goodness-of-fit is considerably improved by the inclusion of latent variables (unobserved common factors), possibly accounting for micro-contagion effects. Failing to include such variables can result in significant underestimation of tail risk.

e) Other important aspects to emerge from our examination of the model specification process include: (i) the model's ability to handle low-quality data (missing values, outliers, structural breaks); (ii) the time period used for calibration, which should span at least one full business cycle to ensure capturing the cyclical effects on default probabilities; (iii) an evaluation of parameter stability and of model robustness.

7.2. The formulation of stress scenarios and stress test methods

The models used to simulate macroeconomic scenarios range from more structural, which are better suited for policy analysis, to pure statistical methods that model the multivariate distribution of macro-financial variables using nonlinear dependence structures (e.g., based on multivariate copulas). An intermediate option consists of reduced-form models such as VAR or VECM, which retain some of the desirable policy-analysis features of a structural model combined with some of the flexibility of a more statistical approach. However, macro models are generally local approximations of equilibrium relationships. They are not necessarily suitable for assessing the effect of large shocks, which are very likely to produce non-linearities and regime shifts. This results in uncertainty over the size and sometimes the sign of the response. Whichever model is chosen, it is essential that the stressed macroeconomic variables be internally consistent.

So far financial institutions have had trouble selecting "big picture" macroeconomic scenarios and have preferred to calibrate shocks directly in terms of micro-variables. For individual firms, therefore, models such as VAR or VECM based on just a few variables can be feasible for designing internally consistent macroeconomic scenarios in a simple and transparent way and conducting macro stress tests without requiring particularly substantial resources.

7.3. Impact measures and the estimation of a loss distribution

While early stress testing exercises concentrated mostly on expected losses, most of the recent methodologies estimate the entire portfolio loss distribution.

The loss distribution provides a measure of the credit VaR (economic capital or capital at risk) as well as other measures of "tail risk" under stress. In particular, the shape of the right-hand tail of the portfolio loss distribution is to a large extent dependent on key risk factors such as portfolio concentration and on correlations between risk components (PD, LGD, and exposure-at-default, EAD), which are not captured by other risk metrics such as expected losses. Stressed loss distributions can be used to examine stress scenarios in a consistent setting, and in particular to evaluate the future capital needs of banks to comply with their economic capital constraints under stress conditions, as required in the more general Pillar II stress test.

Our survey found basically two approaches to estimating credit loss distributions in the context of a macroeconomic multi-factor credit risk model. A first approach applies only Monte Carlo simulations of innovations in macroeconomic factors to obtain stressed aggregate or sectoral PDs. This implies: (i) treating every loan in the estimation bucket (aggregate or sector) as equally risky regardless of the credit quality of borrowers; (ii) assuming that realized losses are always equal to expected losses or else that banks hold an infinitely granular portfolio. This would result in an underestimation of risk.[30] In a second approach the simulation of random innovations of the macroeconomic factors is supplemented with a full-blown portfolio credit risk model, which generates loss distributions with greater variance and fatter tails.

In estimating the baseline and stressed loss distributions, much attention has been given to modeling default rates; there has not been much progress in modeling LGDs and EADs, and in most cases, ad-hoc values for LGDs are assumed (e.g., downturn LGDs and EADs are typically kept constant). However, in stressed scenarios PDs often increase as the financial

[30] For the first remark, see Boss, Breuer, Elsinger, Jandacka, Krenn, Lehar, Puhr, and Summer (2006, OeNB), for the second see Alessandri, Gai, Kapadia, Mora, and Puhr (2007, BoE).

strength of households and firms deteriorates, LGDs increase as recovery rates fall with asset prices, and EADs increase as credit lines are drawn on in worsening financial conditions. Ignoring these correlations among PDs, LGDs and EADs can result in a considerable underestimation of tail losses. It is accordingly important to model the joint behavior of these three variables in stress scenarios, as their correlations tend to increase in stress conditions.

8. Concluding remarks

This paper reviews the quantitative methods developed at selected central banks and supervision authorities for stress testing credit risk. The focus is on macro stress testing. i.e. the linkage of the macroeconomic drivers of stress with bank-specific measures of credit risk, with a view to helping supervisors in reviewing stress tests for compliance with Basel II and contributing to the on-going research efforts to integrate macroeconomic oversight and prudential supervision.

