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Stress-testing financial systems: an overview of current methodologies

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Abstract

This paper reviews the state-of-the-art of macro stress-testing methodologies. Substantial progress has been made both in the econometric analysis of financial soundness indicators and in the simulation of value-at-risk measures to assess system-wide vulnerabilities. However, a number of methodological challenges still remain concerning the correlation of market and credit risks over time and across institutions, the limited time horizon generally used for the analysis and the potential instability of reduced-form parameter estimates because of feedback effects. Further research in this area might also focus on how to use macro stress-testing techniques as an operational tool to incorporate financial stability considerations into monetary policy decision-making.

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Introduction[1]

Macro stress-testing refers to a range of techniques used to assess the vulnerability of a financial system to "exceptional but plausible" macroeconomic shocks.[2] Stress-testing at the level of individual institutions has been widely applied by internationally active banks since the early 1990s.[3] Bank regulators require the use of stress-tests for monitoring both market and credit risks. Macro stress-testing, as a tool to assess the vulnerability of entire financial systems, is instead much more recent. It has been an important component of the Financial Sector Assessment Programs (FSAPs) launched by the IMF and the World Bank in the late 1990's and has become an integral part of the financial stability toolbox of policymakers.[4]

Macro stress-testing has received considerable attention in the last few years. Central banks and international organisations have taken the lead in this area of research, given their particular concern for financial stability issues. This paper attempts to critically review the state-of-the-art of macro stress-testing methodologies. Its slightly more technical flavour complements the survey studies already available, which either focus on the specific FSAP experience or provide a broader overview of the macro stress-testing process for policymakers. In particular, Blaschke et al. (2001) and IMF and World Bank (2003) review the basic analytical tools used by FSAPs across countries, while Drehmann, Hoggarth, Logan and Zicchino (2004) describe a number of approaches and results of macro stress-tests carried out as part of the FSAP for the UK. Jones, Hilbers and Slack (2004) provide a general non-technical description of macro stress-testing and Worrell (2004) discusses an integrated approach to macro stress-tests, early warning systems and financial soundness indicators. Several studies on the procyclicality of credit and market risk measures, recently surveyed by Allen and Saunders (2004), have attempted to incorporate macroeconomic factors into risk measurements. Furthermore, a few recent papers have broadened the analysis to account for potential domino effects in interbank markets or endogenous portfolio adjustments and spillovers on asset prices, drawing on the literature about financial contagion and systemic risk, surveyed for example by De Bandt and Hartmann (2001).

This paper distinguishes between two main methodological approaches to macro stress-testing:

- a "piecewise approach" that evaluates the vulnerability of the financial sector to single risk factors, by forecasting several "financial soundness indicators" (such as non-performing loans, capital ratios and exposure to exchange rate or interest rate risks) under various macroeconomic stress scenarios;
- an "integrated approach" combining the analysis of the sensitivity of the financial system to multiple risk factors into a single estimate of the probability distribution of aggregate losses that could materialise under any given stress scenario.

Both of these approaches will be analysed emphasising their main strengths and weaknesses. What emerges from this survey is that, while substantial progress has been made in developing quantitative techniques that help assess the vulnerability of financial systems, a number of methodological challenges still need to be overcome. In particular, macro stress-testing needs to pay closer attention to the correlation of risks and of risk measures over time and across institutions, to the length of the time horizon used for simulations and to the potential instability of all reduced-form parameter estimates because of feedback effects. Further research in this area might also focus on how to use macro stress-testing techniques as an operational tool to incorporate financial stability considerations into monetary policy decision-making.

1 I would like to thank Claudio Borio, Allen Frankel, Ilhyock Shim, Kostas Tsatsaronis and Goetz Von Peter for their helpful comments. The views expressed in this paper are the author's own and do not necessarily reflect those of the Bank for International Settlement.

2 This follows the IMF definition. See Blaschke et al. (2001) and IMF (2003).

3 See CGFS(2001) for a survey of current practice.

4 FSAPs primarily involve macroprudential surveillance, assessment of macrofinancial linkages and the development of financial infrastructure (codes and standards, legal and supervisory framework, payment systems).

As illustrated in Graph 1, macro stress-tests are performed in a number of stages including:

i) defining the scope of the analysis in terms of the relevant set of institutions and portfolios;

ii) designing and calibrating a macroeconomic stress scenario;

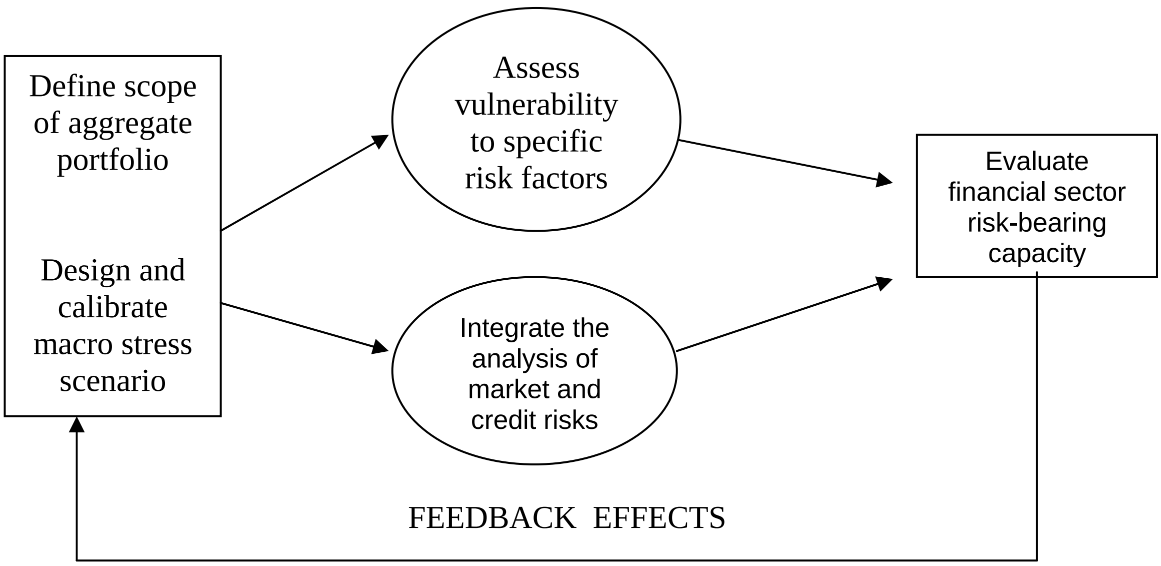
iii) quantifying the direct impact of the simulated scenario on the balance sheet of the financial sector, either focusing on forecasting single financial soundness indicators (FSIs) under stress or integrating the analysis of market and credit risks into a single estimate of the probability distribution of aggregate losses that could materialise in the simulated stress scenario;

iv) interpreting results to evaluate the overall risk-bearing capacity of the financial system;

v) accounting for potential feedback effects both within the financial system and from the financial sector onto the real economy.

Section 1 introduces a simple analytical framework to distinguish the main conceptual differences between macroeconomic forecasting, the analysis of early warning indicators and stress-testing. Section 2 provides a brief overview of the macro stress-testing process as outlined above. Section 3 reviews current models and methodologies in more analytical detail focusing in particular on the two oval boxes illustrated in Graph 1. Section 4 analyses the key remaining methodological challenges for macro stress-testing, paying particular attention to the treatment of feedback effects. Section 5 summarises the main conclusions.

Graph 1 – Overview of macro stress-testing



1. Macroeconomic forecasts, early warning indicators and stress-tests

Aggregate stress-tests can usefully complement the financial stability toolbox for market monitoring, as they provide forward-looking information on the impact of possible extreme events on the financial system.[5] Before describing the building blocks of macro stress-testing, it may be useful to outline the main conceptual differences between macroeconomic forecasting, the analysis of early warning indicators and stress-testing.[6]

[5] See CGFS(2000).

[6] See Worrell (2004) for further discussion of how these tools could be combined into an integrated framework.

A simple framework for macroeconomic forecasting can be described as follows:

$$E(\tilde{X}_{t+1}) = g_1\{X^t, Z^t\} \qquad (1)$$

where we denote throughout with a tilde the unknown future value of a random variable and with a superscript t a history of past realisations of a random variable up to time t. The basic problem of forecasting consists in estimating a function g_1 that maps a history of past realisations of macroeconomic variables X and of other relevant factors Z into a vector of future expected macroeconomic outcomes. Forecasts are drawn largely from historical data in order to predict *the most likely* outlook for the macroeconomy as a whole or for a particular sector (for example the financial sector). By contrast, early-warning models and stress-testing are both concerned with *unlikely* events that – if realised - could however lead to severe consequences. While early-warning models focus on estimating the probability of crises, macro stress-testing attempts to evaluate the resilience of the financial system in the event of a crisis.[7]

Using the same notation introduced above, models of early-warning indicators of financial crises can be generally described as follows:

$$P(\tilde{X}_{t+1} \geq \overline{X}) = g_2\{X^t, Z^t\} \qquad (2)$$

Here the problem is to identify a subset of X and Z as leading indicators to predict the probability of a crisis, where a crisis can be defined as the binary event occurring if a set of macroeconomic variables X exceed some critical thresholds (i.e. crisis if $\tilde{X}_{t+1} \geq \overline{X}$, no crisis otherwise[8]). In this framework, several studies have estimated the likelihood of exchange rate, banking or "twin" crises mainly using probit/logit models or discriminant analysis.[9]

While early warning models use historical data as an input to predict the probability of a crisis, macro stress-testing simulates "crisis events" (whether based on historical data or not) as an input to assess the vulnerability of the financial system under extreme but plausible stress scenarios. As will be further illustrated in the remainder of this paper, the possible consequences for financial stability of a macroeconomic stress scenario (such as $\tilde{X}_{t+1} \geq \overline{X}$) can be evaluated as follows:

$$\Omega(\tilde{Y}_{t+1} / \tilde{X}_{t+1} \geq \overline{X}) = f\{X^t, Z^t\} \qquad (3)$$

where:

- $\tilde{Y}_{t+1} / \tilde{X}_{t+1} \geq \overline{X}$ indicates the uncertain future realisation of an aggregate measure of distress for the financial system ($\tilde{Y}_{t+1}$) in the event of a simulated macroeconomic stress scenario (i.e. conditional on a tail realisation of $\tilde{X}_{t+1} \geq \overline{X}$). The most common measure of financial sector vulnerability used in macro stress-testing is the ratio of potential losses over available capital.
- Ω(.) is the risk metric used to compare financial system vulnerability across portfolios and scenarios. In what we define later as the "piecewise approach", individual financial soundness indicators are predicted mainly as point estimates under any assumed stress scenarios. In this case, the risk metric operator is not very different from a simple conditional expectation as in (1), although restricted to tail events. Studies adopting a more "integrated approach" to assessing financial sector

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[7] As noted by the Committee on the Global Financial System (2000), stress tests estimate the exposure to a specific event, but not the probability of the event occurring. Thus they can provide information on how much could be lost conditional on a given scenario, but not how much is likely to be lost a priori.

[8] One could think, for example, of the budget or current account deficits exceeding a sustainable level or non-performing loans in the banking system running out of control.

[9] A useful survey of this literature can be found in Flood and Marion (1999).

vulnerability, instead, consider the entire probability distribution of portfolio losses $\tilde{Y}$ potentially arising in any given stress scenario.[10] This allows to analyse both expected and unexpected losses, while the choice of any particular percentile along the distribution (i.e. the degree of confidence) depends mainly on the targeted level of risk tolerance. In this case, Value-at-Risk represents a commonly used risk metric (Ω) to compare different loss distributions associated with various portfolios or scenarios.

- f (.) is the loss function that maps an initial set of simulated macroeconomic shocks to the final impact measured on the aggregate portfolio of the financial sector. This function includes as arguments risk exposures, default probabilities, correlations, feedback effects, and provides the link between changes in macroeconomic fundamentals and aggregate financial distress.

2. Overview of macro stress-testing

2.1 Defining the scope of the analysis

A key step in macro stress-testing is that of selecting the set of relevant financial institutions. When assessing the risk exposure of the financial system, should the analysis be restricted to large banking institutions relevant for systemic stability or should it also include, for example, foreign banks, non-banks, insurance companies or pension funds? How to deal with financial conglomerates? Furthermore, which asset classes within any given financial institution should be included in the stress-testing exercise? For banks, should the risk exposure be measured both in the trading and in the banking books? Defining the relevant portfolio for macro stress-testing depends partly on the nature of the risks to be analysed and partly on data availability.[11]

Because of data constraints, many methodological papers have constructed hypothetical portfolios whose composition is intended to mimic the distribution of assets and risk exposures within a given financial system. By contrast, in those studies that use actual data, the analysis has often been confined to a few large banks of systemic importance, also reflecting the broader availability of public market data on these institutions. As for the choice of asset classes to include in the analysis, macro stress-tests have so far mostly focused on the banking books, with special attention to both corporate and consumer loans and interbank loans. A few studies have been able to disaggregate corporate exposures by industrial sector.

