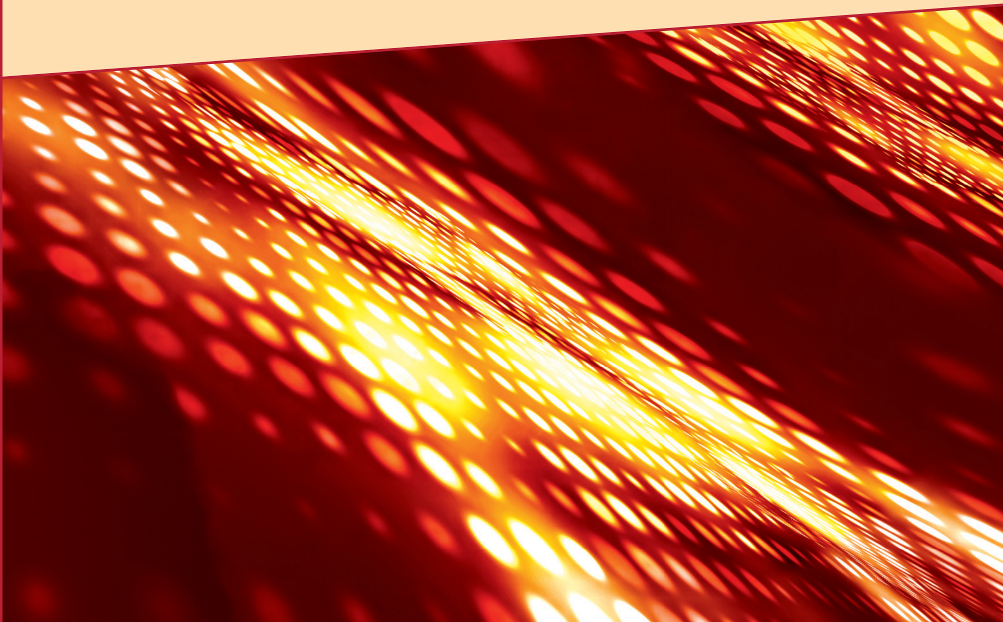
Risk books

Stress Testing

Approaches, Methods and Applications

EDITED BY AKHTAR SIDDIQUE
AND IFTEKHAR HASAN



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Published by Risk Books, a Division of Incisive Media Investments Ltd

Incisive Media
32–34 Broadwick Street
London W1A 2HG
Tel: +44(0) 20 7316 9000
E-mail: books@incisivemedia.com
Sites: www.riskbooks.com
www.incisivemedia.com

ISBN 978-1-78272-008-9
British Library Cataloguing in Publication Data
A catalogue record for this book is available from the British Library

Publisher: Nick Carver
Editorial Development: Amy Jordan
Commissioning Editor: Sarah Hastings
Managing Editor: Lewis O'Sullivan
Designer: Lisa Ling

Copy-edited by Laurie Donaldson
Typeset by Tricolour Design

Printed and bound in the UK by Berforts Group

Contents

Acknowledgements from the Editors

We would like to acknowledge advice from and discussions with colleagues in various settings. Akhtar would like to acknowledge discussions with colleagues from the OCC, Federal Reserve Banks and the FDIC during examinations as well as in policy settings. Encouragement from Mark Levonian and Mike Carhill are particularly acknowledged. We would also like to thank Clayton Lamar for research assistance and help.

To the people in our lives. For Akhtar, the children in his life, Ayaan, Aahil and his nieces Babu and Putul but above all, his parents, wife: Deepa, sister: Moon, and his in-laws. For Iftekhar, his parents, parents in-law, siblings, nephews, nieces, and his spouse.

Foreword

Stress testing is a tool. It is a tool used in many fields, particularly where failure of some component of a complex system can have seriously adverse consequences and high costs: aircraft wings, highway bridges, coronary arteries.

And financial institutions.

Financial firms have long used stress testing as a tool in various aspects of financial management. Firms use stress tests to assess the impact of adverse events on various elements of the organisation, or on the organisation as a whole, to gauge their ability to absorb those stresses and carry on with core activities. Stress testing can reveal vulnerabilities and point the way to actions that reduce those vulnerabilities.

But disruptions in financial markets and continuing economic weakness around the world have focused greater attention on stress testing and its potential value. A widely acknowledged lesson of the global financial crisis was that unusually stressful events or combinations of events can and do occur, and that stress testing can help assess the potential impact of those events and guide appropriate preparation and response. Apart from its role as a tool for management, stress testing fosters a culture of conscientious attention to risk. A common theme in post-crisis discussions with senior management has been that stress testing helps create a robust dialogue around risks and risk management inside any firm.

"Stress testing" really describes a class of tools rather than a single tool. Variations in stress-testing tools – the methods – roughly match the variation in the specific ways stress testing is used – the applications. Chapters of this book highlight distinct but related aspects of stress testing in both methods and applications. Some of the chapters emphasise risk management in the areas of credit risk, market risk, operational risk, liquidity risk and others; other chapters address the role of stress testing within the broader management environment of financial firms, as well as how to ensure that stress testing remains a relevant and effective tool.

With such variety in methods and applications, it is perhaps no surprise that overall approaches to stress testing vary as well. Responsibilities for the many different aspects of stress testing may be centralised or distributed; specific management uses of the results may make sense in certain environments but not in others. There is no secret formula – many different approaches can succeed. Indeed, approaches to stress testing should be expected to vary, because stress tests add their greatest value when they are organised, executed and used in ways that take into account the unique characteristics, operating environment and management style of the firms or institutions using them.

Several chapters also address the increasingly prominent use of stress testing in the supervision and regulation of financial firms. This has been one of the most notable developments in international financial supervision over the last few years, as the renewed focus on stress testing within financial firms has been matched by a simultaneous increase in attention from the supervisory community. Financial authorities around the world have gravitated towards stress testing as a powerful way to promote the health of the firms they regulate. Institutional supervisors tend to focus on effective use of stress testing for institutional risk management, consistent with the ongoing use of stress testing as a risk-management tool. Macroprudential regulators also have recognised the potential value of stress testing, with an emphasis on financial stability applications. Several highly visible system-wide stress-testing exercises – some of which are discussed in this book – were key elements of the public-sector response to the financial crisis; they were used to assess the scope of the problems, evaluate the resiliency of large financial firms and provide transparency and assurance to financial market participants and others.

Effective stress testing relies on three major elements. First comes the selection of meaningful stresses, either hypothetical or actual scenarios, or more abstract approaches based on simulation of risk factors. Second is the translation of those stresses into the impact on the firm, or on the part of the firm subject to stress testing. And third is the assessment of the stress-testing results, the evaluation of the impact of the stress. Relevant measures of impact vary depending on the focus of a specific stress test – liquidity, earnings, credit losses, capital, financial stability – but ideally point the way towards meaningful response and action.

In scenario development, stress translation or impact assessment, stress testing remains a tool in evolution. In particular, while stress-testing practices may converge over time towards a somewhat more standard set of methods and applications, the end state is unlikely ever to evolve to a single, uniform design. This is one of those cases in which details must be tailored to the specific use; no single stress-testing methodology will be appropriate for all applications at all times.

The combination of rapid change in stress-testing methods and increased supervisory focus makes this volume especially relevant, timely and useful. The book rewards readers with comprehensive and thoughtful discussions of stress testing in its many forms, covering a broad range of real-world applications and real-world concerns, and drawing on the knowledge of an impressive set of contributors. Its emphasis on both methods and applications, combined with a consideration of multiple approaches, sets it apart from other offerings with narrower focus.

Many of the contributors are quantitative experts from across the global regulatory community. Readers anxious for insight into supervisory perspectives and expectations can find much to consider in these chapters. A window into the thinking of the supervisory community is always valuable for regulated firms. But supervisory authorship has additional value in this case. Individual financial practitioners know a great deal about practices at their own firms, but less about current approaches, methods and applications elsewhere. In such a rapidly changing field, a narrow focus on practices at any single firm can be misleading. Best practices diffuse across the industry over time, but supervisors have a unique and explicitly horizontal perspective on stress testing, combining insights from the many variations in stress-testing practices they are able to observe across the regulated financial spectrum, and speeding the recognition and adoption of best practices.

As readers consider the chapters of this book, they should not be blind to the fact that, as valuable as the stress-testing tool may be, it is still only one of many tools that can and should be used. There are other valid ways to measure or assess risk. There are also many ways to control that risk. Any tool requires the hand of a skilled user to make it effective. Ultimately, tools, even good ones, are no substitute for sound judgement based on experience. Stress testing must be intelligently applied, with expertise and insight.

With this book as a guide, both financial regulators and financial practitioners can gain insights that will help them do their jobs more effectively. If broader and more thoughtful use of stress testing reduces the impact of future stress events, then time spent with this volume will be time well spent indeed.

Mark Levonian

Senior Deputy Comptroller, US Office of the
Comptroller of the Currency
March 2013

About the Editors

Iftekhar Hasan is the E. Gerald Corrigan Chair in International Business and Finance at the Schools of Business of Fordham University, New York and concurrently serves as a scientific advisor to the Bank of Finland in Helsinki. His research focus is primarily in the areas of financial intermediation, capital market and corporate finance. He is also affiliated as a research associate at the Berkley Center of the Stern School of New York University. Hasan has held visiting positions at universities and organisations in several countries. He is the managing editor of the Journal of Financial Stability and an associate editor in several other journals. Hasan is currently the president of the Eurasia Business and Economics Society. A Fulbright Specialist Scholar, Hasan has over 250 publications in print, including 12 books and edited volumes and over 160 peer-reviewed journal articles in reputed finance, economics, management, operation research, accounting, and management information system journals. He received his PhD from the University of Houston and also received a "Doctor Honoris Causa" from the Romanian American University in Bucharest.

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Introduction

Akhtar Siddique; Iftekhar Hasan
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Banks across the globe faced significant challenges during the 2007–9 financial crisis. Declining capital ratios, equity prices, government takeovers and subsidies by the public sector have been norms rather than special cases in many healthy "free-market" economies. The crisis caused the confidence of investors, market makers and lenders to plummet. Local and international regulators attempted to restore confidence across the banking system in general, but particularly with the goal of boosting lending and capital structure. Among other initiatives, regulators are trying to implement stress testing of banks in order to lower or even prevent the possibility of a future banking crisis. The exact details of these tests vary according to specific economies and regulators, but all are intended to examine how banks perform under an adverse or unexpected economic environment, with regard to both macroeconomic uncertainty or bank-specific asset-liability and off-balance-sheet activities. These tests are designed not only to understand the vulnerability of banks, but also to make sure that banks are prepared to face adverse situations with the capital to mitigate potential losses or non-performing assets.

This book considers the stress testing of financial institutions. In the wake of the crisis, stress testing has received prominent media coverage. Many research papers and several books have been published on stress testing. The primary goal of all these initiatives, including the efforts undertaken by this book, is to better understand effective stress testing. As per the subtitle, this book focuses on stress-testing approaches and methods, as well as applications. This book takes a comprehensive approach and covers a wide array of stress-testing methods and scenarios. It makes a significant contribution, as the authors are primarily drawn from regulatory bodies around the world. The authors have considerable experience in the field, as they have been studying and engaged in stress testing at financial institutions for years, and many have been involved in the policy consequences and development that stem from effective stress testing.