As a result of the IMF’s Financial Sector Assessment Programs, central banks have acquired specific modeling expertise in this sector. The review shows the modeling and organizational complexity of macro-stress testing, which involves a number of stages. The first step is to design a coherent macroeconomic stress scenario that is consistent with the application of a macro-econometric model. The second step, since these models generally do not include the financial sector, is to apply “satellite” models to measure credit risk, mapping the macroeconomic variables onto some measures of banks’ asset quality. The third step is the assessment of losses under stress scenarios, evaluating them in connection with variables that gauge the banking system’s ability to withstand shocks.

The paper outlines and compares features of the approaches adopted at the various authorities and traces the latest developments. In particular: (i) in devising scenarios central bank researchers increasingly adopt models that are more flexible and easier to use, such as VARs and other strictly statistical rather than structural models; (ii) the satellite models for credit risk display a great variety of statistical methods, dependent variables, and levels of aggregation, while the explanatory variables are more uniform and not numerous (sometimes the goodness-of-fit may not be a prime consideration); the most recent models, when data are available, incline towards a sectoral aggregation, which permits distinguishing between cyclical and acyclical sectors; (iii) unlike the early macro-stress testing, which assessed the impact of stress scenarios on expected losses, current research projects tend to envisage an assessment of the entire portfolio loss distribution and unexpected losses under stress conditions.

Finally, the paper analyzes and discusses a series of methodological aspects with a view to improving macro-stress testing models. A number of research programs are working to overcome some of these limitations. In particular, the current objectives are to extend time horizons and build in banks’ actions to adjust balance sheets in response to the stress scenarios (as, for example, by changing lending and borrowing policy). In this way it would be possible to take account of the potential transmission, and amplification, of a shock within the financial system to the real economy.

TABLE 1: MACRO STRESS TESTING OF CREDIT RISK - METHODOLOGY OF SELECTED AUTHORITIES							
Agency	**credit risk model**		**data and estimation**	**macroeconometric model**	**stress methodology**	**impact measure**	**reference**
	dependent variable	**independent variables**					
Bank of England	logit transformation of aggregate default rates	- GDP growth - short-term IR - equity return	linear OLS regressions on quarterly data (various samples)	Macroeconomic scenarios are generated by a two-country GVAR (UK, US) model, which includes six country variables and a foreign variable (see ECB box)	Conditional/unconditional GVAR simulations, historical recessions, parameter breaks	*stressed asset distribution*	Alessandri-Gai-Kapadia-Mora-Puhr (2007)
Bank of Italy	- corporate default rate - ouput gap - inflation rate - 3m IR - real exchange rate		1990(1)-2005(2); quarterly data; VAR(1) estimation	The BOI's quarterly macroeconometric model. For shocks affecting the Euro-area and/or the world economy, satellite models used for the Eurosystem projections or IMF models were also applied	The outputs of the macro model (stressed output gap and interest rate) are the input of the credit risk VAR model	*stressed default rates and expected losses*	Marcucci-Quagliariello (2005); Laviola-Marcucci-Quagliariello (2006)
	logit transformation of sectoral default rates (8 corporate sectors)	GDP growth, equity index, competitiveness index, interest rate, two contagion latent factors depending on the sector	1990(1)-2006(3); quarterly data; SUR estimation	the BOI's quarterly macroeconometric model (under way)	the output of the macro model in term of stressed macroeconomic variables are the input of the sectoral credit risk model (under way)	*stressed credit loss distributions (under way)*	Fiori, Foglia, Iannotti (2008)
Bank of Japan	probit transformation of the probability of a rating transition	- GDP growth - ratio of interest-bearing liability to cash flow	data on bank borrowers SUR regression for a system of 5 equations (one for each rating category) 1985-2005	a VAR model comprised of five variables: GDP CPI bank loan outstanding effective exchange rate call rate	VAR forecasts to: i) a negative GDP shock, of which probability is one percent; b) a negative GDP shock equivalent to the financial crisis since 1997	*maximum loss* to capital derived from a Monte Carlo simulation	Bank of Japan, Financial System Report (2007)
Bank of Spain	probit transformation of the default rate	- quarterly change in real GDP growth - variation of three-month real interest rate - term spread - six sectoral variables - two latent factors	10 sectoral equations for corporates; 2 equations for households; 1984Q4-2006Q4	VAR(1) estimation for the macroeconomic variables and for the latent factors	an artificial shock (3 standard deviations) to the GDP and interest rate variables is introduced in the vector of innovations	*Stressed credit loss distribution*	Jimenez-Mencia (2007)
De Nederlandsche Bank (DNB)	logit transformation of the default rate	- real GDP growth - term spread	a system of 2 simultaneous equations; annual data 1990-2004; panel estimation	i) the domestic macroeconomic model developed at the DNB plus NIGEM world model. They are used to generate projections of the macroeconomic variables given the initial shock to the exogenous variables; ii) a VAR(2) model for the macroeconomic variables included in the credit risk equations.	First type of stress: the deviations of the macro variable from the baseline scenarios - obtained as output of the macroeconomic model - are input in the credit risk model	First type of stress*: stressed PDs, expected losses*	van den End-Hoeberichts-Tabbae (2006)
	logit transformation of the LLP ratio	- real GDP growth - long-term IR - logit transformation of the default rate			Second type of stress: the stressed (future) values of the macro-variables as projected by the macroeconomic model are used to estimate a AR(2) o a VAR(2) model for the macroeconomic variables of the credit risk equations	Second type of stress: *a stressed credit loss distribution is simulated by taking random draws of the innovations in the macro variables used in the "stressed" VAR(2) model*	
Deutsche Bundesbank	logit transformation of the LLP ratio	- lagged dependent variable - credit growth - real GDP growth - variation short-term IR	a system of 2 simultaneous equations; panel data from 1993; dynamic panel estimation	The macroeconometric model developed at the Bundesbank used to generate projections of the macroeconomic variables	Given the initial shock to the exogenous variables, the stressed values of the macroeconomic variables are used to project an after-shock value of the variables that are input of the credit risk model	*loan loss provisions*	Deutsche Bundesbank (2006)
	credit growth	- lagged credit growth - real GDP growth - variation short-term IR					