Even once the scope of the analysis has been identified in terms of a given set of institutions and asset classes, measuring risk exposure is not an easy task. In fact, portfolios are in continuous evolution over time according to the specific investment and hedging strategies of individual institutions. The actual exposure on any single credit obligation may follow pre-determined loan disbursement and repayment profiles or be characterised by an a priori uncertain drawing pattern (eg lines of credit). Furthermore, as will be discussed later, financial institutions may reallocate their portfolio in response to macroeconomic shocks and therefore change their risk exposure endogenously.

2.2 Designing and calibrating macroeconomic stress scenarios

There are a number of elements involved in the design of any stress scenario including the choice of the type of risks to analyse (market, credit, interest rate, liquidity, etc..), whether single or multiple risk factors are to be shocked, what parameter(s) to shock (prices, volatilities, correlations), by how much (based on historical or hypothetical scenarios) and over what time horizon.

[10] The probability distribution of portfolio losses conditional on any simulated stress scenario should be distinguished conceptually from the unconditional probability that any stress scenario might in fact materialise. Estimating the latter probability is among the objectives of models of early-warning indicators, while macro stress-testing – as mentioned – evaluates the impact of extreme but plausible shocks (possibly in the form of a probability distribution of losses as opposed to a point estimate) without generally attempting to quantify the likelihood of their actual occurrence.

[11] CGFS(2000) outlines four possible cases concerning the scope of the reporting population with differing implications for computational accuracy and reporting burden (full universe, actual frequent market participants, regulated frequent participants and dealer firms only).

The analysis of a wide range of risk factors enhances the predictive power of the stress-test at the cost, however, of an increased computational burden. Similarly, simulating a comprehensive scenario including multiple shocks allows more realistic predictions than focusing on ad-hoc sensitivities of single parameters.

One of the key decisions is how to calibrate the size of the shocks to use for stress-testing. Setting the hurdle too low or too high might make the whole exercise meaningless. In general, shocks can be calibrated to the largest past movement in the relevant risk variables over a certain horizon (change from peak to trough or deviation from trend) or be based on historical variance (unconditional or conditional). Alternatively, with sufficient data, one can attempt to estimate the joint empirical distribution of past deviations from trend of the relevant risk variables and use its quantiles for simulating the stress scenario.

It is important to capture in the simulated scenario the second-round effects on any other economic variable that might be affected by the original shock (for example, a severe oil shock is likely to affect GDP as well as inflation, interest rates, etc). Ideally, structural macro-econometric models should be employed to fully characterize the interacting shocks affecting key real economy indicators or asset prices that define the scenario of interest. Alternatively, one could use reduced-form reaction functions, assuming for example that the interest rate is set by the monetary authorities following a Taylor rule or that prices and unemployment rates are governed by a Phillips curve. In fact, identifying all second-round effects of a given set of shocks is among the major challenges encountered in designing a comprehensive and internally consistent macroeconomic stress scenario.

2.3 Assessing system vulnerability to specific risk factors

Having selected the scope of the portfolio and designed a stress scenario, the impact of macroeconomic shocks on the stability of the financial system can be measured using a number of different indicators. So-called Financial Soundness Indicators (or FSIs) have been used to separately quantify the systemic importance of various sources of risk. FSIs comprise financial sector measures of capital adequacy, asset quality, earnings and profitability, liquidity and sensitivity to market risk (including interest rate and foreign exchange risk) as well as indicators of market liquidity, corporate and household financial health and real estate prices. There is a core set and an encouraged set of FSIs. They have become an essential part of the macroprudential surveillance carried out by the IMF across countries. A full list is provided in the appendix.

The sensitivity of these indicators to adverse changes in macro fundamentals can be estimated on historical data and then used to simulate the impact on the financial system of possible stress scenarios in the future. Depending on data availability, the econometric analysis could exploit both the time series and cross-sectional dimensions. Time series analysis is useful to assess the building up of financial sector vulnerabilities over time. Additionally, panel studies can evaluate the role of country-specific or bank-specific factors.

Each financial soundness indicator is designed to capture the sensitivity of the financial system to a specific risk factor (credit or market risk). The reliance on individual balance sheet measures (non-performing loans, loan-loss provisions, foreign exchange or interest rate open positions) characterises what we call the "piecewise approach" to macro stress-testing. All of these indicators contribute valuable information to the analysis of financial stability but none of them can provide in and of itself a comprehensive assessment of the various sources of risk to which the financial sector is exposed. To obtain a fuller picture of system-wide vulnerabilities, the inter-relationships among FSIs should also be studied. We will return on this in section 3.1.

2.4 Integrating the analysis of market and credit risks

The various risks monitored through financial soundness indicators may all be correlated and are certainly not mutually exclusive (eg an oil price shock is likely to have repercussions on inflation and interest rates and therefore can be a source of interest rate risk as well as credit risk, commodity price risk, etc..). Therefore, in order to evaluate the vulnerability of the financial system to a given stress scenario, economists are looking for an integrated risk model that jointly accounts for multiple sources of risk as opposed to relying on different indicators that separately quantify the impact of individual risk factors.

In essence, a risk model is an analytical tool that maps a given macro scenario and relevant portfolio into a probability distribution of losses, from which various risk measures can be derived. Under specific distributional and parameter assumptions, it provides a common metric to compare the vulnerability of different portfolios to a given shock or the impact of different stress scenarios on a given portfolio. There are many different modelling approaches to compute expected and unexpected losses on a portfolio and several alternative risk measures that can be drawn from a given loss distribution. A number of studies have applied to macro stress-testing value-at-risk (VaR) measures, so far mainly used for the risk management of individual financial institutions. Saying that a given portfolio has a 1-year VaR of $ X at a 99% confidence interval means that the quality of the portfolio is such that – whatever happens – there is only a 1% chance of having a loss greater than $ X for the year.

Losses due to market risk are computed by analysing how the market value of individual instruments in a given portfolio changes over a set horizon as a result of the co-movement of a vector of relevant risk factors. A number of pricing models are used to estimate how correlated changes in interest rates, foreign exchange rates, equity or bond prices, etc might affect the valuation of different market portfolios (bonds, equities, derivatives, etc). *Local* valuation methods usually employ first or second-order approximations to estimate the sensitivity of the portfolio to the risk factors around its present market value and then use it to infer the change in value (i.e. the loss distribution) under different stress scenarios. *Full* valuation methods instead recalculate the value of the portfolio in each scenario using a new vector of prices either inferred from historical analysis or drawn from known distributions using Monte Carlo simulations. The choice between local or full valuation methods involves a trade-off between accuracy and computational burden.

In many applications – and in particular when stress testing banks – the key risk factor, which accounts for most of the potential balance sheet losses, is credit risk. This can be simplified to a binary process (default/no default, like in the default mode approach) or more accurately described along a discrete rating scale accounting for different degrees of creditworthiness (the mark-to-market approach). While the techniques for analysing market risk are more standardised[12], credit risk modelling is probably the area where most of the attention has focused lately. Two main classes of credit risk models have emerged in the literature. *Reduced-form* models assume an exogenous functional form for the relationship between default probabilities and a number of primary, possibly correlated, risk factors whose evolution over time follows data-driven stochastic processes. *Structural* models track more explicitly the impact of risk factors on the assets and liabilities of obligors and derive default probabilities based on the distance between the expected value of the assets at maturity and the default threshold determined by the level of the liabilities.[13]

Changes in macroeconomic fundamentals or in asset prices may directly affect the market value of banks' assets and liabilities. Moreover, large swings in asset prices can lead to significant volatility in debt-to-income ratios for both households and firms. The impact of asset price shocks on the solvency of banks' obligors and, in turn, on the credit quality of banks' portfolios, represents a primary source of concern in the analysis of systemic risk. In fact, a given macroeconomic shock can lead to both market losses and to changes in the credit quality of the obligors (which implies potential mark-to-market losses in the loan book). Thus, it would be desirable to integrate the analysis of market and credit risks, as will be further explained in Section 3.2.1.[14]

2.5 Aggregation and interpretation of results

Both bottom-up and top-down approaches have been used in macro stress-testing with varying responsibilities and computational burden falling on supervisors vis-à-vis individual financial institutions. The former approach relies on banks to compute themselves potential loss distributions conditional on a given stress scenario and then report them to the central bank for aggregation. The latter depends instead mostly on supervisors to carry out the analysis at a centralized level.

The top-down approach appears preferable, given the difficulties of comparability among the different methodologies and modelling assumptions used by various institutions.[15] However, supervisors do not

[12] Also the much broader availability of data on market losses allows the estimation of empirical distributions from historical experience. Data on credit losses is in comparison much more limited.

[13] For a detailed review, see for example Crohuy, Galai and Mark (2000).

[14] The recent emergence of the Credit Default Swap market has generated increased attention for techniques integrating the analysis of market and credit risks.

[15] As noted by CGFS(2000), unless financial institutions are asked to run an exhaustive set of common scenarios, aggregating results of a limited number of "similar" scenarios already available at individual banks might encounter severe problems of

always have access to detailed and disaggregated data on individual portfolio positions or the expertise to evaluate complex transactions.

Once the relevant portfolio data have been gathered from the industry, stress tests in the top-down approach can be performed either on the balance sheet of individual institutions separately or directly on a consolidated portfolio representative of the whole banking system. The former approach allows capturing correlations and interlinkages among the risks faced by individual institutions but is more problematic as regards the aggregation of individual risk measures. Conversely, stress-testing the consolidated balance sheet of the whole banking sector avoids problems of aggregation but overlooks the endogenous risk arising from feedback effects or possible contagion in the interbank market.

In the integrated approach described in section 3.1, aggregate potential losses from both market and credit risk need to be gauged against the risk-bearing capacity of the banking system. In general, the aggregate capital cushion (usually Tier 1 + Tier 2 capital) represents the common denominator of the metric used to assess the vulnerability of various financial systems to different shocks over time. Alternatively, aggregate default frequencies and severities can be simulated over a wide range of scenarios and compared to a target level of risk tolerance. Under the piecewise approach described in section 3.2, instead, the information obtained from the analysis of individual financial soundness indicators needs to be combined for an integrated assessment of the overall vulnerability of the financial system to any given stress scenario.

2.6 Feedback effects

Given the network of inter-bank exposures, losses or defaults of individual banks might have contagion effects on other banks that would otherwise be solvent. Including inter-bank linkages in macro stress-testing allows to evaluate the systemic importance of individual shocks as their impact spreads among financial institutions via a domino effect. Conversely, analysing the vulnerability of the consolidated balance sheet of the whole banking system, netting out interbank exposures, might lead to underestimating systemic risk. While the amount of endogenous risk due to “contagious” defaults may change from country to country depending on the volume and concentration of interbank exposures as well as on the extent of the safety net, the overall advantage of analysing interbank linkages is that it leads to a better understanding of the micro dynamics of systemic risk.

On the other hand, the analysis of interbank linkages represents only a first step in incorporating feedback effects into macro stress-testing as it maintains the assumption of banks keeping a fixed portfolio over the simulation horizon, which yields a static matrix of interbank claims. In reality, banks will attempt to re-optimise their exposures, including inter-bank exposures, away from those sectors/obligors most affected by an adverse shock and thus most in need of liquidity. Section 4 will therefore distinguish between “static” feedback effects, arising in particular from interbank exposures outstanding at any point in time, and “dynamic” feedback effects owing to behavioural responses. The degree to which financial institutions might succeed to immunise their balance sheets from any given shock depends on the nature and timing of the shock itself, the size and diversification of the banks’ portfolios as well as on the availability of information and liquidity in the market.

It is not clear a priori whether incorporating endogenous reaction functions into macro stress-testing models will lead to more or less systemic risk. In principle, banks’ endogenous responses are geared to minimise risks. This would suggest that the ultimate effect on their balance sheets of an adverse macroeconomic shock should be lower if measured within a general equilibrium framework. However, it has been argued that rational risk-minimising behaviour by individual institutions can actually result into domino effects, creating more endogenous risk in the aggregate. Furthermore, endogenous responses to the shocks by all agents in the economy might bring about changes in economic policies or in aggregate demand and supply components, which will in turn feed back on the macroeconomy changing the impact of the original shock. Therefore, capturing all second-round effects of a given stress scenario requires the analysis of feedback effects both within the financial sector and from the financial sector onto the real economy.

As will be described in the following section, macro stress-testing relies on a variety of statistical models to forecast the impact of a given scenario on the vulnerability of the financial sector. These models contain a number of parameters (such as default probabilities, default volatility and

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comparability and might provide a misleading picture of the vulnerability of the financial sector. Furthermore, using incompatible valuation assumptions in the models of individual institutions might lead to significant measurement error in the results of aggregate stress tests.

correlations, etc.), which are estimated based on historical data. The existence of feedback effects in response to the exogenous shocks has led researchers to worry about the potential instability of reduced-form parameter estimates, in the spirit of the *Lucas critique*. Feedback effects and potential parameter instability will be discussed in section 4.