Regulators maintain an external view, albeit an external view that is very often closely focused on the financial institutions. In comparison, "quants" at a bank can focus more on the implementation details. Nevertheless, the regulatory view has the advantage of being exposed to different approaches, methods and applications at different institutions. Regulators can therefore weigh in on the relative strengths and weaknesses of different banks. This comparative ability has become particularly important, as smaller institutions that did not typically engage in significant stress testing are now expected to do so. Moreover, stress testing has been evolving very rapidly, and, given that the contributors to this book have been a part of this evolution, they can provide insight into the development and situation of stress testing.

Stress testing has many approaches. For example, at many institutions, finance and treasury have had ownership of the budgeting process. Hence, centralised stress testing could be housed in such a central function. Other institutions have taken a more decentralised approach, wherein the central function has only acted as an aggregator. Effective stress testing does not need a given organisational form or approach. However, a given organisational form will require certain aspects to ensure effectiveness. For example, in a decentralised approach towards stress testing, consistency across the organisation becomes important, and the institution will need to find ways of ensuring that consistency.

An important element to stress testing is that the processes in it need to be effective. That generally has required a build-out of processes and functions. Stress testing includes not only the enterprise-wide stress tests that look at the bank's projected capital with scenarios based on macroeconomic variables, but also other types of stress testing, such as portfolio and transaction-level stress tests.

Given that stress testing is generally conducted for distinct risks, such as credit, counterparty credit, market, liquidity and so forth, the contributions to the book start with governance and controls, and the bulk of the book is devoted to separate chapters on the different risks.

In Chapter 1, David Palmer considers governance and controls for the stress testing of financial institutions. Stress testing is highly technical, makes many assumptions and entails much uncertainty, and so appropriate governance and controls are crucial. Proper stress-testing governance and controls not only confirm that stress tests are conducted in a rigorous manner, but also help ensure that stress tests and their outcomes are subject to oversight.

Differentiation between the roles of the senior management and the board of directors is considered in this chapter. The role of an internal audit should not be forgotten in concerns about governance. The role of validation is also discussed, both in terms of how validation needs to examine data and inputs and how to ensure the integrity of the process. What differentiates validation of stress-testing from validation of models is the emphasis on the process, as well as the need to validate the framework. Very usefully, the chapter provides pointers on the policies, procedures, and documentation for stress testing. Given the recent implementation of enterprise-wide stress testing at most financial institutions, such policies, procedures and documentation are often less developed.

Chapter 2 examines the relationship between the various risk-management tools used by financial institutions and stress testing, particularly the value-at-risk-type, enterprise-wide risk measures. Akhtar Siddique and Iftekhar Hasan discuss consistency between the other risk metrics and stress tests. They then discuss how stress-testing has begun to impact other risk measures.

It is important to note that stress testing has played two distinct roles in the regulatory responses to the financial crisis. The first is the stress tests conducted by the regulators, for example the SCAP in the US and the EBA's stress tests in Europe. Another role has been to increase the amount of capital required of financial institutions by incorporating stressed inputs into the capital calculations. This has happened for market risk in Basel 2.5, as well as for counterparty credit risk in Basel III. This chapter discusses both variants of the interaction that stress testing has had with capital regulation.

Dilip Patro, Akhtar Siddique and Sun Xian discuss stress testing for market risk in Chapter 3. Given the very large number of positions as well as the large number of inputs required, market risk poses challenges for stress testing. The authors discuss the differences between stress testing for market and credit risk (equivalently between trading book and banking book) The difficulty in utilising macroeconomic scenarios into market risk stress tests is another point they focus on. Horizon, and the difficulty in incorporating the aftershock from market events as well as the impact of hedging, are then discussed. The last section focuses on revaluation of the values and/or computation of P&L under the stressed scenarios. This discusses the challenges that banks face in the revaluation as well as what to be concerned about in these areas.

David Lynch, in Chapter 4, discusses stress testing for counterparty credit risk. Counterparty credit risk (CCR) was one of the key avenues through which the financial crisis manifested itself. The measurement and management of counterparty credit risk has become greatly sophisticated over the past 20 or so years. However, stress testing of counterparty credit risk has not kept pace with the evolution of counterparty credit risk measurement and management.

An important aspect of counterparty credit risk that needs to be recognised is that it may be approached by either a credit or market risk perspective. The duality of CCR has led to the adoption of measures that manage to capture some facet of CCR. In terms of credit risk: current exposure, peak exposure and expected exposure are all important measures. In terms of market risk: credit valuation adjustment's (CVA), valuation and the risk generated by changes in CVA are important. Although treating CCR either way is a valid method for portfolio management, failing to consider both opens an institution to risks from the unconsidered perspective, and a single-view approach is better for trading activities and risk-management discipline. Furthermore, there is an unusual problem associated with CCR: wrong-way risk. Wrong-way risk is a type of risk that occurs when exposure is correlated with a counterparty's credit quality, so that exposure increases as the counterparty becomes likelier to default. This does not happen when exposure is fixed, as with a loan, so the application of banking-book risk metrics to CCR can cause considerable difficulties.

Given such a large amount of information, understanding and interpreting stress tests at a portfolio and a counterparty level becomes difficult. The sheer variety of risk measures ensures that stress testing for CCR is a complicated task, but financial institutions are beginning to address these complications and are finally conducting stress tests that go beyond simple tests of current exposure. This is an exciting moment for CCR stress testing, as the best-practice methodologies are only just now being developed.

In Chapter 5, Bakhodir Ergashev and Brian Clark provide background on the current state of operational risk modelling and consider the challenges in the field today. Although data limitations are one of these challenges, there are several areas where merely increasing the quality and quantity of operational loss data is not enough. Significant research is required to address these challenges and to further the field.

Stress testing operational risk increases these challenges even more. Most of these challenges are a consequence of the fact that operational risk exposure is driven by infrequent large events. To model the aggregate loss distribution, for instance, we need additional loss data. Stress testing insufficiently accurate static models only amplifies the model's risk, and modelling dependence with the macroeconomic environment is even more challenging, due to the lack of strong supportive evidence.

Despite the many challenges and limitations associated with operational risk modelling, the authors have offered a variety of fruitful possibilities for institutions to test operational risk exposure. We are currently in a nascent moment for the development of methodology, and, although some methods may appear more useful than others, additional research will be required to determine the utility of any particular one. The authors currently recommend that banks employ an array of models, thereby both providing a variety of perspectives and contributing to possible future research.

Paul Calem and Arden Hall offer an overview of the current regulatory stress-testing environment in Chapter 6. They provide a particularly useful perspective on the limitations of stress testing. The authors focus specifically on the stress testing of balance-sheet loan losses, but much of their work is applicable to bank capital stress tests generally. Given that a balance-sheet loan-loss stress test is based on predictions of borrower repayment under extreme conditions that are generally outside the scope of historical precedents, such testing presents major modelling challenges. Yet, despite such challenges, balance-sheet stress testing can offer a useful view of a financial institution's sensitivity to adverse shocks, and Calem and Hall propose a framework for such testing. A careful and controlled balance-sheet loan-loss stress test can pinpoint sources of risk, order institutions according to risk, indicate the quality of a bank's risk position over time and provide benchmarks for understanding an institution's risk-management processes and capital adequacy. Stress testing can also evaluate the risk sensitivity or risk composition of an institution's loan portfolio.

In Chapter 7, Michael Carhill and Jonathan Jones examine stress-test modelling for loan losses and reserves. Their contribution is driven by their experience of looking at the stress-testing practices of institutions. They observed the decision-making processes at large financial institutions as executives decided that models capable of estimating credit losses conditional on economic scenarios were required for enterprise-wide capital planning and stress testing. A number of supervisory and regulatory developments account for this interest in deploying economic factors in stress testing. Such developments include: the Advanced Internal Ratings Based (AIRB) approach of Basel II; the recommendations of the Basel Committee on Banking Supervision; the Federal Reserve's Supervisory Capital Analysis Program (SCAP) exercise and the following Comprehensive Capital Analysis and Review (CCAR) bank stress tests; and the Dodd–Frank Wall Street Reform and Consumer Protection Act of 2010.

Carhill and Jones present their first-hand observations in this chapter, including their evaluation of the strengths and weaknesses of the approaches they witnessed. They also identify potential challenges and pitfalls that need to be addressed when developing macroeconomic-based credit risk stress-testing models. However, given that this field is rapidly evolving and no best practices have yet been established, the reliability of these models is still questionable. Nonetheless, the financial crisis has made clear the need for banks to include economic and market factors in credit risk models in order to produce accurate stress loan-loss estimates.

Olivier de Bandt, Nicolas Dumontaux, Vincent Martin, and Denys Médée examine in Chapter 8 stress testing for credit risk and focus on risks arising from corporate loans and other credit exposures. Corporate credit risk – known also as wholesale credit risk – is highly important when stress testing global firms. Credit risk is a huge source of risk for banks and is very relevant to an institution's financial solvency. The crisis has underscored the need for stress-testing banks' portfolios, as institutions have incurred significant losses from structured US subprime-related assets. This chapter develops the foundations of a Basel II-type modelling effort to perform credit stress-test scenarios through credit-migration matrices (or transition matrices), which have already been implemented in France and are currently used for top-down stress-test exercises.

Credit risk stems from either actual defaults or migrations of credit ratings, and several model approaches are available to quantify this type of risk. These models may be structural, in which a firm's value and capital structure are modelled, or reduced, in which credit events are exogenous to a firm. The authors use a reduced form in which events are triggered by macroeconomic shock. The authors also focus on credit migrations. The model rests on the premise that the evolution of rating transitions can be linked to a synthetic credit indicator.

In Chapter 9, Paolo Bisio, Demelza Jurcevic, and Mario Quagliariello examine and evaluate the 2011 EU-wide stress tests conducted by the European Banking Authority (EBA) among 91 banks. The objective of the stress tests was to evaluate the EU banking system and the solvency of institutions under scenarios imposed by supervisors. After describing the sample selection, macro scenario and methodology, the authors note that the EBA is satisfied with the progress made by banks in fulfilling the recommendations to ensure appropriate mitigating actions based on the exercise's results.

Needless to say, the overall assessment was not without its criticisms – the EBA received negative feedback on some of its assumptions – but the 2011 exercise was a partial success when assessed against the benchmarks of analytical rigour, communication and resulting actions. The development of a stress-test methodology and its early publication was received positively. The presence of an organised quality-assurance and robust peer review was perceived as helpful as regarding interpretation of the methodology and the development of micro parameters from the macro scenario. The coordinated and extensive disclosure of results was seen as a significant victory for proponents of transparency and was welcomed by market participants and the public.