TABLE 1 (continued): MACRO STRESS TESTING OF CREDIT RISK - METHODOLOGY OF SELECTED AUTHORITIES

Agency	credit risk model		data and estimation	macroeconometric model	stress methodology	impact measure	reference
	dependent variable	independent variables					
ECB	EDF of euro area corporates	- euro area real GDP - CPI inflation - real equity prices - real euro/US$ exchange rate - short tem IR	regression model of the median EDF (1 aggregate/8 sector specific); quarterly data, 1992-2005	Macroeconomic scenarios are generated by a global VAR (GVAR) model which includes 7 variables (six country/region variables and a vector of foreign variables specific to each country/region) and 33 countries, where 8 of the 11 countries that originally formed the euro area are grouped together and the remaining 25 countries are modelled individually by a VECM	The impulse responses from the GVAR model to 5 standard deviation shocks to one of the macrovariable of the GVAR model	*Stressed credit loss distribution*	Castrén-Dées-Zaher (2008) Castrén-Fitzpatrick-Sydow (2008)
French Banking Commission and Banque de France	logit transformation of the probability of a rating transition	- GDP - short-term IR - long-term IR	logit/probit estimation based on observed transition matrices and macroeconomic variables	The Mascotte macroeconometric model developed by the Banque de France for macroeconomic forecasts	The outputs of the macro model (stressed GDP, s.t. and l.t. interest rates) are the input of the credit risk model	*Stressed solvency ratio* as a result of stressed risk-weighted assets (via credit risk model) and a stressed capital (via an intermediation income model, not described here)	Commission Bancaire (2007)
Norges Bank	Loan loss ratio RWD=PD*DEBT probability of bankruptcy (PD)	- lagged risk-weighted debt (RWD) - house prices (first difference) age, size, accounting variables measuring corporate earnings, liquidity and financial strenghts	A logit model that predicts individual bankruptcy probabilities estimated using the entire population of enterprises (about 400.000) in Norges Bank's accounts database for the period 1990-1996.	The scenarios were developed using Norges Bank's macroeconomic model. Projections from this model were used as a baseline scenario	The change in the macrovariables from the macroeconometric model are translated into changes in accounting variables and a stressed PD is obtained	*Expected losses*	Eklund-Larsen-Berhardsen (2001) Hagen-Lund-Nordal-Steffensen (2005)
Österreichische Nationalbank (OeNB)	first difference of the logit transformation of industry default rates	depending on the industry: - real GDP - Industrial Production - Unemployment Rate - Equipment Investments - Oil (Brent) in Euro - Real Short-term IR - Real 5y IR all variables (except unemployment rate) were taken as logarithmic changes of the moving average over four quarters	ML estimation of the first difference of the logit transformation of observed industry default rates; independent estimation for 7 sectors (total 11 sectors); quarterly data: 1969-2007	i) within SRM: Modeling of the joint distribution of macroeconomic and market risk factors through a t-grouped copula approach with 4 groups (macroeconomic variables, interest rates, fx-rates, equity price indices) ii) For FSAP 2007: Domestic model developed at the OeNB plus NiGEM world model to