Table 1 - Schematic classification of current macro stress-testing methodologies.

	"PIECEWISE APPROACH" Forecasting models of individual financial soundness indicators	"INTEGRATED APPROACH" Combining the analysis of multiple risk factors into a single portfolio loss distribution
MAIN MODELLING OPTIONS	• time series or panel data • reduced-form or structural models	• macro-econometric risk model á la Wilson (1997) • micro-structural risk model á la Merton (1974)
PROS	• intuitive and with low computational burden • broader characterisation of stress scenario • monetary policy trade-offs	• integrates analysis of market and credit risks • simulates shift in entire loss distribution driven by the impact of macroeconomic shocks on individual risk components • has been applied to capture non-linear effects of macro shocks on credit risk
CONS	• mostly linear functional forms have been used • parameter instability over longer horizons • no feedback effects • loan loss provisions and non-performing loans may be noisy indicators of credit risk	• non-additivity of value-at-risk measures across institutions • most models so far have focused on credit risk only, usually limited to a short-term horizon • available studies have not dealt with feedback effects or parameter instability over a longer horizon

3. A review of macro stress-testing methodologies

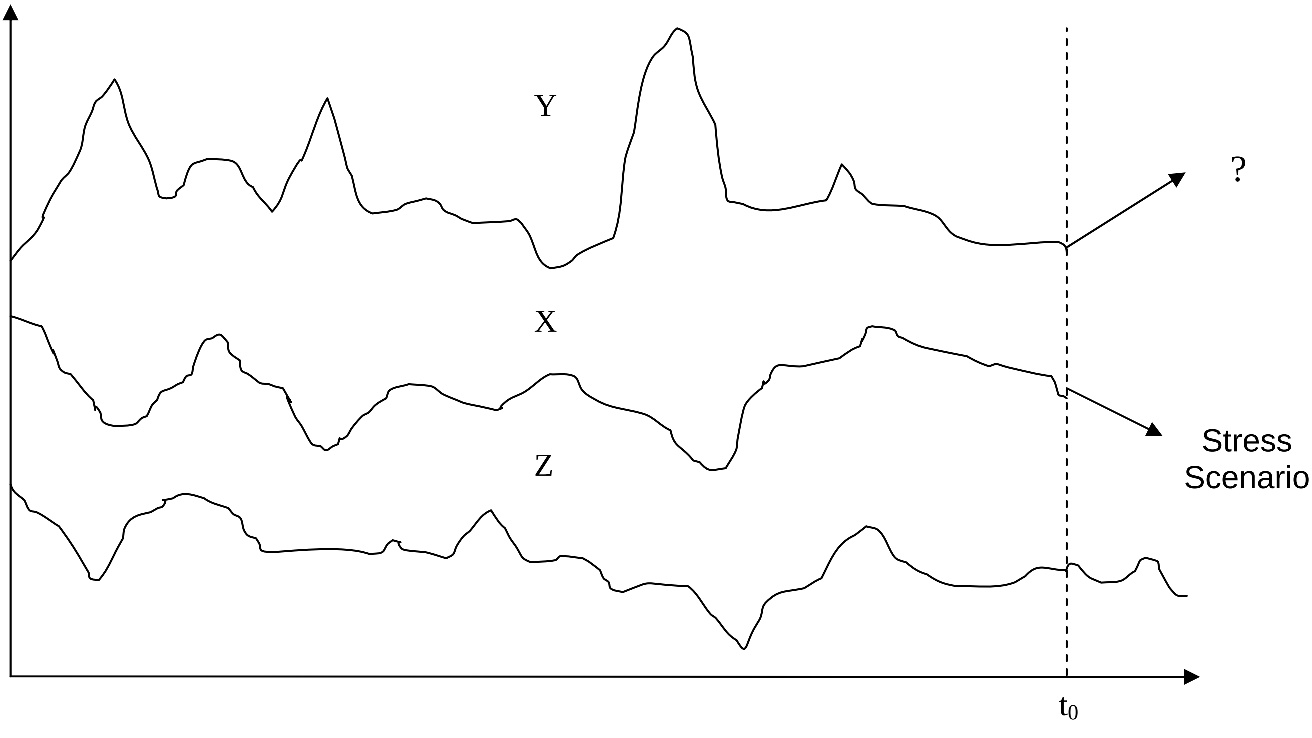
This section presents the two approaches to macro stress-testing most commonly adopted so far. The reliance on forecasting models of single financial soundness indicators under stress characterises what we call the "piecewise approach". In this framework, each indicator (such as non-performing loans or loan-loss provisions) adds potentially useful information for an overall assessment of the vulnerability of the financial sector. A number of other studies have attempted instead to combine the analysis of multiple risk factors into a single estimate of the probability distribution of aggregate losses that could materialise under any given stress scenario. This is what we refer to as the "integrated approach".

As illustrated in table 1, for each of these two approaches we will first explain the basic analytical framework and then proceed to review the main modelling options proposed by recent macro stress-tests and compare their most important strengths and weaknesses.

3.1 Piecewise approach

A number of econometric models have been proposed to estimate on historical data a direct relationship between macro fundamentals (X) and several risk measures (Y) such as the financial soundness indicators reported in the appendix. Estimated coefficients have then been used to simulate the impact of adverse macro scenarios on the vulnerability of the financial system (Graph 2).

Graph 2 - Predicting the impact of macroeconomic shocks on financial soundness indicators



Using the general framework introduced in section 1, this approach to macro stress-testing can be represented as follows:

$$E\left(\tilde{Y}_{i,\,t+1} / \tilde{X}_{t+1} \geq \bar{X}\right) = f\{X^{t}, Z_{i}^{t}\} \qquad (4)$$

where, for each portfolio i [16] and time t, some measure of distress Y (usually Y = loan loss provisions, non-performing loans or write-offs) is estimated as a typically linear function of past realisations of a vector X of relevant macro variables (including GDP, inflation, interest rates and the degree of indebtedness). Certain models include also a vector Z of exogenous possibly bank-specific variables (such as measures of bank size, capitalisation, or cost-efficiency). As noted, under this approach macro-stress testing amounts to forecasting a measure of distress (Y) under extreme assumptions for the conditioning set of macroeconomic variables (i.e. a tail realisation of $\tilde{x}_{t+1} \geq \bar{x}$).

Econometric models following this approach can be classified into two main categories:

a) models that estimate equation (4) as a reduced-form relationship using either time-series or panel data techniques;

b) models that analyse the vulnerability of the banking system to changing macrofundamentals in the context of economy-wide or interindustry structural models.

Several papers adopting each of these modelling options will be briefly reviewed in the following sub-sections. In particular, studies using structural macroeconometric models appear to achieve a more complete characterisation of the stress scenario including the repercussions of the original exogenous shock on all other relevant macroeconomic variables. They also allow to evaluate trade-offs and potential conflicts between the pursuit of monetary and financial stability or to assess structural interdependencies and production flows among industries.

In general, both reduced-form and structural econometric models linking bank losses to macrofundamentals are appealing for being very intuitive and straightforward to implement. On the other hand, this approach has a number of limitations, relating in particular to the rigid linear relationships usually estimated between bank risk and macro-fundamentals and to its narrow applicability for computing mainly banks' expected losses as opposed to characterising the entire loss distribution. This will become clearer as we discuss models adopting an integrated approach to macro stress-testing in section 3.2.

Finally, a number of studies have indicated that loan loss provisions and non-performing loans are only imperfect proxies of the evolution of credit risk in the banking sector over the business cycle. In particular, the accumulation of loan loss provisions may only in part be due to credit risk and loan impairment. Other bank-specific considerations related to income-smoothing policies or forward-looking risk management appear to also play an important role. Furthermore, loan loss provisions are tax deductible in most countries and can be used, to some extent, to meet regulatory capital requirements instead of having to raise new equity on the market.

Time series analysis. Several studies have used non-performing loans, loan loss provisions or composite indices as the metrics to assess the vulnerability of the financial system over time. [17] Hanschel and Monnin (2003) construct a composite stress index for the Swiss banking system, combining deviations from trend of several balance sheet and market-based indicators of financial instability. Although the index appears to capture well the worst stress times in the history of Swiss banking, its robustness for out-of-sample forecasts is limited due to the short time series of annual data available and its high sensitivity to the choice of the component variables. Kalirai and Scheicher (2002) estimate a time series regression of aggregate loan loss provisions in the Austrian banking system as a function of an extensive array of macroeconomic variables. These include indicators of general economic activity (GDP, output gap and industrial production), price stability (CPI inflation and money growth), income, consumption and investment in the household and corporate sectors, financial market indicators (interest rates and stock market indices) and finally variables affecting external solvency (exchange rates, exports and oil prices). Hoggarth and Zicchino (2004) estimate a more parsimonous model using a vector autoregressive (VAR) approach. They focus on the link between loan write-offs (both in the aggregate and disaggregated between household and corporate sectors) and the UK output gap, retail and house price inflation, nominal short-term interest rate and the real exchange rate. Finally, Saurina and Delgado (2004) use cointegration techniques to study both the short-term and long-term time-series properties of the relationship between either loan loss provisions or non-performing loans and a limited set of indicators of macroeconomic activity,

[16] As described later in this section, panel data studies have estimated equation (4) on the portfolios of aggregate banking systems across countries or individual banks within a single country.

[17] Different from the literature on early-warning systems, these risk measures are not leading indicators of the probability of a crisis, but actual loss metrics to be evaluated under different possible crisis scenarios.

unemployment, interest rates and indebtedness. The vulnerabilities of commercial banks and savings banks are analysed separately, while non-performing loans are disaggregated between the corporate and the household sectors.

Panel data regressions. Another set of papers has added to the time series analysis also a cross-sectional dimension. A number of reduced-form models have been estimated using panel data either for aggregate banking systems across countries (Bikker and Hu (2002), Pesola (2001), Cavallo and Majnoni (2002), Laeven and Majnoni (2003)) or individual banks within a single country (Carling et al (2003), Salas and Saurina (2002), Pain (2004), Gerlach (2003), Quagliariello (2004)). Both static and dynamic models have been proposed where the dependent variables remain fundamentally loan loss provisions, non-performing loans and profitability measures (eg net interest margin), while bank-specific characteristics are added to the macrofundamentals among the explanatory variables. The cross-sectional component makes it possible to evaluate the differential impact of business cycle fluctuations on the vulnerability of financial institutions of various size, portfolio diversification and with different histories of bad debts. In particular, Carling et al (2003) focus on corporate bankruptcy risk as a proxy for the vulnerability of banks' balance sheets. They estimate corporate bankruptcy-risk using a probit model on panel data with both macro and firm-specific risk factors. Using a separate vector autoregressive (VAR) model, they also find that the lagged frequency of bankruptcies in the corporate sector is an important determinant of macroeconomic activity in Sweden.

Structural models. A few studies have attempted to embed the reduced-form equation (4) into structural macroeconometric models generally used by central banks in the monetary policy decision-making process. Hoggarth et al (2003) extend the Bank of England's Medium-Term Macroeconometric Model to include relationships between write-off rates and liquidation rates for the corporate sector and between write-off rates and the proportion of credit card debt in arrears for the household sector. Both corporate liquidation rates and household credit card arrears are in turn estimated as a function of macrofundamentals. Oung (2004) and Demuynck (2004) augment the *Mascotte* macroeconometric model of the Banque de France to assess the impact of multiperiod (2-year horizon) stress scenarios on several measures of bank profitability and vulnerability. Dynamic panel data techniques are employed to estimate non-performing loans and interest margin, while an ordered logit model is used to explain migration probabilities of banks' corporate obligors in terms of macrofundamentals. Evjen et al (2003) use the RIMINI model of the Norwegian Central Bank to estimate the impact on the stability of the banking system of both a demand and a supply shock. Banks' loan losses are predicted as a function of proxies for the debt-servicing capacity of the household and corporate sectors. The macroeconomic analysis is integrated by the use of a microeconomic scoring model (SEBRA) that estimates firms' default probabilities based on actual and projected balance sheet data. The authors also show that incorporating in the analysis an inflation targeting monetary policy response function (via a standard Taylor rule) reduces bank losses in the scenario characterized by demand-side shocks but increases financial instability in the scenario with supply-side shocks. In this case, in fact, higher interest rates further increase unemployment and, coupled with higher wage growth, reduce firms' profitability thus jeopardizing their debt-servicing capacity. Chirinko and Guill (1991) use a macroeconometric model of the US economy to assess the impact of a set of exogenous shocks (to the exchange rate, federal funds rate, fiscal deficit and primary commodity prices) onto a broader set of interest rates, prices and final demands disaggregated by industrial sector. The vector of final demands by industry, basic assumptions about technical progress, labor force and capital stock as well as estimates of industry wages and prices are then entered into an inter-industry input-output model. The authors argue that since approximately 50% of all production in the United States is for intermediate goods or supports other industry production, it is critical to consider not only final demands by industry but also production flows between industries. The input-output model computes industry-specific revenue and cost variables under each macroeconomic scenario. Along with the interest rates variables predicted by the macroeconometric model, industry-specific sales revenues and costs for labor and intermediate inputs are then used in a panel OLS regression to estimate bank loan losses on corporate loans by industrial sector.