Robert Scavotto and Robert Skinkle argue in Chapter 10 that, during stress testing of internationally active financial institutions, individual-country characteristics can produce great variation in the stress-test results. Therefore, to perform reliable stress testing we must first approach the estimation of regional or global regressions with caution. Many challenges emerge in cross-country testing, including very basic factors, such as the development of datasets and the acquisition of an understanding of qualitative factors that may be relevant to certain countries. Drawing upon their own experiences in cross-county stress testing, the authors determine that a best-practice methodology entails pursuing an individual-country approach with specific stratifications. The authors' examination of the Korean consumer market as a case study is a well-reasoned approach and provides a novel methodology for any researchers interested in performing cross-country systemic stress tests.

In Chapter 11, Benjamin M. Tabak, Solange M. Guerra, Sergio Rubens Stancato de Souza and Rodrigo Cesar de Castro Miranda discuss the effects of the financial crisis on the Brazilian banking system and liquidity risk. Liquidity risks have risen in the wake of the financial crisis, and there is a need for measures to restore confidence and increase liquidity to enable financial institutions to handle additional risks. Liquidity crises are less frequent than other types, but their impacts can be very significant. Such low-frequency, high-impact events are troubling, insofar as they are not often easily planned for, yet can have as comparably devastating results as more common crises. As expected, liquidity stress tests are not currently as well developed as credit and market risk stress tests, although there is now increased interest in the threats posed by liquidity risks as a result of the financial crisis

Most central banks do not publish the results from their liquidity stress tests, a fact that is indicative of liquidity-modelling complexity and lack of data. The Central Bank of Brazil, however, has published its results since 2009, and provides a useful case study for discussing liquidity stress testing in general. The authors examine the liquidity stress-testing approach that is under use in the Central Bank of Brazil and their methodology and results provide a crucial foray into a field that is in dire need of quality research.

Kapo Yuen discusses in Chapter 12 the question of the severity of supervisory adverse scenarios and provides a methodology to compare the severity of different adverse macroeconomic scenarios. Since 2009, the Federal Reserve System has conducted an annual stress test on the US banking system, called the Comprehensive Capital Analysis and Review (CCAR). During this annual exercise, the Federal Reserve Board provides a supervisory macro scenario for stress testing, but also requires that each financial institution submit an individualised scenario that is particularly relevant to that institution's specific features. The instructions for that individualised scenario are somewhat abstract: they indicate that the scenario must reflect "a severely adverse economic and financial market environment", but the question of what constitutes "appropriate severity" is left unclear. Yuen poses several questions in attempting to determine the severity of a stress scenario: How can we measure severity? How severe is an individualised scenario versus the supervisory macro scenario? Are the individualised scenarios credibly severe? The financial crisis may be a useful starting point to measure severity, but Yuen wonders whether banks have actually changed; severe stress scenarios must be developed that will result in estimates of losses that demonstrate vulnerabilities. In posing these questions, Yuen demonstrates a methodology that can be used to assess the severity of a particular scenario and offers some possible alternate methodologies, as well.

The editors hope readers will learn about both the practical elements of stress testing and stress-testing principles from this book. More practically, they will also learn the pitfalls to avoid while conducting stress testing. The authors have been involved in matters relating to stress testing for many years and have also seen many other good books on stress testing. However, what those books appeared to lack was the discussion of the comparative merits and demerits of various approaches. The regulatory community (at least those members engaged in active conduct or examinations of stress testing) is uniquely suited to this role given its view of stress-testing practices across different institutions. This insight motivated the editors to bring these chapters together.

The views expressed in this chapter are those of the authors alone and do not necessarily represent those of the Comptroller of the Currency or Bank of Finland.

1

Governance over Stress Testing

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Governance and controls are a very important aspect of stress testing, yet are sometimes overlooked or given insufficient attention by financial institutions.[1] Proper governance and controls over stress-testing not only confirm that stress tests are conducted in a rigorous manner, but also help ensure that stress tests and their outcomes are subject to an appropriately critical eye. Governance and controls are particularly needed in the area of stress testing given the highly technical nature of many stress-testing activities, the generally large number of assumptions in stress-testing exercises and the inherent uncertainty in estimating the nature, likelihood and impact of stressful events and conditions.

While the exact form of governance and controls over stress-testing activities can and should vary across countries and financial institutions, there are some general principles, expectations and recommendations that financial institutions can follow. The manner in which the principles, expectations and recommendations outlined in this chapter are applied at any given financial institution should involve a "tailored" approach that is specifically tied to the size, complexity, risk profile, culture and individual characteristics of that institution.

This chapter discusses key elements of effective governance over stress testing, including: governance structure; policies, procedures and documentation; validation and independent review; and internal audit. It also discusses other aspects of stress-testing activities that should be considered and reviewed as part of the stress testing governance process.

GOVERNANCE STRUCTURE

Governance structure is one of the primary elements for sound governance over stress testing. While institutions may have different structures based on the legal, regulatory or cultural norms in their countries, it is generally expected that every institution has separation of duties between a board of directors and senior management. This separation of duties is equally important for stress-testing activities, as it helps ensure there is proper oversight and action taken on an ongoing basis. The board and senior management should share some responsibilities – albeit to varying degrees of detail – but also have distinct responsibilities in other cases. Together, an institution's board and senior management should establish comprehensive, integrated and effective stress testing that fits into the broader risk management of the institution.

Board of directors

In general, the board of directors has ultimate oversight responsibility and accountability for the entire organisation. It should be responsible for key strategies and decisions, define the culture of the organisation and set the "tone at the top". This applies to stress-testing as well, as the board is ultimately responsible for the institution's stress-testing activities, even if the board is not intimately involved in the details. Board members should be sufficiently knowledgeable about stress-testing activities to ask informed questions, even if they are not experts in the technical details. The board should actively evaluate and discuss information received from senior management about stress testing, ensuring that the stress-testing activities are in line with the institution's risk appetite, overall strategies and business plans, and contingency plans – directing changes where appropriate.[2] Board members should also ensure they review that information with an appropriately critical eye, challenging key assumptions, ensuring that there is sufficient information with appropriate detail and supplementing the information with their own views and perspectives.

Stress-testing results should be used, along with other information, to inform the board about alignment of the institution's risk profile with the board's chosen risk appetite, as well as inform operating and strategic decisions. Stress-testing results should be considered directly for decisions relating to capital and liquidity adequacy, including capital contingency plans and contingency funding plans. While stress-testing exercises can be very helpful in providing a forward-looking assessment of the potential impact of adverse outcomes, board members should ensure they use the results of the stress tests with an appropriate degree of scepticism, given the assumptions, limitations and uncertainties inherent in any type of stress testing. In general, the board should not rely on just one stress-test exercise in making key decisions, but should aim to have it supplemented with other tests and other quantitative and qualitative information. The board should be able to take action based on its review of stress-test results and accompanying information, which could include changing capital levels, bolstering liquidity, reducing risk, adjusting exposures, altering strategies or withdrawing from certain activities. In many cases, stress-testing activities can serve as a useful "early-warning" mechanism for the board, especially during benign times (ie, non-stress periods), and thus can be useful in guiding the overall direction and strategy for the institution.

Senior management

Senior management has the responsibility of ensuring that stress-testing activities authorised by the board are implemented in a satisfactory manner, and is accountable to the board for the effectiveness of those activities. That is, senior management should execute on the overall stress-testing strategy determined by the board. Senior management duties should include establishing adequate policies and procedures and ensuring compliance with them, allocating appropriate resources and assigning competent staff, overseeing stress-test development and implementation, evaluating stress-test results, reviewing any findings related to the functioning of stress-test processes and taking prompt remedial action where necessary.

In addition, whether directly or through relevant committees, senior management should be responsible for regularly reporting to the board on stress-testing developments (including the process to design tests and develop scenarios) and on stress-testing results (including those from individual tests, where material), as well as on compliance with stress-testing policies. Senior management should ensure there is appropriate buy-in at different levels of the institution, and that stress-testing activities are appropriately coordinated. Such coordination does not have to mean that all stress-testing exercises are built on the same assumptions or use the same information. Indeed, it can be very useful to conduct different types of stress tests to achieve a wide perspective. But senior management should be mindful of potential inconsistencies, contradictions or gaps among its stress tests and assess what actions should be taken as a result. At a minimum, this means that assumptions are transparent and that results are not used in a contradictory manner.

Senior management, in consultation with the board, should ensure that stress-testing activities include a sufficient range of stress-testing activities applied at the appropriate levels of the institution (ie, not just one single stress test). Another key task is to ensure that stress-test results are appropriately aggregated, particularly for enterprise-wide tests. Senior management should maintain an internal summary of test results to document at a high level the range of its stress-testing activities and outcomes, as well as proposed follow-up actions. Sound governance at this level also includes using stress testing to consider the effectiveness of an institution's risk-mitigation techniques for various risk types over their respective time horizons, such as to explore what could occur if expected mitigation techniques break down during stressful periods.

Stress-test results should inform management's analysis and decision-making related to business strategies, limits, capital and liquidity, risk profile and other aspects of risk management, consistent with the institution's established risk appetite. Wherever possible, benchmarking or other comparative analysis should be used to evaluate the stress-testing results relative to other tools and measures – both internal and external to the institution – to provide proper context and a check on results. Just as at the board level, senior management should challenge the results and workings of stress-testing exercises. In fact, senior management should be much more well versed in the details of stress testing and be able to drill down in many cases to discuss technical issues and challenge results on a granular level.

Senior management can and should use stress testing to supplement other information it develops and provides to the board, such as other risk metrics or measures of capital and liquidity adequacy. When reporting stress-testing information to the board, senior management should be able to explain the key elements of stress-testing activities, including assumptions, limitations and uncertainties. Reports from senior management to the board should be clear, comprehensive and current, providing a good balance of succinctness and detail. Those reports should include information about the extent to which stress test models are appropriately governed, including the extent to which they have been subject to validation or other type of independent review (see below). Senior management, as part of its overall efforts to ensure proper governance and controls, is also responsible for ensuring that staff involved in stress testing operate under the proper incentives. Finally, senior management should ensure that there is a regular assessment of stress-testing activities across the institution by an independent, unbiased party (such as internal audit – see below).

Senior management should ensure that stress-testing activities are updated in light of new risks, better understanding of the institution's exposures and activities, new stress-testing techniques, updated data sources and any changes in its operating structure and its internal and external environment. An institution's stress-testing development should be iterative, with ongoing adjustments and refinements to better calibrate the tests to provide current and relevant information. In addition, management should review stress-testing activities on a regular basis to confirm the general appropriateness of, among other things, the validity of the assumptions, the severity of tests, the robustness of the estimates, the performance of any underlying models and the stability and reasonableness of the results. In addition to conducting formal, routine stress tests, management should ensure the institution has the flexibility to conduct new or ad hoc stress tests in a timely manner to address rapidly emerging risks and vulnerabilities.