project macroeconomic variables given an initial shock	i) Within SRM: risk factors (macroeconomic variables and market risk factors) are increased by percentage or percentage points or set to the stressed value ii) For Fsap: Projected outputs of the macroeconometric model are used as input for the credit risk model	- Stressed Capital Adequacy Ratio (CAR) and expected losses; - with the Systemic Risk Monitor (SRM) wherein the credit risk model is integrated a loss distribution is estimated using a modified version of Credit Risk Plus	Previous version in: Boss-Breuer-Elsinger-Krenn-Lehar-Puhr-Summer (2006); current version is planned to be published in 2008
Sveriges Riksbank	- EDF of Swedish listed companies - domestic industrial product index - domestic consumer price index - nominal domestic 3m IR		Monthly data 1997-2006 VECM estimation	The DSGE model used for policy simulation generates forecasts and stress scenarios for the three macro variables included in the VEC-model.	The VEC-model is used to forecast a stressed EDF by conditioning the model on ad-hoc stressful scenario based on the DSGE model.	*- Conditioned or stressed EDFs* *- The conditioned or stressed EDFs are also used as inputs for the simulation of a credit loss distribution*	Åsberg and Shahnazarian (2008) Riksbank Financial Stability Report (2006)
Swiss National Bank	logit transformation of the LLP ratio	- GDP growth - unemployment rate - level of 3m IR - corporate bond spread - bank control variables	1987-2004; static and dynamic panel estimation		Macroeconomic variables are replaced by the values assumed in the stress scenarios. Given an initial shock to one of those variables, the change in the remaining variables is determined through historical correlations	*Loan loss provisions*	Lehmann-Manz (2006)

REFERENCES

ALESSANDRI, GAI, KAPADIA, MORA AND PUHR (2007), *A framework for quantifying systemic stability*, December, preliminary paper presented at the workshop "Stress Testing of Credit Risk Portfolios: The Link between Macro and Micro", hosted by the BCBS and the DNB, Amsterdam, 7 March 2008.

ÅSBERG AND SHAHNAZARIAN (2008), *Macroeconomic impact on expected default frequency*, WP. 219, Sveriges Riksbank, January.

BANK OF JAPAN (2007), *The Framework for Macro Stress-Testing of Credit Risk: Incorporating Transition in Borrower Classifications*, Financial System Report, September.

BCBS (2005), *International Convergence of Capital Measurement and Capital Standards. A Revised Framework*, November.

BCBS (2006), *Studies on credit risk concentration*, WP no. 15, November.

BCBS (2008), *Liquidity Risk: Management and Supervisory Challenges,* February.

BERGE AND LINDQUIST (2007), *A suite-of-models approach to stress testing financial stability*, preliminary paper presented at the "2nd Expert Forum on Advanced Techniques on Stress Testing: Applications for Supervisors", IMF and DNB, Amsterdam, October 23-24.

BLASCHKE, JONES, MAJNONI, AND MARTINEZ PERIA (2001), *Stress Testing of Financial Systems: An Overview of Issues, Methodologies, and FSAP Experiences*, IMF WP, no. 88.

BONTI, KALKBRENER, LOTZ, AND STAHL (2006), *Credit risk concentration under stress*, Journal of Credit Risk, vo.2, no.3, 115-136.

BOSS (2003), *A macroeconomic model for stress testing the Austrian credit portfolio*, OeNB Financial Stability Report, Vol. 4, pp. 64-82.