3.2 Integrated approach

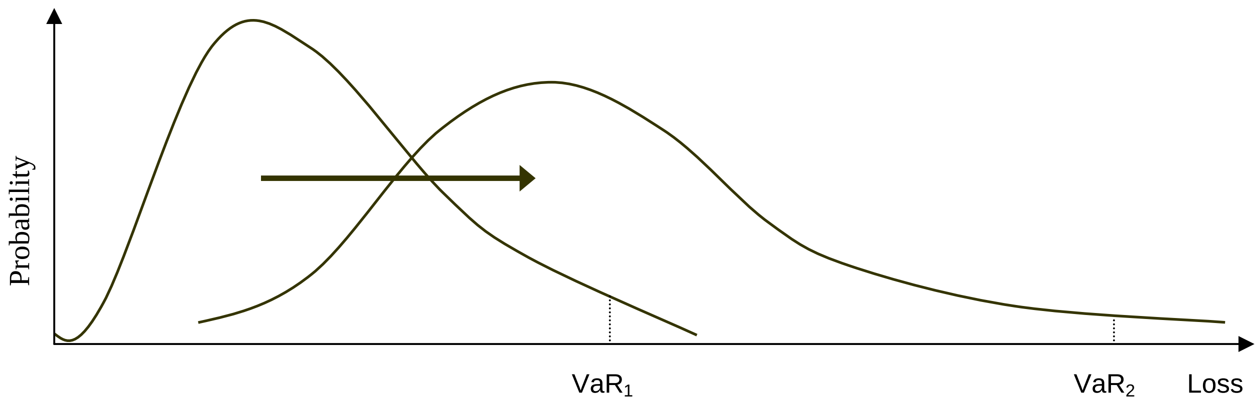
In a mark-to-market framework, portfolio managers at several financial institutions revalue their assets and liabilities on a daily basis under many different stress scenarios. For each simulated economic environment (prices, interest rates, foreign exchange rates, GDP growth, etc..) a conditional probability distribution of losses can be estimated. As a summary statistic of this distribution, the value-at-risk measure is often used to quantify with a single number the sensitivity of the portfolio to different sources of risk. Moving from a micro to a macro perspective, several studies have recently attempted to develop a similar “integrated approach” for macro stress-testing incorporating macrofundamentals into value-at-risk measures as follows:

$$VaR_{i,t}\,(\tilde{Y}_{i,\,t+1} / \tilde{X}_{t+1} \geq \bar{X}) = f\,\{ E_{i,t}(X_t);\ P_t(X_t);\ PD_t(X_t);\ LGD_t(X_t);\ \Sigma_t(X_t) \} \tag{5}$$

$$X_t = h\,(X_{t-1}, \ldots X_{t-p}) + \varepsilon_t \tag{6}$$

The portfolio of the aggregate banking system is identified by a vector E of both credit exposures and market positions and is valued at time t based on a vector of prices P, default probabilities PD, loss given default LGD and a matrix of default volatilities and correlations Σ. All parameters are functions of a vector X of macroeconomic variables, which in turn are assumed to evolve over time following an autoregressive stochastic process. In this framework, a stressed scenario can be simulated by selecting an appropriate vector of correlated innovations ε_t in equation (6). Shocks to the macroeconomic variables in X in turn affect the prices of market positions as well as the credit quality and expected recovery in the loan book. In section 4, we will argue that also default volatilities and correlations and the portfolio itself may adjust endogenously as a response to severe macroeconomic shocks. The overall vulnerability of the banking system is mapped by the function f {.} into a probability distribution of losses conditional on the simulated macroeconomic stress scenario, i.e. $\tilde{Y}_{i,\,t+1} / \tilde{X}_{t+1} \geq \bar{X}$. Moving from a “normal” to an adverse macroeconomic environment is likely to produce a shift in the conditional loss distribution and the corresponding value-at-risk, as shown in Graph 3. The value-at-risk is the risk metric (corresponding to Ω(.) in the general framework of section 1) commonly used to measure the vulnerability of a portfolio to any given macroeconomic scenario.

Graph 3 - Shift in the probability distribution of losses conditional on an adverse macroeconomic scenario.



This approach extends the methodology illustrated in section 3.1 in at least two dimensions:

i. it offers a framework within which one can integrate the analysis of market and credit risks (see section 3.2.1), instead of relying on several different vulnerability indicators;

ii. it allows to model the link between each of the arguments of the loss function f{. } and changes in macrofundamentals X, as opposed to estimating a direct linear econometric relationship between indicators of financial stability and macroeconomic variables as in equation (4). Specifying in equation (5) the individual components of market and credit losses as a function of the macroeconomy could potentially address concerns of parameter instability allowing for all risk parameters to be time or state-dependent (more on this in section 4.2). This approach also adds flexibility to analyse non-linear relationships between macroeconomic shocks and default or loss measures (see section 3.2.2).

To anticipate our findings, it appears that both properties i. and ii. of the integrated approach laid out above have not been fully exploited yet in the macro stress-testing literature. In fact, relatively few studies have developed integrated market and credit risk models. In particular, market risk assessments by supervisors mostly adopt a micro approach, in the same spirit of VaR stress-tests performed by the risk management departments of individual financial institutions. In this sense, a system-wide operational framework to deal with market risk is not yet available. Furthermore, most papers have assumed all the components of the loss function in (5) other than the default probabilities as constant, or derived from an exogenous distribution, instead of modelling them endogenously (more on this in section 4).

When applied at the level of individual institutions, a basic problem of value-at-risk measures is their non-additivity across portfolios.[18] For this reason, most studies have focused on a stylised aggregate portfolio that consolidates assets and liabilities of the whole banking sector. In so doing, however, they have not been able to capture the risk of domino effects among single financial institutions. Recently, the literature has emphasised that widely-used risk measures like standard deviation and value at risk fail to satisfy a number of fundamental axioms that should characterise the risk preferences of rational individuals. Coherent risk measures, like the expected shortfall, have been proposed as reflecting several properties of expected utility maximization under more general conditions. [19] However, as shown for example by Yamai and Yoshiba (2002), both VaR and expected shortfall (although the latter to a lesser degree) might underestimate credit risk in the case of fat-tailed loss distributions.

3.2.1 *Integrating the analysis of market and credit risks*

Both reduced-form and structural models have been used to integrate the analysis of market and credit risks. In the reduced-form literature[20], credit risk is driven by a default intensity process which is affected by market stress. The structural approach to credit risk, instead, explicitly models the link through which asset price volatility impacts the creditworthiness of banks' obligors (both firms and households).[21] This latter approach has often been preferred for the purposes of macro stress-testing. We will provide here a brief description of how a portfolio simulation model can be used to integrate the analysis of market and credit risks, based on the paper by Barnhill, Papapanagiotou and Schumacher (2000).

Under a mark-to-market approach, a probability distribution of losses can be derived by measuring the impact of a large set of adverse scenarios on the market value of banks' assets and liabilities. A scenario is simulated by drawing a set of interest rates, foreign exchange rates, the inflation rate, sectoral equity and regional real estate price indices from correlated exogenous stochastic processes. Those assets and liabilities that only bear market risk are simply revalued using discounted cash flow techniques based on the simulated scenario for inflation, exchange rates and the risk-free term

[18] Assuming that potential losses of bank A and B are correlated, the VaR of the consolidated portfolio is generally not equal to the sum of the VaR of the individual banks.

[19] In particular, four desirable properties of risk measures have been identified by the literature: translation invariance, monotonicity, subadditivity and positive homogeneity. (for more details see for example Artzner, Delbaen, Eber and Heath (1999))

[20] See for example: Jarrow and Turnbull (2000), Jobst and Zenios (2001), Kijima and Muromachi (2000) and Walder (2002).

[21] Examples of this approach include: Barnhill and Maxwell (2002), Bucay and Rosen (1999) and Iscoe, Kreinin and Rosen (1999).

structure of interest rates. The valuation of loans instead requires an integrated analysis of market and credit risks. In the event of no default, loans are priced discounting their future expected cash flows with the simulated interest rate that corresponds to their credit rating in any given scenario. In case of default, their pay-off is given instead by the recovery value net of transaction costs. Recovery rates are drawn from an exogenous beta distribution. What drives default probabilities and their volatilities/correlations is the credit rating of the obligors, which depends on the simulated scenario. In particular, the credit quality of corporate loans is assumed to be a function of firm leverage (debt to total assets). Given the value of liabilities, firm leverage is mainly driven by the evolution of the market value of the firm's equity (whose systematic component follows the simulated path of sectoral equity indices). The credit quality of mortgage loans is instead assumed to vary as a function of the ratio of the remaining notional value of the loan to the value of the property. This fluctuates in each scenario following the evolution of the simulated regional real estate price indices. Calibrating and applying the model to a set of hypothetical banks operating in South Africa as of 1999, the authors conclude that the credit quality of the loan portfolio is the most important risk factor. They also show that, taken individually, market risk, credit risk, portfolio concentration, asset and liability maturity mismatches are all significant sources of risk. However, they are clearly not additive and are therefore best evaluated in an integrated framework as a set of correlated risks.

3.2.2 Modelling default probabilities as nonlinear functions of macrofundamentals

Several recent papers (including Boss (2003), Virolainen (2004) and Vesala (2004)) have analysed the impact of macrofundamentals on the credit quality of banks' obligors using the framework of Wilson (1997)[22].

First, the average default rate for industry *j* is modelled by the logistic functional form[23] as:

$$PD_{j,t,s} = \frac{1}{1+\exp(y_{j,t,s})}\,, \tag{7}$$

where $PD_{j,t,s}$ is the probability of default for a counterparty in industry *j* at time *t*, in the state of the world *s* and $y_{j,t,s}$ is an industry-specific index of macroeconomic variables X (such as GDP growth, interest rates, etc.), whose parameters are estimated as follows:

$$y_{j,t,s} = \beta_{j,0} + \beta_{j,1} X_{1,t,s} + \beta_{j,2} X_{2,t,s} + \ldots + \beta_{j,n} X_{n,t,s} + \upsilon_{j,t,s}\,, \tag{8}$$

A higher value for $y_{j,t,s}$ implies a better state of the economy with a lower default probability and vice versa. Equations (7) and (8) can be seen as a multifactor model for determining industry-specific average default rates. The systematic risk component is captured by the macroeconomic variables $X_{i,t}$ with an industry-specific surprise captured by the error term υ. Individual functions can be estimated for each industry allowing the explanatory macroeconomic variables to differ between industries.

The second step is to model and estimate the development of the individual macroeconomic time series describing the health of the economy. Usually, a set of univariate autoregressive equations of order p (AR(p)) are used for this purpose, as follows:

22 The model was initially developed for McKinsey & Co. and was known as *CreditPortfolioView*. The analysis here follows closely Virolainen (2004).

23 The logistic functional form is widely used in modelling bankruptcies to ensure that default rate estimates fall in the range [0,1].

$$X_{i,t} = k_{i,0} + k_{i,1} X_{i,t-1} + k_{i,2} X_{i,t-2} + ... + k_{i,p} X_{i,t-p} + \varepsilon_{i,t} \tag{9}$$

where k_i is a set of regression coefficients to be estimated for the ith macroeconomic factor, and $\varepsilon_{i,t}$ is a random error assumed to be independent and identically normally distributed.

Equations (7)-(9) together define a system of equations governing the joint evolution of the industry-specific default rates and associated macroeconomic factors with a ($j + i$) $\times$ 1 vector of error terms, or innovations, E, and a ($j + i$) $\times$ ($j + i$) variance-covariance matrix of errors, Σ, defined by

$$E = \begin{pmatrix} \upsilon \\ \varepsilon \end{pmatrix} \sim N(0,\Sigma) \quad , \quad \Sigma = \begin{bmatrix} \Sigma_{\upsilon} & \Sigma_{\upsilon,\varepsilon} \\ \Sigma_{\varepsilon,\upsilon} & \Sigma_{\varepsilon} \end{bmatrix} \tag{10}$$

The final step is to utilise the parameter estimates and the error terms together with the system of equations to simulate future paths of joint default rates across all industries over some desired time horizon. Using Monte Carlo methods, it is then possible to determine credit loss distributions for portfolios of interest conditional on the simulated macro scenarios.