POLICIES, PROCEDURES AND DOCUMENTATION

Having clear and comprehensive policies, procedures and documentation is integral to sound stress-testing governance. These areas provide the important codification of an institution's practices and allow the institution as a whole to follow the same general principles and standards for its stress-testing activities. Thus, in order to promote a sound control environment and allow for consistency and repeatability in stress-testing activities across the entity, the institution should have written policies that direct and govern the implementation of stress-testing activities in a clear and comprehensive manner. It is generally expected that these policies would be approved and annually reassessed by the board. Stress-testing policies, along with procedures to implement them, should:

❑ describe the overall purpose of stress-testing activities;
❑ articulate consistent and sufficiently rigorous stress-testing practices across the entire institution;
❑ indicate stress-testing roles and responsibilities, including controls over external resources used for any part of stress testing (such as vendors and data providers);
❑ describe the frequency and priority with which stress-testing activities should be conducted;
❑ outline the process for choosing appropriately stressful conditions for tests, including the manner in which scenarios are designed and selected;
❑ include information about validation and independent review of stress tests;
❑ provide transparency to third parties for their understanding of an institution's stress-testing activities;
❑ indicate how stress-test results are used and by whom, and outline instances in which remedial actions should be taken; and
❑ be reviewed and updated as necessary to ensure that stress-testing practices remain appropriate and keep up to date with changes in market conditions, the institution's products and strategies, its risks, exposures and activities, its established risk appetite and industry stress-testing practices.

In addition to having clear and comprehensive policies and procedures, an institution should ensure that its stress tests are documented appropriately, including a description of the types of stress tests and methodologies used, test results, key assumptions, limitations and uncertainties, and suggested actions. Among other things, documentation:

- ❏ allows management to track results and analyse differences over time, including changes due to methodologies and assumptions as well as changes due to market conditions or other external factors;
- ❏ is a vital aspect of stress-testing governance as it allows third parties to evaluate stress tests and their components, including for validation and internal audit review;
- ❏ provides for continuity of operations, makes compliance with policy transparent and helps track recommendations, responses and exceptions; and
- ❏ is a useful tool for stress-test developers, as it forces them to think clearly about their stress tests, categorise the components of the tests and describe choices made and assumptions used.

Documenting stress tests takes time and effort, so institutions should therefore provide incentives to produce effective and complete documentation. Developers of stress tests should be given explicit responsibility during development for thorough documentation, which should be kept up to date as stress testing and application environment change. In addition, the institution should ensure that other participants document their work related to stress-testing activities, including validators, reviewers and senior management. For cases in which a bank uses stress tests from a vendor or other third party, it should ensure that appropriate documentation of the third-party approach is available so that the stress test can be appropriately understood, validated, reviewed, approved and used.

VALIDATION AND INDEPENDENT REVIEW

Another key element of governance over stress testing is validation and independent review. Stress-testing governance should incorporate validation or other type of independent review to ensure the integrity of stress-testing processes and results. Such unbiased, critical review of stress-testing activities gives additional assurance that the stress tests are functioning as intended. In general, validation and independent review of stress-testing activities should be conducted on an ongoing basis, not just as a single event. In addition, validation and review work for stress testing should be integrated with an institution's general approach to validation and independent review of its quantitative estimation tools – although stress tests may need to be validated and reviewed in a particular manner. Specifically, because stress tests by definition aim to estimate the potential impact of rare events and circumstances, conducting more traditional outcomes analysis used in a more data-rich environment may not be possible. For instance, statistical backtesting of stress-test estimates against realised outcomes may not be feasible.

To address challenges associated with validating stress tests, some institutions may try to test their models using data from non-stress periods, ie, during "good times" or in a "baseline" setting. Such testing can be beneficial to determine whether the stress test generally functions as a predictive model under those conditions. If the stress test does not perform well in a more data-rich environment, that would certainly raise questions about its usefulness. However, while "baseline" outcomes showing good test performance can provide some additional confidence in the stress test, those outcomes should not be interpreted as sufficient for the designated task of estimating stress outcomes. For instance, markets and market actors can behave quite differently in stress environments, and assumed interactions among variables can change markedly (such as higher incidence of nonlinearities). Thus, the model used in a baseline situation may actually require a different specification to properly estimate stress outcomes (or an entirely new model may be needed for stress periods). There can be additional challenges when upgrades or enhancements are made to stress tests, because it may not be immediately clear that the upgraded or enhanced model actually performs better. Here, too, assessing the baseline outcomes can provide some assurance about such changes, but cannot offer full confirmation. In sum, even with rigorous quantitative analytics, there can remain very real limitations in the extent to which stress tests can be formally validated or otherwise fully assessed in terms of quantitative performance.

As an additional response to these validation issues, given the limitations of relying on outcomes analysis, an institution may need to rely on other aspects of validation and independent review of stress tests – such as a greater emphasis on conceptual soundness of the stress test, additional sensitivity testing, and simulation techniques. Or an institution may choose to create holdout sample portfolios and run them through its stress-test model. Benchmarking to internal or external models, tools or results can also be beneficial, but institutions should be careful that the benchmarks appropriately fit the institution's risks, exposures and activities. Finally, expert-based judgement should be applied to ensure that test results are intuitive and logical, and to add additional perspective on stress-test performance.

Despite these additional efforts, institutions may continue to be challenged in trying to fully validate their stress tests to the same extent as other models, given the limitations in conducting performance testing. Such limitations do not mean that those stress tests cannot be used, but there should be transparency about validation status, and information about the lack of full validation should be communicated to users of stress-test results. For cases in which validation and independent review have identified material deficiencies or limitations in a stress test, there should be a remediation plan to explain how the stress test will be enhanced or its use limited, or both. Identified deficiencies in stress tests should be communicated to all stress-test users.

Additional areas of validation and independent review for stress tests that require attention from a governance perspective include:

- ensuring that there is appropriate independence and effective challenge in the validation and review process;
- including validation and independent review of the qualitative or judgemental aspects of a stress test – such aspects can be an integral component of a stress test and thus should be reviewed in some manner, even if they cannot be tested in a quantitative/statistical sense;
- ensuring that stress tests are subject to appropriate development standards, including a clear statement of purpose, proper theory and design, sound methodologies and processing components, and developmental testing (including testing of assumptions);
- acknowledging limitations in stress-testing methodologies, even if they represent best practices;

- recognising any data limitations or weaknesses in data quality;
- ensuring that stress tests are implemented in a rigorous manner that is appropriate for the stated use, and accounting for any changes to the developed stress test that occur during implementation;
- monitoring performance on an ongoing basis and assessing any degradation in performance (where possible);
- expressing stress-test uncertainty and inaccuracy, including in the form of confidence bands around estimates and/or factors not observable or not fully incorporated; and
- ensuring that vendor or other third-party models are sufficiently validated, including their implementation, to ensure they function as intended and are appropriate for the institution's use.

INTERNAL AUDIT

An additional aspect of governance and controls is the role of internal audit. An institution's internal audit function evaluates practices in a range of risk-management areas, and stress-testing activities should be among them. Internal audit should provide independent evaluation of the ongoing performance, integrity and reliability of stress-testing activities. It is not expected that internal audit will have full knowledge of all stress-test details, or will have to independently assess each stress test used. Rather, internal audit should look across the firm's stress-testing activities and ensure that, as a whole, they are being conducted in a sound manner, are appropriate for the intended purpose and remain current. There should also be an assessment of the staff involved in stress-testing activities regarding their expertise and roles and responsibilities.

Internal audit should also check that the manner in which all material changes to stress tests and their components are appropriately documented, reviewed and approved. In addition, it should evaluate the validation and independent review conducted for stress tests, including all the items listed above relating to validation. In order to conduct such evaluations, internal audit staff should possess sufficient technical expertise to understand the stress tests and challenge their processes and results. It is also important to review the manner in which stress-testing deficiencies are identified, tracked and remediated. On the whole, internal audit serves the valuable task of assessing the full suite of stress-testing activities across the institution on a regular basis to evaluate whether, as a whole, such activities are functioning as intended, in adherence with policies and procedures and serving the institution properly.

OTHER KEY ASPECTS OF STRESS-TESTING GOVERNANCE

This final section outlines some key aspects of stress-testing governance that should also receive attention, and areas in which governance should be exercised. These include stress-testing coverage, stress-testing types and approaches and capital/liquidity stress-testing. The manner in which these areas are addressed can and should vary across institutions. But, at a minimum, these are areas of stress testing that should be addressed in some way by senior management, evaluated as part of the internal control framework and summarised for review by the board.

Stress-testing coverage

- ❏ Appropriate coverage in stress-testing activities is important, as stress-testing results could give a false sense of comfort if certain portfolios, exposures, liabilities or business-line activities are not included; this underscores the need to document clearly what is included in each stress test and what is not being covered.
- ❏ Effective stress testing should be applied at various levels in the institution, such as business line, portfolio and risk type, as well as on an enterprise-wide basis; in some cases, stress testing can also be applied to individual exposures or instruments (eg, structured products).
- ❏ Stress testing should capture the interplay among different exposures, activities and risks and their combined effects; while stress testing several types of risks or business lines simultaneously may prove operationally challenging, an institution should aim to identify concentrations and common risk drivers across risk types and business lines that can adversely affect its financial condition – including those not readily apparent during more benign periods.
- ❏ Stress testing should be conducted over various relevant time horizons to adequately capture both conditions that may materialise in the near term and adverse situations that take longer to develop.

Stress-testing types and approaches

- For any scenario analysis conducted, the scenarios used should be relevant to the direction and strategy set by its board of directors, as well as sufficiently severe to be credible to internal and external stakeholders; at least some scenarios should be of sufficient severity to challenge the viability of the institution.
- Scenarios should consider the impact of both firm-specific and systemic stress events and circumstances that are based on historical experience as well as on hypothetical occurrences that could have an adverse impact on an institution's operations and financial condition.
- An institution should carefully consider the incremental and cumulative effects of stress conditions, particularly with respect to potential interactions among exposures, activities, and risks and possible second-order or "knock-on" effects.
- For an enterprise-wide stress test, institutions should take care in aggregating results across the firm, and business lines and risk areas should use the same assumptions for the chosen scenario, since the objective is to see how the institution as a whole will be affected by a common scenario.
- Consideration should be given to reverse stress tests that "break the bank" to help an institution consider scenarios beyond its normal business expectations and see what kinds of events could threaten its viability (even if it is difficult to estimate their likelihood).

Capital and liquidity stress testing

- Stress testing for capital and liquidity adequacy should be conducted in coordination with an institution's overall strategy and annual planning cycles; results should be refreshed in the event of major strategic decisions, or other decisions that can materially impact capital or liquidity.
- An institution's capital and liquidity stress testing should consider how losses, earnings, cashflows, capital and liquidity would be affected in an environment in which multiple risks manifest themselves at the same time – for example, an increase in credit losses during an adverse interest-rate environment.

- ❑ Stress testing can aid contingency planning by helping management identify exposures or risks in advance that would need to be reduced and actions that could be taken to bolster capital and liquidity positions or otherwise maintain capital and liquidity adequacy, as well as actions that in times of stress might not be possible – such as raising capital or accessing debt markets.
- ❑ Capital and liquidity stress testing should assess the potential impact of an institution's material subsidiaries suffering capital and liquidity problems on their own, even if the consolidated institution is not encountering problems.
- ❑ Effective stress testing should explore the potential for capital and liquidity problems to arise at the same time or exacerbate one another; for example, an institution in a stressed liquidity position is often required to take actions that have a negative direct or indirect capital impact (eg, selling assets at a loss or incurring funding costs at above market rates to meet funding needs), which can then further exacerbate liquidity problems.
- ❑ For capital and liquidity stress tests, it is beneficial for an institution to articulate clearly its objectives for a post-stress outcome, for instance to remain a viable financial market participant that is able to meet its existing and prospective obligations and commitments.