BOSS, BREUER, ELSINGER, JANDACKA, KRENN, LEHAR, PUHR, AND SUMMER (2006), *Systemic Risk Monitor: A Model for Systemic Risk Analysis and Stress Testing of Banking Systems*, OeNB Internal technical report.

CASTRÉN, DÈES, AND ZAHER (2008), *Global Macro-financial Shocks and Expected Default Frequencies in the Euro Area*, ECB WP no. 875, February.

CASTRÉN, FITZPATRICK, AND SYDOW (2008), *Assessing Portfolio Credit Risk Changes in a Sample of EU Large and Complex Banking Groups in Reaction to Macroeconomic Shocks*, mimeo.

CHAN-LAU (2006), *Fundamentals-Based Estimation of Default Probabilities: A Survey*, IMF WP, no. 149.

ČIHÁK (2007), *Introduction to Applied Stress Testing*, IMF WP no. 59.

COMMISSION BANCAIRE (2007), *The French approach of stress-testing credit risk: the methodology*, Direction de la Surveillance generale du systeme bancaire, internal document.

DEUTSCHE BUNDESBANK (2007), *Research Task Force questionnaire: stress test experiences*, internal document.

EKLUND, LARSEN, AND BERHARDSEN (2001), *Model for analyzing credit risk in the enterprise sector*, Economic Bulletin, 3, Norges Bank.

FINANCIAL STABILITY FORUM (2008), *Report on Enhancing Market and Institutional Resilience, Follow-up on Implementation,* October 2008

FIORI, FOGLIA, AND IANNOTTI (2008), *Beyond Macroeconomic risk: the role of contagion in corporate default correlation*, mimeo. An earlier version of the paper has been presented at the "2nd Expert Forum on Advanced Techniques on Stress Testing: Applications for Supervisors", IMF and DNB, Amsterdam, October 23-24.

HAGEN, LUNG, NORDAL, AND STEFFENSEN (2005), *The IMF's stress testing of the Norwegian financial sector*, Economic Bulletin, 4, Norges Bank.

HALDANE, HALL, AND PEZZINI (2007), *A new approach to assessing risks to financial stability*, Financial Stability WP no. 2, Bank of England, April.

IMF AND THE WORLD BANK (2003), *Analytical tools of the FSAP*.

JIMÉNEZ AND MENCÍA (2007), *Modelling the distribution of credit losses with observable and latent factors*, Documentos de Trabajo n.0709, Bank of Spain.

JONES, HILBERS, AND SLACK (2004), *Stress Testing Financial System: What to Do When the Governor Calls*, WP no. 127, International Monetary Fund.

LAVIOLA, MARCUCCI, AND QUAGLIARIELLO (2006), *Stress Testing Credit Risk: Experience from the Italian FSAP*, Banca Nazionale del Lavoro Quarterly Review, vol. LIX, no. 238, September.

LEHMANN AND MANZ (2006), *The Exposure of Swiss Banks to Macroeconomic Shocks – an Empirical Investigation*, WP no. 4, Swiss National Bank.

MARCUCCI AND QUAGLIARIELLO (2005), *Is Bank Portfolio Riskiness Procyclical? Evidence from Italy using a Vector Autoregression*, Journal of International Financial Markets, Institutions & Money, Vol. 18, Issue 1, February, pp. 46-63.

PESARAN, SCHUERMANN, TREUTLER, WEINER (2006), *Macroeconomic Dynamics and Credit Risk: A Global Perspective*, Journal of Money, Credit and Banking, Vol.38, no. 5, August.

SEGOVIANO, M (2006), *Conditional Probability of Default Methodology*, Financial Market Group, London School of Economics, Discussion Paper no. 558.

SORGE AND VIROLAINEN (2005), *A comparative analysis of macro-stress testing with application to Finland*, Journal of Financial Stability, 2, pp. 113-151.

SVERIGES RIKSBANK (2006), *Using external information to measure credit risk*, Financial Stability Report, 1.

SWINBURNE (2007), *The IMF's Experience with Macro stress-testing*, presentation at the ECB conference on "Simulating Financial Instability", Frankfurt, 12-13 July.

VAN DEN END, HOEBERICHTS, AND TABBAE (2006), *Modelling Scenario Analysis and Macro Stress-testing*, wp No. 119, De Nederlandsche Bank.

WILSON (1997), *Portfolio Credit Risk (I)*, Risk, vol.10, no.9 September.

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