An alternative to the model of Wilson (1997) is the firm-level structural approach originally proposed by Merton (1974). Gray, Merton and Bodie (2004) extend this framework to study both corporate and sovereign default risks. Derviz and Kadlcakova (2003) incorporate business cycle effects into a hybrid model including features of both the structural and reduced-form approaches.

The papers by Drehmann and Manning (2004) and Pesaran et al (2004) have recently studied the nonlinear relationship between default probabilities and macroeconomic variables within the Merton framework for the purpose of macro stress-testing. Both papers model the relationship between firm default probabilities and macrofundamentals in three stages. First, they make an assumption on the joint evolution of exogenous macroeconomic and market factors. Drehmann and Manning (2004) consider only i.i.d. innovations in systematic factors for the UK and assume that they are jointly normally distributed. Pesaran et al. (2004) instead estimate a Global Vector Autoregressive Model (or GVAR) that allows for serial correlation of macroeconomic factors over time and captures also the interdependencies between business cycles across countries. Second, a multi-factor regression is performed on a firm-level panel to link macroeconomic and market factors to corporate returns on equity. Third, as a proxy for asset values, equity returns are entered into the Merton framework in order to obtain individual firms' probabilities of default, conditional on a given macroeconomic scenario. Instead of using a fixed default threshold (usually based on the book value of firm liabilities), Pesaran et al. (2004) assume that default occurs when equity/asset values fall by more than a certain percentage in one quarter. The percentage is different by firm's credit rating and is estimated looking at the historical co-movement of equity returns and rating actions.

As discussed above, the Wilson (1997) framework allows to model directly the different sensitivities of default probabilities in various industrial sectors to specific sets of macroeconomic variables. In comparison, the Merton approach adds one more step by modelling first the response of equity prices to macrofundamentals and then mapping asset price movements into default probabilities. The former approach is quite intuitive and computationally less demanding. The latter has instead the advantage of relying almost exclusively on forward-looking equity prices and credit ratings. However, it can be considerably more data-intensive as it analyses default risk at the level of individual firms.

Finally, in those countries where disaggregated corporate balance sheet and credit register data are available, scoring models have been used to estimate default probabilities both under "normal" and "stressed" economic environments.

4. Measuring endogenous risk in macro stress-testing

4.1 Longer horizon and feedback effects

Most macro stress-tests performed to date have shown that the first-year effects of macroeconomic shocks are very small compared to current levels of capitalisation in banking systems across countries. Historical experience, however, suggests that systemic episodes are the result of financial system strains that persist for a number of years and progressively weaken the cushioning capacity of capital. It would be desirable, therefore, to lengthen the horizon of macro stress-tests (so far typically limited to one year) allowing for serially correlated shocks to build up economic imbalances over time (see Pesaran et al. (2004)).

Moreover, there are good reasons to believe that risk measurement and risk management horizons should roughly correspond. In other words, the impact of a given stress scenario on the financial system should be followed through time at least as long as necessary for financial institutions and monetary authorities to take remedial action. Empirical evidence appears to confirm that, especially during times of generalised macroeconomic turmoil, recapitalisation of distressed banks might take longer than the one-year horizon usually adopted in risk management. In particular, analysing the behaviour of US commercial banks that suffered large losses and recovered[24] between 1984 and 1999, Barakova and Carey (2002) find that more than half of undercapitalised banks took longer than 1 year to rebuild their capital base after incurring severe losses. They note that equity issuance was a key component of the recapitalisation process in most cases. In the short run, however, the opaqueness of banks' balance sheets and the serial correlation of credit losses make it difficult for investors to accurately price an equity issuance in the midst of financial distress. Therefore, they argue that banks may need to carry enough capital buffer to survive several years of large losses before being able to raise new equity.

Lengthening the horizon for macro stress-testing will further reduce the applicability of the ceteris paribus (or partial equilibrium) assumption inherent in most credit risk models. In fact, the risk exposure of the financial system is to some extent endogenous. When faced with a given adverse shock, all agents in the economy (monetary authorities, financial institutions, firms and households) will re-optimise their behaviour accordingly. Whether demand or supply considerations prevail to determine banks' endogenous response to adverse macroeconomic shocks, it is clear that capturing the interlinkages both within the financial sector and between the financial sector and the real economy might provide a fuller picture of the actual risk exposure of the financial system under a given stress scenario.

The few studies that have started to explore these interlinkages and feedback effects in the context of macro stress-testing can be categorised into three main groups.

1. Several papers, keeping the portfolio of each institution fixed (i.e. assuming no endogenous reallocation), have attempted to measure the risk of "contagious" defaults through domino effects in the interbank market.
2. Some studies have analysed endogenous portfolio reallocation and feedback effects within the financial sector. The endogenous portfolio reoptimisation in response to macroeconomic shocks affects aggregate demand in the securities markets and feeds back through changes in asset prices into more endogenous portfolio adjustments via an iterative process until a new equilibrium is reached.
3. Finally, a few papers have looked at the relationship between financial and macroeconomic instability and at the predictive power of financial variables to forecast economic activity.

In the three following subsections, we will briefly describe the main findings of each of these strands of the literature, as they relate to macro stress-testing, pointing out the key remaining challenges for further research.

[24] Several measures are proposed to define the entry and exit of banks from distress. According to their primary definition, distress initiates when a bank's equity-to-assets ratio falls below 2 per cent and ends when the ratio rises above 5 per cent. Additional measures used for robustness checks involve the timing of loan loss provisions and regulatory CAMEL rating actions.

4.1.1 *Inter-bank linkages*

Even assuming that financial institutions do not reallocate their portfolios during the stress-test horizon (no behavioural responses), the failure of one or more banks can potentially generate domino-effects through the chain of bilateral exposures outstanding in the interbank market. This "hidden" correlation among financial institutions can be a source of "endogenous risk" in addition to the "exogenous risk" generated by the initial macroeconomic shocks. Therefore, looking only at the aggregate "macro portfolio" of the banking sector, ignoring inter-bank exposures, might lead to underestimating the overall risk in the system.

Interbank contagion has usually been modelled in the theoretical literature as a liquidity crisis in the framework of Diamond and Dybvig (1983). Contagion arises as failing banks default on their interbank obligations, like in Allen and Gale (2000), or alternatively when banks "run" to withdraw their deposits at other banks, even if perfectly solvent, because of widespread liquidity concerns in the banking system, as in Freixas, Parigi and Rochet (2000). Other channels of contagion that have been studied include gridlocks in the payment systems, cross-ownership links among banks and information asymmetries (see for example Giesecke (2004)).

Empirical tests for interbank contagion have followed two main approaches. One set of papers has looked for correlation in the probability of bank survival over time (eg. Calomiris and Mason (2000)) or across banks (eg. Gropp and Moerman (2004), Gropp and Vesala (2004) and Hartmann, Straetmans and de Vries (2004)[25]) controlling for macroeconomic conditions and other systematic factors. A second set of papers has focused on estimating a matrix of actual interbank exposures and then simulating the impact on the system of the failure of one or more banks.[26] Examples include Sheldon and Mauer (1998) for the Swiss banking system, Wells (2002) for the UK, Blavarg and Nimander (2002) for Sweden, Furfine (2003) for the US Federal Funds market, Upper and Worms (2004) for Germany and Degryse and Nguyen (2004) for Belgium. Most of these papers focus on the structure of interbank linkages and assess the risk of contagion by letting each bank go bankrupt and then computing the effect of the simulated failure on every other bank in the system.

Elsinger, Lehar and Summer (2004), instead, embed the analysis of interbank linkages within a simulation model for measuring both market and credit risks arising from macroeconomic shocks. They also employ the network clearing framework, first developed by Eisenberg and Noe (2001), that allows them to look at the banking system not as a single entity but as a matrix of interbank claims and liabilities, potentially exacerbating any exogenous shock into a systemic crisis. In particular, in Elsinger er al (2004) a banking system is fully characterised by a matrix of interbank exposures and a vector that represents banks' net worth excluding interbank positions. The initial state of banks' net worth is estimated from balance sheet or market data and then shocked simulating various market and credit loss scenarios.[27] As a result of the correlated shocks, any particular bank can suffer direct losses large enough to fail. This is called "fundamental default". On the other hand, banks – that would otherwise be solvent – could default in a simulated scenario only because other banks are not able to honour their interbank obligations. This is labeled "contagious default" and captures the possibility of a systemic crisis. Thus, contagious defaults may occur as second-round effects in the interbank clearing algorithm.[28]

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[25] These papers assess the degree of potential interbank contagion in Europe by analysing whether a large shock to any given bank in the system significantly increases the probability that other banks will also experience large shocks, ceteris paribus. Each of the three studies cited in the text uses a different technique measuring contagion either as an increase in conditional default probabilities, via an ordered logit model or using multivariate extreme value theory.

[26] The interbank matrix framework had previously been used in studies of payment system interlinkages (eg. Humphrey (1987) and Angelini et al (1996)).

[27] Summer et al. (2002) simulates shocks to banks' net worth by quantifying separately market and credit loss scenarios, using historical simulation for the former and Creditrisk+ for the latter. Summer et al. (2004) uses instead the historical co-movement of banks' equity prices to estimate the geometric Brownian motion governing the dynamics of banks' assets. Finally, Summer et al (forthcoming) aims at integrating the simulation of market and credit losses and tying it more closely to macroeconomic fundamentals.

[28] Accounting for inter-bank linkages in macro stress-testing involves computing the possible outcomes that can arise in the payment flows at each point in time following a given stress scenario. This requires some assumptions about banks' interbank lending exposures and the resolution of insolvencies in order to pin down a unique equilibrium. In particular, proportionate debt servicing is assumed in case of interbank defaults and an entropy optimisation algorithm is used to estimate the missing information in the matrix of interbank claims. This latter technique distributes the mass of interbank claims as evenly as possible among the unknown cells of the matrix.

Most papers analysing interbank linkages conclude that the risk of contagion through this channel is quite limited and becomes only significant under rather extreme macroeconomic scenarios. While the amount of endogenous risk due to “contagious” defaults may change from country to country depending on the volume and concentration of interbank exposures as well as on the extent of the safety net, the overall advantage of analysing interbank linkages, however, is that it leads to a better understanding of the micro dynamics of systemic risk in the financial sector. Furthermore, this framework allows to distinguish among systemic and non-systemic shocks and could potentially aid bank supervisors in localising risks of domino effects before they happen. The incidence and severity of defaults over a given set of scenarios can be analysed both at the level of individual institutions or aggregated for the whole banking system.

Models of interbank linkages, however, have their own limitations. In particular, Van Lelyveld (2004) finds that the method usually adopted to fill in the matrix of interbank linkages might lead to somewhat unrealistic results. In the absence of data on actual interbank positions, the general approach has been to distribute the flows of interbank claims as evenly as possible across the missing rows and columns in the matrix of interbank exposures. Given the limited information available on banks' bilateral positions, this method minimises the matrix estimation error ex ante. It could however substantially underestimate systemic risk, if in reality interbank flows are concentrated among a limited number of large banks. The failure of any of them would produce in fact much larger cumulative losses than would be captured under the modelling assumption of a perfectly interconnected system. Additionally, these models while providing a broader picture of systemic risk, are still confined to a short simulation horizon and lack an explicit treatment of endogenous portfolio adjustments, feedback effects or conditional variance-covariance matrices, as will be discussed in the following sections.

4.1.2 Endogenous portfolio adjustment and feedback on asset prices

Most of the literature on interbank contagion reviewed in the previous section finds that the likelihood of large losses due to domino effects is in most cases very small. Cifuentes, Ferrucci and Shin (2004) argue that this is not surprising, since bank portfolios and asset prices are assumed to remain fixed throughout the simulation horizon. In fact, they illustrate how capital requirements may induce endogenous portfolio restructuring leading to a chain of asset sales in the middle of an economic downturn. Declining asset prices further deteriorate the marked-to-market capital position of financial institutions and contribute therefore to propagating the impact of the initial adverse macroeconomic shock within the financial system.

Introducing endogenous portfolio reallocation and feedback effects on asset prices, some of the key results obtained by the interbank contagion literature may no longer hold. In particular, under the assumption of portfolio invariance, Allen and Gale (2000) have shown how more diversified interbank credit structures lead to safer systems. Intuitively, sharing a given credit loss among a larger number of banks, reduces the loss amount faced by each individual bank and therefore decreases the likelihood of domino effects. By contrast, Cifuentes, Ferrucci and Shin (2004) argue that this might no longer be the case if portfolios and asset prices are allowed to adjust endogenously. In their model, a more interconnected system may lead to a longer chain of asset sales with a larger overall decline in asset prices and a more severe negative wealth effect on the balance sheets of financial institutions.

Goodhart, Sunirand and Tsomocos (2003) provide a general equilibrium framework that can be used to analyse the endogenous response of banks during crisis events. They allow for multiple credit and asset markets (including the interbank market) and for banks' heterogeneity. One implication of their model is that the degree of contagion in the event of a crisis is reduced if banks have more diversified investment opportunities. In this case, in fact, they can better absorb the exogenous shocks restructuring their positions across several markets, without causing any major change in credit or asset prices.