CONCLUSION

Similar to other aspects of risk management, an institution's stress-testing will be effective only if it is subject to strong governance and effective internal controls to ensure the stress-testing activities are functioning as intended. Strong governance and effective internal controls help ensure that stress-testing activities contain core elements, from clearly defined stress-testing objectives to recommended actions. There are many elements that contribute to effective stress-testing governance, foremost being the role of the board and senior management. Stress testing can be a very powerful risk-management tool, but the board and senior management should challenge stress-testing processes and results, demonstrating a solid understanding of their assumptions, limitations and uncertainties. Additionally, strong governance helps ensure that stress testing is not isolated within its risk-management function, but is firmly integrated into business lines, capital and asset–liability committees and other decision-making bodies. Finally, strong governance can help institutions continue to recognise the difficulty in estimating the impact of stressful events and circumstances, thereby acknowledging that stress-test results should be used only with sound judgement and a healthy degree of scepticism.

The views expressed in this chapter do not necessarily represent the views of the Federal Reserve Board or the Federal Reserve System.

1 For the purposes of this chapter, the term "stress testing" is defined as exercises used to conduct a forward-looking assessment of the potential impact of various adverse events and circumstances on a banking institution.

2 Risk appetite is defined as the level and type of risk an institution is able and willing to assume in its exposures and business activities, given its business objectives and obligations to stakeholders.

2

Stress Testing and Other Risk-Management Tools

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The later chapters in this book are focused on various elements and aspects of stress testing. Stress tests have gained in prominence since the financial crisis of 2007-9. However, stress testing existed in the arsenal of risk managers well before the financial crisis. But it has not existed in isolation: along with stress tests, risk managers have always used other tools.

In our experience, quite sophisticated stress testing existed in many banks' management of market risk before the 2007–9 crisis, and it often focused on the trading book. This included both transaction and portfolio-level stress testing. In contrast, stress testing of credit risk was more likely to be at a transaction level. Portfolio-level stress testing was often rudimentary, if it existed all. Enterprise-wide stress tests tended to be rudimentary (with one or two notable exceptions), as well, especially for institutions that had large banking books.

Risk management in financial institutions has always relied on a panoply of tools and measures. Textbooks on risk management at financial institutions describe various other tools such as position limits and exposure limits, as well as limits on the Greeks, such as on delta or vega.[1]

In this chapter, we discuss the relationship between those other tools and stress testing. We first focus on similarities, differences and consistencies between them. We then discuss the ongoing evolution whereby stress testing has affected other risk-management tools. We also discuss how other risk-management tools are affecting stress testing.

Of the other risk measures, we focus on the value-at-risk (VaR) measures. These include the economic capital (EC) measures. This choice is motivated by the fact that such metrics are designed to capture risk across different types (such as market, credit, interest rate, etc.) in a manner similar to stress testing. Additionally, regulatory capital models as used in Basel II/III can also be viewed as akin to EC models. Enterprise-wide risk limits have often been based on value at risk or its variants. More concretely, many institutions have expressed their risk appetite in terms of a very high percentile such as 99.97% EC.

ENTERPRISE-WIDE STRESS TESTING

As is well known, an important use of stress testing has been to acquire enterprise-wide views of risk, especially in the supervisory stress tests run by regulators around the world. These are the enterprise-wide stress tests.

At a basic level, different risk-management tools can produce different results because of differences in the inputs. For both VaR measures and stress tests, the inputs are data and scenarios.

A stress test may be viewed as translation of a scenario into a loss estimate. In a similar vein, EC or VaR methods also involve translation of scenarios into loss estimates. The distribution of the loss estimates are then used to derive the VaR at a high percentile such as 99% or 99.9%. In practice, stress tests usually focus on a few scenarios, whereas VaR measures commonly utilise a very large number of scenarios.

Hence, as long as identical inputs and similar definitions of loss estimates are used between stress tests and EC/VaR methods, there can be consistency between stress tests and EC/VaR methods, at least when identical scenarios are used.

However, in practice, the loss estimates are often defined quite differently between stress tests and EC methods. In particular, a significant difference is that losses in stress tests have more often than not taken an accounting view rather than a "market" view commonly attempted in EC methods.

The second significant difference has been the horizon. Enterprise-wide stress tests have often examined a long period such as losses over nine quarters in the Dodd–Frank stress tests in the US. In contrast, EC models have focused on losses at a point in time, such as the loss in value at the end of a year.

The final significant difference is the role of probabilities. Scenarios for stress tests can sometimes be generated using distributions of the macroeconomic variables. Therefore, the results of a scenario in a stress test can be assigned a probability, ie, the probability of that scenario. However, probabilities have not played a prominent role in stress tests. For many stress tests conducted around the world, ordinal rank assignments such as "base", "adverse" and "severely adverse" have been done, but with little discussion of the cardinal probabilities attached to them. In contrast, cardinal probabilities generally play a large role in the VaR-type models. For the VaR/EC models using Monte Carlo simulation, there exist complex statistical models underneath. For the VaR models using historical simulation, the history has been viewed as the distribution to draw from. More importantly, in the interpretation and use of the VaR/EC model results, probabilities have played a very large role. A 99.9% VaR loss has often been viewed as a 1-in-1,000 event, albeit with uncertainty (or standard errors) around it.

The last difference has been the approach to scenarios. Stress-test scenarios are often *ad hoc* and conditional, rather than the unconditional scenarios typically generated in VaR-type metrics. Especially, for the regulatory stress tests, the scenario-generation process has looked at the present period as the starting point and then generated two or three hypothetical scenarios from that starting point.

A simple example: stress test

A concrete example can be given for a wholesale portfolio. It is a very simplified example designed to get the idea across rather than provide a guideline to follow. Let us assume the bank is using a two-year scenario that consists of GDP growth and unemployment (see Table 2.1).

Table 2.1 Hypothetical scenarios for two macro variables

Macro variable	1st-year change from base	2nd-year change from base
GDP	–1%	–0.5%
Unemployment	+1%	0%

For wholesale exposures, let us assume that the bank has chosen to model at a portfolio (top-down) level rather than a loan level. At a basic level, the bank needs to estimate the sensitivities of losses in this portfolio to the changes in the two macro variables: GDP growth and unemployment.

Let us assume the following information on the bank's wholesale portfolio (see Table 2.2).

Table 2.2 Portfolio composition for the hypothetical bank

Rating bucket	Balance	1-year default rate (%)	2-year default rate (%)
1	200	0.00	0.00
2	350	0.01	0.02
3	400	0.02	0.10
4	500	0.18	0.53
5	100	1.23	3.31
6	10	5.65	12.35
7	0	21.12	33.53

Let us assume that the bank chooses to use a PD LGD approach. Therefore, the bank needs to compute what the PD is in the stress scenario for each of the two years. Additionally, the bank needs to model which of the exposures transition to a lower rating. Finally, the bank needs to understand what new wholesale loans the bank will generate in the two years and what rating buckets (and PD) the new loans will be in.[2] Based on historical experience, the bank establishes the following first-year and second-year stressed PDs. This may be based on the bank's own historical experience or on industry data. The exposures (EAD) are not expected to change. However, the LGD does change. Using the experience of 2008, the bank finds that, according to Moody's URD data, the LGD for senior unsecured increases from 53% to 63%. The bank chooses to increase its LGD by 10% for all rating buckets. Table 2.3 presents the balances and the stressed parameters for the bank's wholesale portfolio. We are assuming no new business and are not taking into account migration between the two years.

Table 2.3 Projected stressed parameters for the bank's portfolio

Rating bucket	Balance	Stressed LGD	1st-year stressed PD (%)	2nd-year stressed PD (%)
1	100	60%	0.02	0.00
2	200	60%	0.03	0.02
3	400	70%	0.04	0.03
4	500	70%	0.25	0.20
5	100	80%	1.85	1.50
6	200	80%	8.00	8.50
7	500	90%	25.00	20.00

The two-year cumulative loss rate comes out to be 7.44% with these assumptions.

A simple example, continued: EC/VaR.

In the implementation of EC models, banks commonly use a Merton model framework to simulate the defaults and credit quality. In this framework, asset returns are simulated using a factor model framework, and default occurs when the simulated asset value is below a threshold (generally tied to the leverage of the borrower) at the one-year horizon.

In a multifactor setup, for a borrower *i* with default probability PD

$$Z_i < \mathrm{N}^{-1}(PD_i)) \text{ where}$$

$$Z_i = \beta_{i1} GDP + \beta_{i2} Unemployment + (\sqrt{1 - \beta_{i1}^2 - \beta_{i2}^2})\eta_i$$

where Z_i is a unit normal variable and GDP and unemployment are simulated values for the two macroeconomic factors. For credit quality, the simulated asset value (and by extension the simulated leverage) is used to impute a spread. It is common for the shock to the spreads to be modelled as a function of Z_i as well. Banks generally generate the asset values using a correlation matrix using correlations between industries and countries.

Banks run these simulations a number of times, sort the losses from the draws, and arrive at the 99th or 99.9th percentile of the loss distribution as the 99th or 99.9th percentile VaR.

The loss for the stress test may correspond to one of the losses and can allow the user to roughly gauge the severity of the stress test.

USE OF VAR MODELS IN STRESS TESTS

Since the VaR models provide a mechanism for computing loss via

$$Loss = PD \times LGD \times EAD$$

One approach that some institutions have taken is to assess where the losses based on stress tests lie in the loss distribution used in the VaR/EC estimation. This process has been one mechanism to associate probability with a given hypothetical or historical stress scenario. Going one step further, some institutions have also used such mechanisms to tie together scenarios across disparate lines of business.

As an example, if a scenario's loss magnitude translates into a 90th percentile loss on the loss distribution for VaR, the bank may take the 90th percentile loss in the EC model as an approximation to the stressed loss for market risk.

No financial institution can be run with zero risk tolerance, nor can all sources of risk be eliminated. However, clearly, some losses are unacceptable because of their magnitudes, irrespective of the scenarios. For such losses, the likelihood (or probability) of the scenario is not that material. However, for most scenarios, the output tends to be used as the loss in that scenario and the likelihood of that scenario.

The assignment of probability via "matching" the stressed loss to a point on the loss distribution serves the useful purpose of coming up with the probability of that scenario. Since, for the practical implementation of stress tests in risk management, assignment of probabilities to the outcomes is important, the probability arrived via the loss distribution can help make the stress tests more actionable.[3]

STRESSED CALIBRATION OF VALUE AT RISK MEASURES

Another approach to incorporating stress into risk measurement methodologies has been the use of stressed inputs. There have been quite a few variants. This has been particularly useful in the market risk area. The incorporation of stress into the risk measurement as well as capital metrics has occurred in both the supervisory approaches and the many banks' internal approaches.