Some papers have modeled endogenous trading decisions in response to regulatory capital constraints. Danielsson, Shin and Zigrand (2001) develop a dynamic asset pricing model to show that the effect of a common VaR constraint binding during adverse macroeconomic conditions is isomorphic to assuming that the degree of risk aversion of market participants fluctuates with market outcomes and in particular increases in periods of market turbulence. They find that this exacerbates market volatility and leads to overall lower asset prices with deeper and longer troughs along their time paths. Pelizzon and Schaefer (2004) argue that regulatory capital requirements may reduce banks' franchise value and therefore increase their appetite for risk.

Shimizu (1997) provides a simple framework to illustrate the main mechanism through which feedback effects can amplify the impact of an exogenous shock on the financial system.

$$f_{i,t}(x_t) \longrightarrow f_{i,t+1}(x_t + dx) \longrightarrow f_{i,t+2}(x_t + dx) \longrightarrow f_{i,t+2}(x_t + dx + dx') \qquad (11)$$

The portfolio value of the i^{th} agent at time t is indicated as $f_{i,t}(x_t)$ and varies as a function of the specific combination of assets held by the agent (indicated by $f_{i,t}$), and the value of individual assets included in the portfolio, which depends on the time t realisation of a set of risk factors (x_t). In a one-dimensional case, assume that a given stress scenario can be initially described as a discrete shock to a risk factor, i.e. dx. The initial change in portfolio value is given by the impact of the shock on the prices of individual asset holdings, i.e. assuming portfolio invariance $f_{i,t+1} = f_{i,t}$. The following step involves instead optimal portfolio rebalancing for each agent i, where the change in the portfolio from t+1 to t+2 depends on agent i's optimal trading strategies following the initial shock dx. Finally, the optimal responses to the shock from all agents in the market will generate additional demand or supply for the individual assets, which will feed back on their market prices. Therefore, there will be an endogenous discrete adjustment (dx') in the risk factors underlying asset prices, which will add up to the original shock (dx). This is an iterative process that continues until an equilibrium price is reached and no agent will further rebalance the portfolio.

This stylised framework outlines the two main components necessary to the analysis of feedback effects within the financial system:

1) the reaction of market participants to the shock given their heterogeneous trading strategies, ie ($f_{i,t+1} \longrightarrow f_{i,t+2}$);
2) the feedback effect itself, i.e. the impact of the rebalancing of portfolios in 1) onto the aggregate demand and supply for individual assets which in turn may affect their market prices (dx').

Kawahara (1996) shows how the latter effect, i.e. the second-round change in the risk factor market price dx', can be obtained as a function of the net supply/demand imbalance for individual assets induced in the market by the original shock.

Shimizu (1997) also assumes the feedback effect on market prices as a stylised linear function of the induced aggregate trade imbalance (i.e. $dx' = k \sum_{i=1}^{n} \frac{df_i(x)}{dx}$) and focuses most of her attention instead on modelling agents' optimal reactions to the initial shock, i.e. point 1) above. She suggests two approaches to take into account agents' heterogeneous reaction functions in macro stress-testing. A simple method is to map the behaviour of each agent into a stylised trading rule, based on available information on the agent's risk appetite, loss cutting rules, etc.[29] For example, it is possible to distinguish between agents that never trade, agents that buy a constant amount of a given asset each period ("dollar-cost-average strategy") or agents that adopt more complicated portfolio insurance strategy, buying and selling assets in proportion to their price movements. Once agents are mapped into their stylised trading rules, their reaction functions are assumed to be known a priori and therefore their portfolio rebalancing ($f_{i,t+1} \longrightarrow f_{i,t+2}$) can directly be used to compute the total impact of the stress scenario including feedback effects.

A more realistic alternative, instead, is to extract a trading pattern for each agent based on his historical behaviour in response to shocks. Since disaggregated historical data on actual agents' portfolio rebalancing is hardly available, changes of portfolio sensitivity to risk factors or actual profit and loss figures are used as proxies. Assume in other words that a time series of data is available on the impact that a change in risk factor x would have on the value of the portfolio at each point in time

29 This is standard practice in multi-period models of market micro structure with heterogeneous agents. For example, Glosten and Milgrom (1985) distinguish between three stylised types of traders: informed traders, uninformed traders and market makers.

($\frac{\partial f_{i,t}(x_t)}{\partial x}, \frac{\partial f_{i,t+1}(x_{t+1})}{\partial x}, \frac{\partial f_{i,t+2}(x_{t+2})}{\partial x}$, …etc). The historical price movements of risk factor x (i.e. x_t , x_{t+1} , x_{t+2}, ..etc) are also known. This information can be fed into a neural network, which can learn changing patterns of non-linear functions, in order to extract a time-dependent portfolio rebalancing rule for each agent i, i.e. the function that maps $f_{i,t+1} \longrightarrow f_{i,t+2}$.

The multiperiod simulation approach suggested by Shimizu (1997) appears very interesting, but also demanding in terms of data and modelling requirements. Further research should attempt to lengthen the time horizon and to extend the analysis from trading strategies to lending strategies, thus integrating the assessment of feedback effects for both market and credit risks. Moreover, a number of questions would deserve more attention relating in particular to the degree of liquidity of capital markets in times of stress and how it could affect the extent to which financial agents are able to optimally reallocate their portfolios in response to macroeconomic shocks.[30]

4.1.3 Feedback effects onto the real economy

Monetary macroeconomics offers a wealth of models and empirical studies dealing with feedback effects between the real and financial sectors. A large part of the literature has focused in particular on the concepts of the "bank lending channel" and the "financial accelerator".[31] The former relates to the role of the banking sector in the transmission mechanism of monetary policy, the latter focuses on the effect of financial frictions exacerbating business cycle fluctuations. In principle, feedback effects from the financial system to the real economy operate through both demand and supply forces. On the demand side, a deterioration of the financial condition of households and firms will adversely affect their consumption and investment decisions. Unsustainable debt burdens and wealth effects due to lower asset prices can severely depress demand for credit and overall economic activity. On the supply side, a deterioration in the creditworthiness of borrowers will induce banks to tighten lending standards and raise the cost of credit intermediation. Moreover, large credit losses due to loan defaults and market losses driven by falling asset prices can significantly bite into banks' capital buffers. In order to recover adequate levels of capitalisation, banks may need to raise new equity and/or downsize their portfolios. This could lead to a retrenchment of bank lending and possibly a credit crunch. During an economic downturn, when alternative sources of funds in the capital markets are also scarce, a severe contraction of bank credit will significantly hamper investment and economic growth. Declining investment will cause the price-level to continue to fall, which further aggravates the debt burden of borrowers in real terms fuelling a perverse recessionary spiral.

Overall, this literature suggests that deteriorating balance sheet conditions of all agents in the economy "accelerate" the effects of adverse macroeconomic shocks via a contraction of both demand and supply of credit, which in turn further depresses investment, prices and economic activity. Following the same logic, closing the loop in macro stress-testing (see Graph 1) by allowing simulated loan losses to feed back onto the original macroeconomic scenario would lead to a more complete characterisation of systemic risk. Understanding the mechanisms underlying these second-round effects would not only provide a better quantitative estimate of the total impact of a given stress scenario, but might also further regulators' awareness of macrofinancial interlinkages and help develop more effective prudential policies.

A few recent papers have focused on these interlinkages from a financial stability perspective. Carling et al (2003) analyse the relationship between banking sector credit losses and macroeconomic variables such as output, inflation, the nominal interest rate and the real exchange rate. Using a multivariate Granger causality test, they find that the corporate default frequency (a proxy for bank credit losses) is a useful predictor of economic activity. English, Tsatsaronis and Zoli (2003) extract a small number of principal components from a large set of indicators of the condition of financial markets and institutions for the US, Germany and the UK over the period 1980-2002. When tested against other financial variables commonly used in forecasting real activity such as the level and slope

[30] Some preliminary analysis of market liquidity under stress has been done at the Bank of Japan by Muranaga and Ohsawa (1997), Muranaga and Shimizu (1999) and Miyanoya (1999). See also CGFS(2000) for a discussion.

[31] Some of the best known papers in this area are probably Bernanke and Gertler (1989 1990 1999), Greeenwald and Stiglitz (1993), Kiyotaki and Moore (1997) and Bernanke, Gertler and Gilchrist (1999). Numerous empirical studies have analysed the credit crunches in the US in the 1930's (eg. Bernanke (1983) and Calomiris and Mason (2003)) and in the early 1990's (eg. Ashcraft (2003)). See Allen (2004) for a review of the literature on the impact of bank capital constraints on credit creation and economic activity.

of the yield curve and equity prices, they find that their estimated financial factors add significant explanatory power in predicting output and investment at one and two year horizons.

Overall, while the link between financial and macroeconomic stability is generally recognised to be significant, what is still less clear is how to model and calibrate empirically the channels through which financial system turmoil can feed back onto macroeconomic stress scenarios. This is an important area where research is currently in progress.

Von Peter (2004) sets up a broad conceptual framework to illustrate the interconnection between macroeconomic and financial stability. In particular, he emphasises how loan losses, due to an adverse macroeconomic shock, can feed back onto the macroeconomy if banks restrict lending to meet a binding capital constraint.

The paper by Goodhart, Sunirand and Tsomocos (2003) has proposed a rich but tractable framework to capture feedback effects not only among banks but also between the financial sector and the real economy. Financial fragility is analysed as an equilibrium phenomenon, as banks trade off the costs and benefits of their lending and investment choices, including the possibility of capital requirement violations and defaults. In this approach, a negative shock to the financial system can propagate to the real economy through a credit crunch. If banks need to curtail lending in order to increase their capital ratios, a fall in credit supply will aggravate the default probability of households, reduce their consumption and ultimately lower GDP. Goodhart, Sunirand and Tsomocos (2004a) use this framework to conduct a number of comparative statics, analysing the interactions of monetary and regulatory policies, their relationship with financial fragility and the impact on welfare. Goodhart, Sunirand and Tsomocos (2004b) simplify the model and calibrate it to real data at a specific point in time, in order to use it as a stress-testing tool for banks. Finally, Goodhart, Sunirand and Tsomocos (2004c) extend the model to an infinite horizon setting and analyse how financial fragility may build over time based on time series data for the UK.

4.2 Endogenous parameter instability

Second-round effects on financial sector vulnerability are captured to some extent also by the reduced-form models reviewed in section 3.1. Both time-series and panel regressions extract from historical data an ex post relationship between macroeconomic and financial stability indicators that inevitably incorporates past behavioural responses.

Without an explicit analysis of feedback mechanisms, however, there is no guarantee that future behaviour will follow historical patterns. Therefore, reduced-form models estimating a time-invariant relationship between macro factors and financial vulnerability indicators may encounter problems due to parameter instability and reverse causation. Drehmann and Manning (2004) find that the impact of systematic factors on equity prices changes across monetary regimes and business cycles. Similarly, Virolainen (2004) shows how the effect of interest rates on default risk changes sign with Finland's transition from a high inflation to a low inflation environment. Alves (2004) estimates that the long-term co-movement of industry-level EDFs may change depending on macro-fundamentals. Finally, Bangia, Diebold and Schuermann (2002) and Peura and Jokivuolle (2004) use state-dependent rating transition matrices in a Creditmetrics framework.

Furthermore, large macroeconomic shocks may lead to structural breaks. In other words, endogenous responses of economic agents, instead of following similar reaction functions as in the past, might change altogether. This criticism is somewhat reminiscent of the debate among macroeconomic forecasters following the *Lucas critique* and *Goodhart's law* in the 1970s.[32]

In macro stress-testing, it is important to distinguish between exogenous and endogenous parameter instability. An example of the former is the change in banks' exposure and behaviour over time due to exogenous trends like the increased use of credit derivatives or the greater integration and globalisation of financial markets. Endogenous parameter instability instead occurs if estimated coefficients and correlation patterns "break down" as a result of the shocks simulated for macro stress-testing.

[32] Lucas (1976) pointed out that the parameters of macroeconometric forecasting models depended implicitly on agents' expectations of the policy process and were unlikely to remain stable as policymakers changed their behavior. Similarly, Goodhart (1974) emphasised how reduced-form statistical relationships are likely to break down when used for policy purposes.

In this respect, the models analysed in section 3.2 offer some more flexibility compared to rigid reduced-form relationships estimated between macroeconomic and financial stability indicators. In fact, changing feedback mechanisms under stress can potentially affect any of the risk components in equation (5), i.e. credit exposures, default probabilities, recovery rates, as well as default volatilities and correlations. The importance of each of these effects and their implications for macro stress-testing will be discussed more in detail in the following sub-sections.