On the supervisory approaches, the new market risk rule requires banks to use stressed inputs, ie, the revisions to the market risk capital framework (BCBS 2011a) states,

> In addition, a bank must calculate a "stressed value-at-risk" measure. This measure is intended to replicate a value-at-risk calculation that would be generated on the bank's current portfolio if the relevant market factors were experiencing a period of stress; and should therefore be based on the 10-day, 99th percentile, one-tailed confidence interval value-at-risk measure of the current portfolio, with model inputs calibrated to historical data from a continuous 12-month period of significant financial stress relevant to the bank's portfolio.

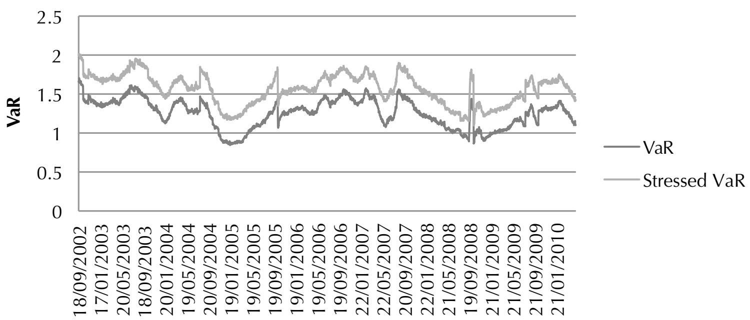
The revisions to the market risk capital framework also explicitly require the use of stress tests: "Banks that use the internal models approach for meeting market risk capital requirements must have in place a rigorous and comprehensive stress-testing program."

Similarly, in the revisions to Basel III (BCBS 2011b), stressed parameters are required: "To determine the default risk capital charge for counterparty credit risk as defined in paragraph 105, banks must use the greater of the portfolio-level capital charge (not including the CVA charge in paragraphs 97–104) based on Effective EPE using current market data and the portfolio-level capital charge based on Effective EPE using a stress calibration. The stress calibration should be a single consistent stress calibration for the whole portfolio of counterparties."

As an illustration, we present some results from Siddique (2010), with six risk factors to simulate the exposures. These are: (1) Three month LIBOR (LIBOR3M); (2) the yield on BAA-rated bonds (BAA); (3) the spread between yields on BAA- and AAA-rated bonds (BAA–AAA); (4) the return on the S&P 500 index (SPX); (5) the change in the volatility option index (VIX); and (6) contract interest rates on commitments for fixed-rate first mortgages (from the Freddie Mac survey) (MORTG). MORTG is in a weekly frequency that is converted to daily data through imputation using a Markov chain Monte Carlo. There are a total of 2,103 daily observations over the period January 2, 2002, through May 10, 2010.

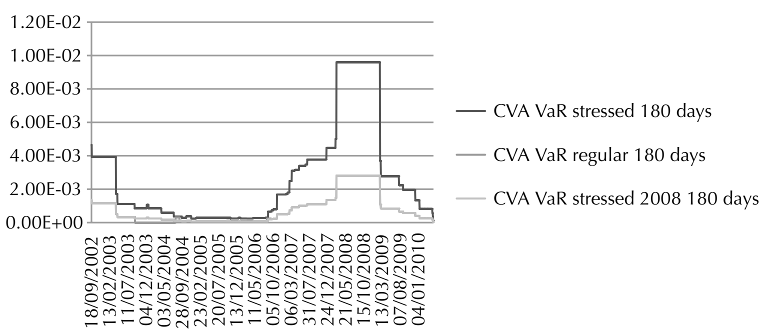
With Monte Carlo, the stressed VaR as 99.9th percentile of a distribution of P&Ls generated using stressed parameters can be constructed. Two separate sets of moments, (1) using the previous 180 days or 750 days' history of the risk factors and (2) the stress period (180 days or 750 days ending in 30.06.09), are used to simulate the risk factors. The 99.9th percentile of the portfolio value is then the 99.9th regular VaR or stressed VaR based on which sets of moments are used. Figure 2.1 illustrates VaR and stressed VaR with a balanced portfolio.

Figure 2.1 VaR and stressed VaR with a balanced portfolio



Source: Siddique (2010)

Figure 2.2 Comparison of VaR & stressed VaR of CVA: different stressed periods



Source: Siddique (2010)

Stressed inputs are also used in the capital charge for credit valuation adjustment (CVA) as mentioned above. To assess the impact of the use of stressed inputs for those metrics, Siddique (2010) carries out some other simulations whose results are presented in Figure 2.2.

Two separate periods are used to compute the stressed calibration: (1) 180 days ending 30.09.08; and (2) 180 days ending 30.06.09. The impact of a stressed calibration appears in the early period in the data, where the CVA VaR is substantially higher than the unstressed (regular) CVA VaR. However, in the latter period the unstressed and stressed VaR are identical. It is important to note that an incorrect stress period (ie, ending 30.09.08) can actually produce VaR lower than an unstressed CVA VaR.

There are both advantages and disadvantage of such stressed risk metrics. An obvious advantage is that, with capital for unexpected losses taking into account stressed environments, capital should be adequate when the next stress or shock occurs. That is, a risk metric with a stressed input is usually going to be more conservative.

However, given that the inputs are always stressed, the risk metric will no longer be responsive to the current market conditions, but primarily depend on the portfolio composition.

Only time will tell what the final impact of the incorporation of stress-testing elements into risk management and capital adequacy metrics will be.

CONCLUSION

Stress testing has played a very large role in the assessment of capital adequacy. It has always played a role in risk management as well, which has become much larger as a result of the 2007–9 financial crisis. However, banks have continued to use other risk-management tools such as VaR as well. Nevertheless, stress testing has influenced those tools and those tools have also been used in stress testing.

The views expressed in this chapter are those of the authors alone and do not necessarily represent those of the Comptroller of the Currency or the Bank of Finland.

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1 See, for example, Hull (2012).

2 For the purposes of this simplified example, we are aware that we are making very strong assumptions and simplifications in this example and are ignoring many elements that banks take into account. For example, banks can find that the underwriting of new loans can actually be stricter in a recession, resulting in a lower PD for new business compared with the existing book.

3 Action triggers (when actions need to be taken) for stress tests can be tied to either the output – for example, if the losses exceed a certain level. Alternatively, they can be tied to the input, ie, if the realised input into a test is below/above a threshold. As an example, a stress test can involve a scenario for GDP growth. If GDP growth in a quarter is below a trigger such as −2%, actions can be taken.

3

Stress Testing for Market Risk

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Stress testing has received increased attention from both financial institutions and regulators since the 2007–9 financial crisis. What constitutes reliable and relevant stress tests, however, still stirs a lot of debate among practitioners, stakeholders and researchers. The development and evolving practices of stress testing in the area of market risk management are reviewed in this chapter. In addition, the ways in which stress-testing methodology can be improved for risk management is presented.

Generally speaking, market risk refers to changes in a financial institution's portfolio values due to unanticipated changes in market risk factors such as the price and volatility of equities, interest rates, credit spreads, the price of commodities and foreign-exchange rates. Stress testing for market risk has been an important component of stress tests, both in the internal stress tests run by banking organisations and in the stress tests run by financial regulators. During the financial crisis of 2007–9, the largest losses were often in portfolios sensitive to market risk. Traditionally, stress tests for market risk have been conducted for portfolios in banks' trading books, by using scenarios of possible states for market risk factors. In order to do so, severe but plausible scenarios are often chosen. The choice of scenarios, therefore, is crucial but sometimes inevitably subjective as well. The traditional approaches for scenarios utilise one of the three methods: standard scenarios, historical scenarios and worst-case scenarios.

In the analysis using standard scenarios, the values of portfolios are estimated by stressing the market risk factors by pre-specified shocks, such as changing equity prices by some standard deviations or increasing oil prices to a certain level. These are also referred to as hypothetical scenarios. In the historical-scenarios analysis, market states for a particular historical time period relevant for the bank's portfolio are used. This may include, for example, the 1987 equity crash, the 2007–9 credit crisis, etc. In the worst-case scenario analysis, an automated search over prospective changes in market states is conducted in order to evaluate profits and losses under that scenario.

The traditional stress tests are easy to conduct but have important limitations. For example, the historical scenarios offer reliable but likely less relevant information for risk management in the future; the standard analysis may not be based on the changes in the market states that are close to a stress event; and the worst-case analysis looks at the impacts of changes that are unlikely to occur. Given the drawbacks of traditional stress tests, risk managers have been compelled to use expert judgement along with the results of the stress analyses before taking actions based on results.

The literature on stress testing has grown rapidly, incorporating many suggestions for improvements in stress-testing methods. For example, to integrate stress testing into formal risk modelling, Berkowitz (1999) proposed a solution that includes assigning probabilities to stress-test scenarios; Artzner *et al* (1999) suggested estimating the expected tail loss to address the drawbacks of market value-at-risk (VaR); and Kupiec (1998) discussed the importance of allowing changes in the market states to be correlated. However, it was the financial crisis of 2007–9 that highlighted the importance of stress testing as an important risk-management and regulatory tool, and, as a result, many large banks have incorporated such practices as part of their enterprise-wide risk management. Furthermore, there have been many statutory and regulatory reforms that have required such practices. There has also been an increasing consensus among practitioners, regulators and researchers that stress tests are important because they help banking organisations to understand market risk exposures that methods such as VaR may miss, depending on how VaR models are developed and implemented. The hope is that such information can be used by executive management for strategic planning, capital adequacy and capital allocation, and other major decisions. Stress tests can also help regulators identify risk concentrations and systemic risk, and take mitigating actions.

This chapter discusses several important aspects of stress testing for market risk. First, we focus on the distinction between stress testing for market risk and the more common stress testing for credit risk. After that, we discuss the role of scenarios in market risk and how they may differ from other types of stress tests. A discussion of the horizon for the stress tests follows. The last section focuses on revaluation of the values and computation of profits and losses under the stressed scenarios followed by concluding remarks.

DISTINGUISHING BETWEEN STRESS TESTING FOR MARKET RISK AND CREDIT RISK

Stress testing for market risk and that for credit risk have the common ultimate goal of estimating the impacts on portfolio values of given plausible and severe events. Stress testing for market risk has become almost synonymous with stress testing of the trading book. The trading book, in contrast with the banking book, is characterised by a large number of instruments as well as a larger number of positions and risk factors. Further, mark-to-market losses for trading books are usually measured at a point in time. In particular, derivative positions that are the result of off-balance-sheet activities by financial institutions are often a major focus of market risk stress tests. Probabilistic risk measures, such as VaR, are the primary tool for measuring risk capital as well as computing regulatory capital for such activities. Basel 2.5 has also introduced a "stressed VaR".

On the other hand, stress testing for credit risk is mostly conducted for portfolios in banking books, which primarily consist of portfolios of loans, securities or positions held as investments as well as direct equity investments. The output for stress testing for credit risk could be accounting losses over a period of time due to the impacts on rating changes, probability of default (PD), and loss-given default (LGD). The selection of scenarios could also be more nuanced for the stress testing of credit risks because different segments (such as utility, banking, real estate) in a portfolio may be exposed to different market states. However, trading-book positions are also subject to credit risk if the risk factors include credit spreads. Furthermore, both trading-book and banking-book positions are subject to default of the counterparty for derivatives or securities financing transactions, which is referred to as counterparty credit risk and is discussed in Chapter 4.