4.2.1 Sensitivity of credit exposures, default probabilities and recovery rates to macroeconomic shocks.

The sensitivity of banks' credit exposures to macroeconomic events is well documented in the literature, although there is no consensus as to whether exposures should be expected to increase or decrease during economic downturns. Asarnow and Marker (1995), Mueller (2000), Baker and Wurgler (2000), Anderson and Sundaresan (2000) and Collin-Dufresne and Goldstein (2001) find that the likelihood of drawing down lines of credit increases with adverse macroeconomic conditions when firms are most in need of liquidity. Conversely, studies focusing on early warning systems (espec. the predictive content of property prices) or statistical provisioning - eg. Goodhart (1995), Mei and Saunders (1997), Lown and Morgan (2001) - suggest that banks tighten lending standards prior to economic downturns and therefore the amount of new risk exposure decreases in the anticipation of adverse macroeconomic conditions.

It is important to bear in mind for macro stress-testing that not only credit exposures but also default probabilities and recovery rates may change in the simulated macro stress scenario, compared to estimates derived from a benign sample period. In fact, several empirical studies have found that both default probabilities and recovery rates are very sensitive to the state of the macroeconomy.[33] For example, Carey (1998) provides evidence of significant differences in default rates between "good" and "bad" years. Altman (2002) documents how default rates increased substantially in the US during the recession of 1990-91 as well as the downturn of 2001-02, compared to the low levels recorded during the expansion years 1993-98.

As for recovery rates, most of the models used for macro stress-testing assume the loss given default parameter to be either fixed or driven by an exogenous stochastic process, unrelated to macroeconomic fundamentals. However, both reduced-form and structural models of credit risk including macrofundamentals consistently find evidence of a negative correlation between LGD and macroeconomic conditions. In particular, Frye (2000) finds that collateral values fluctuate with economic conditions such that recovery rates decline by 20-25% during severe economic downturns. Moreover, a positive correlation is found between LGD and PD values (see Altman, Resti and Sironi (2002)). In fact, the same systematic factors that increase default risk are also likely to drive down collateral values as well as the prices of distressed debt.

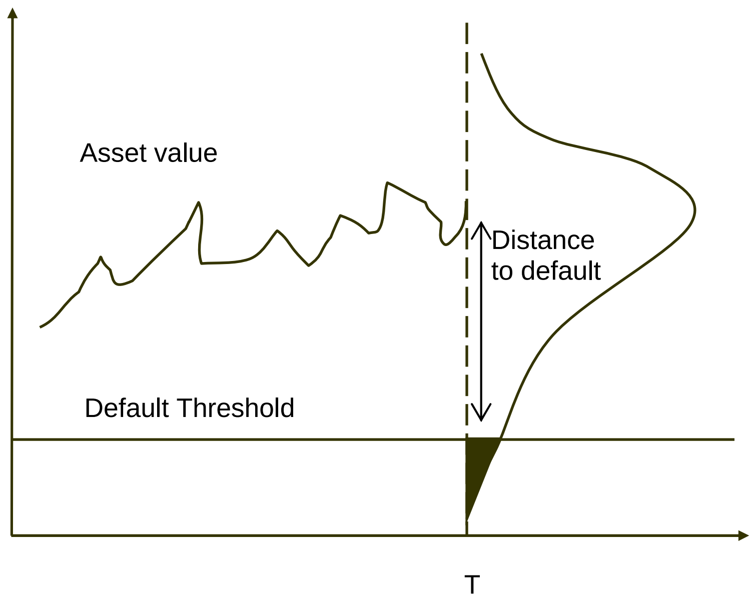
The problem with using for macro stress-testing unconditional PD estimates, or conditional on a benign macroeconomic environment, has surfaced recently in a number of studies analysing Expected Default Frequencies (or EDFs) from Moody's KMV. For example, Alves (2004) estimates a cointegrated vector autoregression model describing both the long-term dynamics and the short-term adjustment of EDFs across major industrial sectors in Europe. Pain and Vesala (2004) perform a firm-level analysis of systematic and idiosyncratic factors determining EDFs.

EDFs are estimated by Moody's KMV using a Merton-type framework, where default probabilities critically depend on the likelihood of the value of the assets falling below the value of liabilities at maturity (i.e. the shaded area represented in Graph 4). Under this approach, Moody's KMV defines "distance-to-default" (see Graph 4) the difference between the expected value of the assets at maturity and the default threshold (usually fixed at the level of short-term liabilities plus ½ of long-term liabilities). EDFs are then estimated based on historical data on a large sample of firms (including firms that defaulted), computing the proportion of firms by region and industry at any given "distance to default" that actually defaulted after 1 year. For any given time horizon, each firm can thus be assigned an EDF based on its "distance to default", which in turn depends primarily on the stochastic process assumed for the evolution of the asset value and the level and composition of the liabilities as illustrated above. As the market value of the assets is not observed, equity returns are used instead as a proxy. For this reason, Moody's KMV best applies to publicly traded companies where the value of

[33] For a more detailed discussion of the literature on the procyclicality of default probabilities, recovery rates and credit exposures, the reader is referred to the recent survey by Allen and Saunders (2004).

the equity is market driven.[34] EDFs represent therefore an empirical measure of the actual probability of default of a firm over a given time horizon.

Graph 4 - The Merton (1974) framework and EDFs



Comparing the results of the EDF-based studies cited above with the papers discussed in section 3.1 suggests that, while backward-looking accounting measures of risk (eg. NPLs or provisions) are very sensitive to the business cycle, market-based forward-looking indicators (such as expected default frequencies) exhibit substantial variability both across firms and over time, but appear to be less responsive to macroeconomic or in general systematic risk factors and are instead driven more by idiosyncratic factors or inter-industry risk correlations.

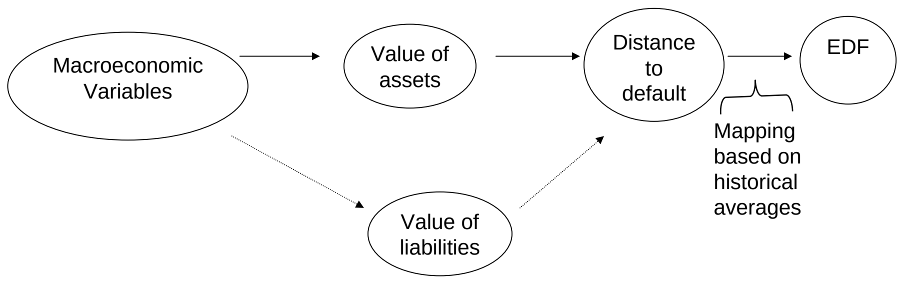
One reason for this puzzle might be that much of the effect of macro shocks on default probabilities is non-linear. Most studies so far have attempted instead to estimate linear relationships between EDFs and macroeconomic fundamentals using either firm-level panel data analysis or vector autoregressions at the industry-level. In particular, the papers by Drehmann and Manning (2004) and Pesaran et al. (2004), already discussed in section 3.2.2, have emphasised how non-linear effects are especially significant in the tails of the distribution of the underlying vector of macrofundamentals, i.e. in periods of macroeconomic stress. A rough intuition for that can be drawn directly from Graph 4. Assume that a negative macroeconomic shock induces a downward shift in the conditional distribution of asset values at maturity such that the shaded area depicted in Graph 4 (representing the probability of default approximated empirically by EDFs) increases by an amount x. Also assume that a favourable macroeconomic shock induces instead an upward shift of the conditional distribution of asset values at maturity such that the shaded area decreases by an amount y. Even if the positive and negative shocks are of the same magnitude and the distribution shifts up or down by the same distance, EDFs (that approximate the shaded area in Graph 4) will respond asymmetrically to positive or negative shocks, due to the non-linearity of the pdf of asset values at maturity (in other words it will be the case that $x > y$).

Another reason for the weak relationship found between EDFs and macrofundamentals could be that much of the business cycle volatility in default probabilities has already been smoothed out in the construction of EDFs. As mentioned earlier, while the link between macroeconomic variables and distance-to-default, through fluctuations in asset/equity values, is forward-looking, the empirical mapping between distance-to-default and EDFs relies on a long backward-looking sample of historical data (see Graph 5). This mapping attaches to any given distance-to-default an unconditional measure of default risk, “averaging” over several upturns and downturns of the cycle.

[34] Vasicek at KMV has however recently extended this approach to model default probabilities of privately-owned firms. For more details on EDFs, see Bohn and Crosbie (2003).

Graph 5

The link between macrofundamentals and EDFs

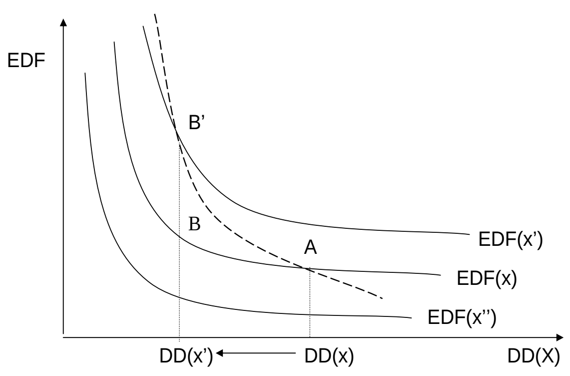


Graph 6 provides some intuition as to why this might in part explain the limited responsiveness of EDFs to macroeconomic shocks. Imagine we could plot three separate curves for EDFs, each computed using only historical bankruptcy data conditional on a given realisation of a vector X of key macroeconomic variables: "normal" times (X=x), recessions (X=x') and expansions (X=x''). From a baseline EDF in point A, assume an adverse macroeconomic shock x' brings firms closer to default (from DD(x) to DD(x')). For simplicity, Graph 6 abstracts from idiosyncratic risks and focuses only on the systematic component of the distance to default. The corresponding impact on EDFs, as measured looking at the KMV's "average" baseline curve (point B), might underestimate the actual increase in default probabilities that should be read off the higher EDF curve, EDF(x'), conditional on a recession (point B'). In fact, when the impact of macroeconomic variables on EDFs is taken into account, the relationship between EDF and distance to default is represented by the dotted line in Graph 6. In other words, since the distance-to-default, as a micro indicator of credit risk, is not a sufficient statistic for EDFs, there might be a number of important macro covariates affecting this relationship. In particular, a recent paper by Duffie and Wang (2004) finds a significant dependence of the level and shape of the term structure of corporate bankruptcy probabilities primarily on the firm-specific distance to default but also on business cycle indicators such as personal income growth.

Finally, there is a number of reasons that might bias the relationship between macroeconomic factors and distance to default (see Graph 5). First, macroeconomic shocks might significantly affect the market value of liabilities. For example, the experience of the East Asian crisis has shown how a significant fall in the local currency can severely increase the default probability of firms with substantial liabilities denominated in foreign currency. This channel is neglected if the default threshold is measured using the book value of debt. Second, severe macroeconomic shocks can bring about changes in conditional volatilities, risk aversion or liquidity factors that might affect equity prices and therefore distance to default over and above actual changes in corporate default probabilities.

Graph 6

'CONDITIONAL' EXPECTED DEFAULT FREQUENCIES



4.2.2 *Conditional default volatility and correlations*

There is evidence that periods of adverse macroeconomic conditions are characterized not only by higher average default rates but also by significantly larger default volatilities and correlations.[35] A recent example of this phenomenon occurred following the Russian crisis in August 1998. Many international banks attributed their higher-than-expected losses to increases in volatility and breakdowns in historical correlations (JP Morgan (1999)).

In terms of the framework in section 3.2, this suggests that the variance-covariance matrix $\Sigma_{i,t,}$ in equation (5) is very sensitive to the vector X of macroeconomic variables. Ceteris paribus, higher volatilities and correlations in an adverse macroeconomic environment may translate into a conditional loss distribution with fatter tails.

Gersbach and Lipponer (2003) estimate that a substantial share of the increase in credit risk (the shift from point VaR_1 to VaR_2 in Graph 3) is due to the widening of the tail (correlation and volatility effects), as opposed to the parallel shift to the right of the whole distribution (which captures the translation of the mean). They note that a macroeconomic shock not only impacts default probabilities but also default correlations. Both effects in turn translate into a higher standard deviation of losses, leading to a distribution with fatter tails. The authors attempt to disentangle the "correlation effect" as the percentage increase in the standard deviation of losses due to the higher default correlation induced by a macroeconomic shock. They find that this component can explain over 50% of total increase in credit risk especially for large portfolios of high-grade obligors with low asset correlation (see Table 2). This would suggest that – unless default correlations are captured endogenously within a multi-sector structural credit risk model à la Merton (see Graph 7) - simulating extreme macroeconomic scenarios, while using relatively low variance-covariance estimates drawn from tranquil times, might lead to significantly underestimating the overall credit risk in the system.