Another source of difference between these two types of risk comes from liquidity risk. The impact of changes in liquidity may have an immediate and severe impact on the value of a trading book position. The 2007–9 financial crisis highlighted the severe impacts of extreme illiquidity, which had received little attention in stress testing before the crisis. While banks, regulators and researchers alike have realised the importance of liquidity risk management, incorporating it in the formal stress testing is less straightforward. Liquidity and stress testing are discussed in more detail in Chapter 11.

Aggregation of results from stress tests

Although researchers have proposed sophisticated approaches in aggregating the results of stress tests from various risk sources, concerns remain in bottom-up approaches because it may significantly underestimate the true total risk (Breuer *et al* 2010). For example, Rosenberg and Schuermann (2006) used an approach to aggregate different risk types such as market, credit and operational. They used a bottom-up approach in which various risks (market, credit and operational) are separately analysed and estimated, and then aggregated to produce the total risk. This aggregation relied on the assumption that risk types are subadditive. For example, as Rosenberg and Schuermann (2006) showed, risks can aggregate with perfect correlation ("add-VaR"), which placed an upper bound on the economic capital a bank would need at a given risk-tolerance or confidence level. Risks could also be aggregated using a copula-VaR approach, in which a joint distribution of loss can be estimated by using the shape and location of each of the risk distributions and a dependence function. In general, the aggregated risk estimated by copula-VaR models has tended to be lower than risk estimated by add-VaR. Regardless of whether researchers/practitioners have used an add-VaR or a copula-VaR method to aggregate risk, each of the risk distributions has been separately estimated. The location and shape of the loss distribution for each risk type remain unchanged under summing (with a correlation coefficient of one, or with some "diversification" discount). However, bank losses associated with different risk types may not be additive. In other words, when the worst-case scenario for market risk has occurred, the chance of the worst-case scenario for credit risk may also have increased. This is plausible because financial markets/instruments have become so developed that credit risk is now borne opaquely by capital markets.

STRESS TESTING MARKET RISK AND CHOICE OF SCENARIOS

As in the stress tests for other risks, market risk stress tests have also relied on hypothetical and historical scenarios. There have been other approaches used in the selection of scenarios, such as via mechanically driven searching. Scenarios used in enterprise-wide stress tests have tended to be focused on macroeconomic and financial variables. The scenarios are often specified as vectors of macroeconomic variables such as GDP, unemployment, inflation, house prices and interest rates. The losses resulting from market risk in such scenarios are often difficult to estimate directly. Financial institutions have generally needed to translate the macroeconomic scenarios into changes in market risk factors such as changes in credit spreads, commodity prices and volatilities of the other factors that are used to compute the losses for the market shocks.

As an example, the valuation of a credit default swap depends on the recovery rate and the default probability of the reference asset. If a macroeconomic scenario has been specified in terms of GDP, the unemployment rate and HPI (House Price Index), the bank has created an auxiliary model that translated the macroeconomic variables into default probabilities and recovery rates. Similarly, for financial products such as securitisations, banks generally use systems such as Intex to value the securities.[1] The inputs for Intex are computed from the macroeconomic scenarios using auxiliary models. For a large proportion, if not all, of the exposures subject to market risk, the necessary variables are the inputs for the pricing models used for the trading-book positions. These inputs are prices, volatilities and other parameters such as correlations. Generally, the stress is modelled as very large movements in these inputs.

Given the fairly large flexibility in how the macroeconomic variables are translated into the variables more commonly used in market risk stress testing, comparability and consistency within and across institutions can be a challenge in market risk stress testing as compared with credit risk stress testing. Therefore, in many of the regulatory stress tests based on the Dodd–Frank Act or the Federal Reserve's CCAR (Comprehensive Capital Analysis and Review) in the United States and the supervisory stress tests run by the European Banking Authority (EBA) in Europe, regulators have specified the values for many of the variables that would constitute the inputs for the market risk valuations systems. However, even in those cases, institutions frequently had to come up with inputs for risk factors that the regulators had not specified.

An additional consideration has been that, unlike with the banking book, where a bank is naturally "long credit", for trading-book portfolios a bank may actually have positions that have gains in an adverse scenario. That imposes additional pressures on how (and how well) the results of a market risk stress test are verified. Given that the scenarios provided by regulators may have failed to encompass all possible risk factors that an institution uses, a greater degree of inconsistency in the market risk stress tests compared with credit risk stress tests occurs. This highlights the importance of effective monitoring by the regulator. Although the regulator's goal of specifying the values for the inputs of the market risk valuations is to enhance consistency and comparability within and across the banks, it encounters problems such as "one size does not fit all" and "catch up with the changes". In order to ensure the market risk stress tests correctly reflect an individual bank's riskiness, the regulator needs to subject the inputs, especially those generated by the institutions, to greater scrutiny to validate their representativeness and comprehensiveness.

TIME HORIZON IN MARKET RISK STRESS TESTS

Stress tests for other risk areas such as credit risk have generally focused on the losses over a long horizon such as the nine quarters used for the Dodd–Frank Act and CCAR stress tests in the United States. An important element of these stress tests has been how the portfolio may have changed in the stressed period, such as new business or changes in the value of the existing portfolio even if they do not default. Historically, stress tests for market risk, such as the stress tests focused on trading portfolios, have had very short horizons, such as ten days or even instantaneous, depending on the nature of the trading frequency of the products in the portfolios. The shorter horizon was motivated by more frequent trading and a shorter holding period that has characterised the trading book.

The choice of horizon not only had a direct impact on the valuation of the portfolios under stress tests, but also had significant implications for how banks took actions (such as reducing exposures) based on the outputs of the stress tests. For example, an important aspect of the choice of horizon is what happens after the initial shock, that is to say the aftershock. Alexander and Sheedy (2008) pointed out that the consequences of a shock event can include some or all of the following: further large moves in the same market (as predicted by volatility clustering); large moves in other markets and higher correlations between markets; and increased implied volatility in option markets and reduced market liquidity. In a portfolio-level stress test of market risk, the horizon used may be the same as the horizon for the VaR, such as ten days. In such a scenario, the aftershock may not materialise.

However, for enterprise-wide stress tests the market risk stress tests generally need to be the same horizon as the stress tests for the other risks, such as credit risk, because a common horizon is needed to put the various risks on a common footing. Two features then can become important. The first is that the aforementioned aftershock is then relevant. Simply, taking the 10-day loss and expanding it to a one-year horizon via a method such as multiplying by the square root of time may misstate the losses, since that ignores the aftershocks.[2] The second is the impact of hedging, other management actions and what assumptions are made regarding hedging. Whether hedging is taken into account and how the hedging is accommodated has varied among institutions. Banks have traditionally argued that they can implement dynamic hedging strategies that can end up reducing the unexpected losses of a portfolio in a significant way. However, in a severely stressed environment it is not clear if the hedging instruments remain available with enough liquidity. The experiences with the 1987 crisis showed that dynamic hedging strategies that worked in normal environments failed to take into account the positive feedback of hedging demand in a stressed environment especially where there very large discontinuities.[3] When lengthening the horizon for the market stress tests while conducting enterprise-wide stress tests, it may be problematic to assume that dynamic hedging is still as effective as in normal markets when everything else is also stressed.

REVALUATIONS AND COMPUTATION OF P&L UNDER THE STRESSED SCENARIOS

Once market stress scenarios are specified, the next step is to revalue the positions in the portfolio under the stressed scenarios. The difference in the value of the positions under the stressed scenario and the current value is the profit or loss (generally referred to as P&L). There are several steps in this process of estimation of stressed P&L that may involve approximations and calibrations. These steps are discussed below.

Mark-to-market versus market-to-model valuations

Valuations for routine risk management and reporting purposes rely on either mark-to-market valuations that use closing market prices from exchanges/market consensus prices from a pricing vendor, or mark-to-model valuations based on analytical or numerical models. These models often have input parameters that are calibrated using current market prices. These pricing models, or "pricers", form the backbone of revaluations or repricing of positions under stressed scenarios. Whether the positions are marked to market or marked to model, the pricing models are used to generate risk sensitivities to risk factors. For example, changes in prices to spot prices are often referred to as delta, while changes in prices to changes in volatility are referred to as vega etc. These risk sensitivities, such as delta, gamma and vega, are based on Taylor-series representation of changes in valuations for changes in risk factors. Banks often use a "bump-and-reprice" approach to estimate these sensitivities.[4] These risk sensitivities are aggregated by product, business unit, legal entity and so forth, based on the granularity of desired risk measurement and risk reporting. Once we have the pricers and/or the risk sensitivities for the positions in the portfolio, the market shocks under stress are applied to reprice those positions.

While in many cases the market shocks may be applied directly to the risk factors, in many other cases it is necessary to apply them as a relative or absolute percentage of the current level of the risk factors. Further, based on how the pricing model takes market inputs, there may be a need for transformation of the stressed scenario risk factor inputs to inputs that can be used in the pricing models. This may also be necessitated by the need to avoid hitting boundary conditions, negative rates or negative forward volatilities.

Revaluations: sensitivity-based, grid-based or full revaluations

When repricing positions under specified scenarios, banks may use risk sensitivities that are usually generated in front-office pricing systems to revalue the positions. Such approximations are reasonable when the risk factor shocks are small. For linear instruments such as cash equity, use of risk sensitivities can be exact. However when revaluing positions for which there is a non-linear relationship between prices and risk factor moves, use of full revaluations using the front-office pricers is recommended, since the Taylor-series approximation using risk sensitivities will not perform well for large moves in risk factors. Apart from use of risk sensitivities using Taylor-series approximations or use of full revaluations where all relevant risk factors are shocked simultaneously, banks may also use what are called valuation grids. These are pre-estimated full revaluations for specified moves in risk factors, and can be for one risk factor or for joint moves in risk factors (two or multidimensional grids). If the stress scenario is in between or outside what are the prespecified grid points (say 1%, 5%, 10% and so forth), interpolation and extrapolation are used to estimate P&L for those scenarios. Although not as reliable as full revaluations using front office systems, grid-based approximation has the advantage of computational speed, especially when dealing with large numbers of positions and/or scenarios.

Revaluations in practice

Banks may use a mix of full revaluation or revaluations using approximations for the various positions. For positions and products that have a non-linear relationship between the prices and the risk factors, full revaluation using front-office systems is the best option. In some cases banks may use middle-office versions of the front-office systems. As long as these are calibrated as frequently as the front-office systems and have the exact implementation, that may be sufficient. Banks may sometimes also have pricers in risk systems that are different from front-office pricers. In such cases it is important to ensure that the valuations from the two systems are consistent and that these models have gone through the model-validation process that is expected of other pricing and risk models.