Table 2: Correlation Effect (in %)

Rating	PD in %	Asset Correlation												
		.001	.05	.1	.2	.3	.4	.5	.6	.7	.8	.9	.95	1.0
AAA	0.02	65	63	61	56	50	44	38	32	25	19	11	7	0
AA	0.05	63	61	59	54	49	43	37	31	25	18	11	7	0
A	0.1	61	59	57	53	48	42	37	31	25	18	11	7	0
BBB	0.25	59	57	55	51	46	41	35	30	24	18	11	7	0
BB	0.5	57	55	53	49	44	39	34	29	23	18	11	7	0
B	2	52	50	48	44	40	36	31	26	22	16	10	7	0
CCC	5	48	46	44	40	36	33	28	24	20	15	10	6	0
CCC	10	44	42	41	37	34	30	26	22	18	14	9	6	0
CC	15	42	40	39	35	32	28	25	21	17	13	9	6	0
C	20	40	39	37	34	30	27	24	20	17	13	8	6	0
D	25	39	38	36	33	29	26	23	20	16	12	8	5	0
D	30	38	37	35	32	29	25	22	19	16	12	8	5	0

Source: Gersbach and Lipponer (2003)

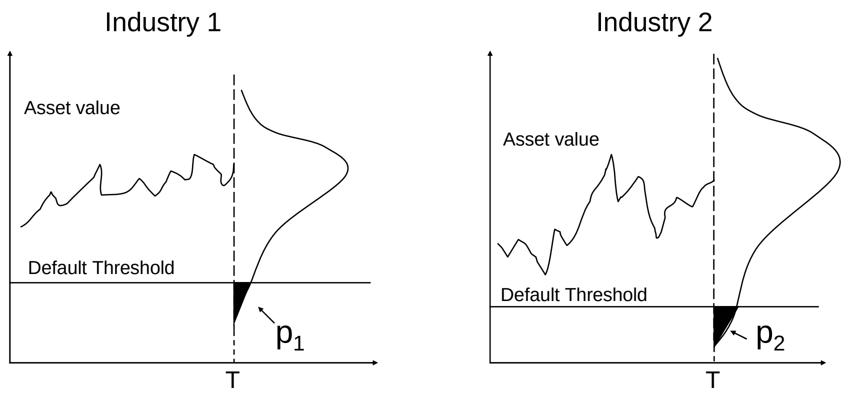
35 A number of recent papers seem to support this conclusion. See for example: Erlenmaier and Gersbach (2001), Zhou (2001), Crohuy, Galai and Mark (2000 and 2001), Longin and Solnik (2001), Das, Freed, Geng and Kapadia (2002), Das, Duffie and Kapadia (2004) and Barnhill and Maxwell (2002). However the literature is still divided on this issue (see the survey by Allen and Saunders (2004)). Here we are interested in the implications of potential endogenous breakdown in default volatility and correlation patterns for macro stress-testing.

A key unresolved issue in macro stress-testing is therefore how to account for "endogenous" conditional volatilities and correlations, i.e. changing as a function of the simulated stress scenario.

A first step in order to make this problem more tractable, especially from an empirical perspective, is to move from the concept of default volatility/correlation to the notion of asset volatility/correlation. Under simplifying distributional assumptions, the Merton (1974) framework allows to draw a direct relationship between these measures. Intuitively, if default is defined as the event that occurs when the stochastic value of assets falls below the fixed liability threshold, then – for given marginal default probabilities p_1 and p_2 - what drives the variance/covariance of default probabilities across two different obligors or industries is uniquely the variance/covariance of the value of the assets (see Graph 7). Assuming asset values to be jointly lognormally distributed and default events drawn from correlated Bernoulli random variables (= default with probability p_i and no default with probability $1-p_i$ for each industry i=1,2), one can establish a one-to-one relationship between default correlation and asset correlation for given p_1 and p_2 (see Gersbach and Lipponer (2003)).

Graph 7

Default correlation and asset correlation



From an empirical perspective, estimating the variance/covariance of asset returns is a more tractable problem compared to analysing the variance/covariance of defaults, which represent rare events. Volatilities and correlations of asset returns are usually estimated by looking at the co-movement of equity indices for individual companies or entire industrial sectors. Market prices for such indices are generally available at high frequencies. Ideally, both market-based (equity or bond indices) and accounting measures should be used as complementary sources of information. It is also important to include in the estimation sample both periods of high and low volatility, if necessary pooling data across countries. Exploiting the cross-sectional dimension might be useful to include more crisis episodes in the sample, provided problems related to the comparability of asset returns and country-specific effects are appropriately dealt with.

Although benefiting from broader data availability, compared to the paucity of default events, there is evidence that asset correlations also increase during economic downturns. From a methodological perspective, there are a number of techniques - so far used especially in the asset pricing literature – that could be applied to macro stress-testing in order to estimate conditional volatilities and correlations.

The GARCH framework (eg. Bollerslev, Engle and Wooldridge,1988; Engle, 2002; Tse and Tsui, 2002; Lediot et al, 2003 and Zaffaroni, 2003) is among the most popular techniques to estimate time-dependent conditional second moments. Apart from capturing the persistence of volatility/correlations over time, GARCH-in-mean models can accommodate also the case when second moments are conditional on the size of macroeconomic shocks and not only on their timing. Regime-switching models (eg. Ang and Bekaert, 1999; Bangia, Diebold and Schuermann, 2001 and Erlenmaier, 2001) might also deserve wider application in macro stress-testing, considering the flexibility they would allow in estimating conditional second moments during stressed regimes vs. normal times.

Some of the literature has entertained the possibility that during economic downturns asset returns are drawn from a truncated distribution, with conditional second moments that are higher than their unconditional counterparts. Closed-form relationships have been developed to correct the bias due to truncation both for the normal and Student t distributions (see Campbell et al., 2002 and 2003). Another useful approach to model size-conditional second moments is extreme value theory (eg. Poon et al., 2004), which offers asymptotic results that apply though to a large range of distributions. In particular, Longin and Solnik (2001) find asymmetric increases of conditional correlations across international equity markets during recessions but no effect during expansions. Finally, using results from the copula literature (eg. Embrechts, McNeil and Straumann, 1999 and Patton, 2001) would allow to model more general dependence structures in the world of non-elliptical distributions[36], going beyond the concepts of linear correlation and Value-at-Risk.

Provided a sufficiently long time series of data is available on the co-movement of asset returns, the various techniques mentioned above could be usefully applied to estimate how conditional volatilities and correlations vary over time as a function of changing macroeconomic fundamentals. These functional relationships can be used to map shocks to macrofundamentals, which affect the level of default probabilities, into shocks to the relevant conditional volatilities and correlations. Letting the estimated variance-covariance matrix of default events $\Sigma_{i,t}$ in equation (5) vary with macrofundamentals might provide a more prudent assessment of systemic risk accounting for the widening of the tail in the conditional loss distribution as shown in Graph 3.

5. Summary and conclusion

Results of recent macro stress-tests have sometimes been criticised of depicting an either too rosy or too bleak picture of financial system vulnerabilities. A good part of the criticism is directed to the choice and calibration of the stress-scenarios. However, significant under- or overestimation of systemic risks can also be ascribed to the use of simplified methodologies often driven by data constraints. In general, while substantial progress has been made in the last few years in developing quantitative techniques that help assess the vulnerability of financial systems, a number of methodological challenges still remain for future research.

In particular, this survey has identified three important areas that would deserve further attention:

- *Non-additivity of risks and of risk measures.* A correlated set of shocks to the pace of macroeconomic activity, interest rates or asset prices may be a source of both market and credit risk for financial institutions. In this sense, given their joint likelihood of occurrence, risks should not be analysed using separate models and then simply added up. A superior approach consists in integrating models of market and credit risks. Similarly, since the potential losses faced by various financial institutions are also correlated, risk measures like value-at-risk, computed as vulnerability indicators of single portfolios or financial institutions, cannot be simply summed up to provide a picture of systemic risk. Instead, a macro portfolio approach is necessary to model the potential losses of the entire financial system.

- *Length of time horizon*. Historical experience suggests that both the build up and resolution of macro-financial imbalances may span several years. Macro-economic shocks are likely to be serially correlated over time. In fact, systemic vulnerabilities arise from the progressive erosion of capital reserves as a result of financial strains that persist over multiple years. Therefore, measuring only the first-year impact of a given stress scenario may underestimate the full impact on the vulnerability of the financial system. Moreover, as the response time necessary for policy makers to deal with potential financial imbalances often exceeds one year, their "risk measurement horizon" should be lengthened accordingly.

- *Feedback effects and endogenous parameter instability.* Measuring the full impact of a set of macroeconomic shocks on the fragility of the financial system over a longer horizon requires also to relax the partial equilibrium (and in particular portfolio

[36] The joint distribution of Normal or Student t random variables, for example, has level curves that resemble an ellypsis. The joint distribution of financial asset returns, with asymmetric fat-tailed marginal distributions, is instead likely to be non-elliptical.

invariance) assumption usually adopted in the risk management practices of individual financial institutions. When faced with an adverse macro scenario, all agents in the economy, and in particular financial institutions, will re-optimise their behaviour accordingly and their responses may or may not follow similar reaction functions as in the past. Risk-minimising responses, that are perfectly rational at the level of individual institutions, have however the potential to ignite domino effects leading to more rather than less risk in the aggregate. In particular, endogenous portfolio adjustments may change the overall risk exposure of the financial system, following a given set of shocks, as well as the volatilities and correlation structures of asset prices or default probabilities. Finally, endogenous portfolio reallocation in a stressed macro scenario can also feed back on equilibrium market prices or macroeconomic activity due to hedging practices or a credit crunch. It is important therefore to account for feedback effects in macro stress-testing and apply estimation methods that allow volatilities and correlations to vary conditional on stress events.

This survey has focused on macro stress-testing models. A more detailed discussion of how to design and calibrate stress scenarios along with a comparative evaluation of the performance of market vis a vis balance sheet risk indicators are left for future extensions. In this respect, an attempt to standardise stress scenarios across countries would be useful to enhance the comparability of results.

Finally, macro stress-testing raises a number of important policy questions that would deserve further attention. Integrated by models of early-warning indicators and macroeconomic forecasts as inputs[37], stress-tests could represent a useful tool to enhance macroprudential policies. The former would help to estimate the probability of adverse macroeconomic shocks, the latter would attempt to quantify their impact on the vulnerability of the financial system. Given the increasing incidence of financial crises around the world, paying closer attention to the vulnerabilities of the financial sector from a macro perspective, and enforcing adequate prudential policies, is crucial to prevent the severe costs of bursting financial bubbles.[38]

Furthermore, macro stress-testing may be useful to address monetary policy trade-offs, incorporating financial stability considerations into monetary policy decision-making. In fact, while the role of the government as lender of last resort should arguably enter risk management considerations rather than risk measurement models, the reaction function of policy interest rates to macroeconomic developments is an integral part of macro stress-testing. For example, using a Taylor rule, the work by Evjen et al. at the Bank of Norway allows to calibrate the possible trade-off between the pursuit of monetary and financial stability in case of an adverse supply shock (eg oil price increase). Moreover, assessing the different degree of vulnerability of a given financial system to either an exchange rate or an interest rate shock, for instance, might also be useful to take more informed monetary policy decisions.

[37] See Worrell (2004) for a discussion of such an integrated approach.

[38] See Borio and White (2004) and Borio (2003) for further analysis of these issues.

Appendix: Financial Soundness Indicators

	DEPOSIT-TAKING INSTITUTIONS
Capital adequacy	Regulatory capital to risk-weighted assets Regulatory Tier 1 capital to risk-weighted assets Nonperforming loans net of provisions to capital Capital to assets Large exposures to capital
Asset quality	Nonperforming loans to total gross loans Sectoral distribution of loans to total loans Geographical distribution of loans to total loans
Earnings and profitability	Return on assets Return on equity Interest margin to gross income Noninterest expenses to gross income Trading income to total income Personnel expenses to noninterest expenses Spread between reference lending and deposit rates
Liquidity	Liquid assets to total assets (liquid asset ratio) Liquid assets to short-term liabilities Spread between highest and lowest interbank rate Customer deposits to total (noninterbank) loans Average bid-ask spread in the securities market Average daily turnover ratio in the securities market
Sensitivity to market risk	Net open position in foreign exchange to capital Gross asset position in financial derivatives to capital Gross liability position in financial derivatives to capital Foreign-currency-denominated loans to total loans Foreign-currency-denominated liabilities to total liabilities Net open position in equities to capital Real estate prices Residential real estate loans to total loans Commercial real estate loans to total loans
	OTHER FINANCIAL CORPORATIONS
	Assets to total financial system assets Assets to GDP
	NONFINANCIAL CORPORATIONS SECTOR
	Total debt to equity Return on equity Earnings to interest and principal expenses Net foreign exchange exposure to equity Number of applications for protection from creditors
	HOUSEHOLDS
	Household debt to GDP Household debt service and principal payments to income

Source: International Monetary Fund, http://www.imf.org/external/np/sta/fsi/eng/fsi.htm

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