Model failures, cross-effects, approximations, specific risk and use of proxies

Sometimes valuation models that are designed for normal market conditions may fail to calibrate or price under extreme scenarios. This could be due to things such as negative interest rates or forward rates or approximations such as moment-matching conditions that do not perform well under higher volatilities. Further, the practice of revaluating positions using risk sensitivities or grids may fail to capture the cross effect of shocks across different asset classes (for example, equities and currencies prices and volatilities). A full revaluation by design may capture such effects while use of risk sensitivities and grids may not. In such cases the banks must estimate the impact of such omissions separately and, if found material, make a conservative adjustment to the loss estimates. Similarly, shocks designed for broad market risk factors will not be sufficient for issuer-specific risk, especially if the bank has a concentration in such positions. In such cases, use of name-specific shocks may be necessary. Furthermore, when proxies are used, it must be noted that there will be a basis between the risk factor and the proxy, and the basis may get exacerbated during periods of stress. There do not exist standard fixes for such issues, and management needs to monitor for such failures and deal with them on a case-by-case basis and apply conservative adjustments as necessary. These issues highlight the need for an effective model risk management process at the institution, which should also scope in use of models for stress testing.[5]

CONCLUSION

Stress testing for market risk is an important tool for risk management, capital adequacy and bank supervision. This chapter summarises the important elements of stress testing for market risk at financial institutions, where different scenarios of market risk factors are developed and portfolios sensitive to market risk are revalued under those scenarios to estimate potential losses. This chapter distinguished stress testing for market risk from stress testing for credit risk, discussed development of stress-test scenarios, importance of time horizons in stress testing and challenges with aggregation of results for various types of risks. Finally, this chapter discussed methods for revaluation of the portfolios under stress scenarios and some things to consider as part of an effective model risk management for stress testing.

The views expressed in this chapter are those of the authors alone and do not necessarily represent those of the Comptroller of the Currency. The authors would like to thank Jonathan Jones and Wenling Lin for helpful comments.

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1 Intex is software widely used by many banks. It has provided deal cashflow models, analytics and structuring software for RMBSs, ABSs, CMBSs, CDOs, CLNs and covered bond securities.

2 Whether applying a simple square-root-of-time rule understates or overstates the losses in such a situation is unclear in the authors' experience, and depends on the assumptions and the markets. In some cases, mean reversion over a one-year period means that a straight square root of time overstates losses.

3 Kambhu (1997) assesses the magnitude of hedging demand from dealers in fixed-income markets.

4 A Taylor series is a series expansion of a function from the values of the function's derivatives at single point.

5 See OCC bulletin 2011–12 for principles of effective model risk management.

4

The Evolution of Stress Testing Counterparty Exposures

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The call for better stress testing of counterparty credit risk exposures has been a common occurrence from both regulators and industry in response to financial crises (CRMPG I 1999; CRMPG II 2005; FRB 2011). Despite this call, statistical measures have progressed more rapidly than stress testing. In this chapter we examine how stress testing may be improved by building off the development of the statistical measures. We begin by describing how the measurement of counterparty risk has developed by viewing the risk as a credit risk and as a market risk. The problems this creates for a risk manager who is developing a stress-testing framework for counterparty risk are then identified. Methods to stress-test counterparty risk are described from both a credit risk perspective and from a market risk perspective, starting with the simple case of stressing current exposures to a counterparty. These stress tests are considered from both a portfolio perspective and individual counterparty perspective. Last, some common pitfalls in stress testing counterparty exposures are identified.

THE EVOLUTION OF COUNTERPARTY CREDIT RISK MANAGEMENT

The measurement and management of counterparty credit risk (CCR) has evolved rapidly since the late 1990s. CCR may well be the fastest-changing part of financial risk management over the time period. This is especially true of the statistical measures used in CCR. Despite this quick progress in the evolution of statistical measures of CCR, stress testing of CCR has not evolved nearly as quickly.

In the 1990s a large part of counterparty credit management involved evaluation of the creditworthiness of an institution's derivatives counterparties and tracking the current exposure of the counterparty. In the wake of the Long-Term Capital Management crisis, the Counterparty Risk Management Policy Group cited deficiencies in these areas and also called for use of better measures of CCR. Regulatory capital for CCR consisted of add-ons to current exposure measures (BCBS 1988.) The add-ons were a percentage of the gross notional of derivative transactions with a counterparty. As computer technology has advanced, the ability to model CCR developed quickly and allowed assessments of how the risk would change in the future.

The fast pace of change in CCR modelling can be seen in the progression of statistical measures used to gauge counterparty credit risk. First, potential-exposure models were developed to measure and limit counterparty risk. Second, the potential-exposure models were adapted to expected positive-exposure models that allowed derivatives to be placed in portfolio credit risk models similar to loans (Canabarro, Picoult and Wilde 2003). These two types of models are the hallmark of treating CCR as a credit risk. Pykhtin and Zhu (2007) provide an introduction to these models. The treatment of CCR as credit risk was the predominant framework for measuring and managing CCR from 2000 to 2006 and was established as the basis for regulatory capital as part of Basel II (BCBS 2005). During this time, risk mitigants such as netting agreements and margining were incorporated into the modelling of CCR. The definitions of these exposure measures used in this chapter follow those in BCBS (2005).

- ❑ Current exposure is the larger of zero and the market value of a transaction or portfolio of transactions within a netting set, with a counterparty that would be lost upon the default of the counterparty, assuming no recovery on the value of those transactions in bankruptcy. Current exposure is often also called replacement cost.
- ❑ Peak exposure is a high-percentile (typically 95% or 99%) of the distribution of exposures at any particular future date before the maturity date of the longest transaction in the netting set. A peak exposure value is typically generated for many future dates up until the longest maturity date of transactions in the netting set.

- Expected exposure is the mean (average) of the distribution of exposures at any particular future date before the longest-maturity transaction in the netting set matures. An expected exposure value is typically generated for many future dates up until the longest maturity date of transactions in the netting set.
- Expected positive exposure (EPE) is the weighted average over time of expected exposures where the weights are the proportion that an individual expected exposure represents of the entire time interval. When calculating the minimum capital requirement, the average is taken over the first year or over the time period of the longest-maturity contract in the netting set.

Furthermore, an unusual problem associated with CCR, that of wrong-way risk, has been identified (Levin and Levy 1999; Finger 2000). Wrong-way risk occurs when the credit quality of the counterparty is correlated with the exposure, so that exposure grows when the counterparty is most likely to default. When exposure is fixed, as is the case for a loan, this does not occur, so adaptation of techniques used in other areas of risk management is more difficult.

At the same time, the treatment of CCR as a market risk was developing, but was largely relegated to pricing in a credit valuation adjustment (CVA), prior to the financial crisis of 2007–9. This was first described for Swaps (Sorensen and Bollier 1994; Duffie and Huang 1996) and has since become widespread due to the accounting requirement of FAS 157 (FASB 2006). The complexities of risk-managing this price aspect of a derivatives portfolio did not become apparent until the crisis. Prior to the crisis, credit spreads for financial institutions were relatively stable and the CVA was a small portion of the valuation of banks' derivatives portfolios. During the crisis, both credit spreads and exposure amounts for derivative transactions experienced wide swings, and the combined effect resulted in both large losses and large, unusual gains. Financial institutions are just now beginning to develop their frameworks to risk-manage CVA. The regulatory capital framework has adopted a CVA charge to account for this source of risk (BCBS 2011).

The treatment of CCR as a credit risk or CCR as a market risk has implications for the organisation of a financial institution's trading activities and the risk-management disciplines (Picoult 2005; Canabarro 2009). Both treatments are valid ways to manage the portfolio, but adoption of one view alone leaves a financial institution blind to the risk from the other view. If CCR is treated as a credit risk, a bank can still be exposed to changes in CVA. A financial institution may establish PFE limits and manage its default risk through collateral and netting, but it still must include CVA in the valuation of its derivatives portfolio. Inattention to this could lead to balance-sheet surprises. If CCR is treated as a market risk, dynamically hedging its CVA to limit its market risk losses, it remains exposed to large drops in creditworthiness or the sudden default of one of its counterparties. A derivatives dealer is forced to consider both aspects.

The view of CCR has implications for how the risk is managed as well. The traditional credit risk view is that the credit risk of the counterparty can be managed at inception or through collateral arrangements set up in advance, but there is little that can be done once the trades are in place. At default the financial institution must replace the trades of the defaulting counterparty in the market all at once in order to rebalance its book. A large emphasis is placed on risk mitigants and credit evaluation as a result.

The view of CCR as a market risk allows that its counterparty credit risk can be hedged. Instead of waiting until the counterparty defaults to replace the contracts, the financial institution will replace the trades with a counterparty in the market before it defaults by buying the positions in proportion to the counterparty's probability of default. Thus a counterparty with a low probability of default will have little of its trades replaced in advance by the financial institution, but, as its credit quality deteriorates, a larger proportion of those trades will be replaced by moving them to other counterparties. At default, the financial institution will have already replaced the trades and the default itself would be a non-event.

IMPLICATIONS FOR STRESS TESTING

The dual nature of CCR leads to many measures that capture some important aspect of CCR. On the credit risk side, there are the important measures of exposure: current exposure, peak exposure and expected exposure. On the market risk side there is the valuation aspect coming from CVA, and there is the risk generated by changes in the CVA, as measured by VaR of CVA, for example. This creates a dazzling array of information that can be difficult to interpret and understand at both portfolio and counterparty levels. The search for a concise answer to the question "What is my counterparty credit risk?" is difficult enough, but an equally difficult question is "What CCR measures should I stress?"

When confronted with the question of stress testing for CCR, the multiplicity of risk measures means that stress testing is a complicated endeavour. To illustrate this complexity we can compare the number of stresses that a bank may run on its market risk portfolio with the number of similar stresses a bank would run on its counterparty credit risk portfolio. In market risk, running an equity crash stress test may result in one or two stress numbers: an instantaneous loss on the current portfolio and potentially a stress VaR loss. A risk manager can easily consider the implications of this stress.

In contrast, the CCR manager would have to run this stress at the portfolio level and at the counterparty level, and would have to consider CCR as both a credit risk and a market risk. The number of stress-test results would be at least twice the number of counterparties plus one.[1] The number of stress-test results would at least double again if the risk manager stressed risk measures in addition to considering instantaneous shocks.[2] The number of stress values that can be produced can bewilder even the most diligent risk manager, and overwhelm IT resources.

Despite this array of potential stress results, a risk manager must stress-test counterparty exposures to arrive at a comprehensive view of the risk of the financial institution's portfolio.[3] This chapter provides a description of the types of stress tests that can be run to get a picture of the CCR in a financial institution's derivative portfolio.

STRESS TESTING CURRENT EXPOSURE

The most common stress tests used in counterparty credit are stresses of current exposure. To create a stressed current value, the bank assumes a scenario of underlying risk-factor changes and reprices the portfolio under that scenario. Generally speaking, a financial institution applies these stresses to each counterparty. It is common practice for banks to report their top counterparties with the largest current exposure to senior management in one table, and then follow that table with their top counterparties, with the largest stressed current exposure placed under each scenario in separate tables.

For example, Table 4.1 shows an example of what a financial institution's report on its equity crash stress test for current exposure might look like. The table lists the top 10 counterparties by their exposure to an equity market crash of 25%. It shows the following categories: the counterparty rating, market value of the trades with the counterparty, collateral, current exposure, and stressed current exposure after the stress is applied but before any collateral is collected. This provides a snapshot of which counterparties a CCR manager should be concerned about in the event of a large drop in equity markets. A financial institution would construct similar tables for other stresses representing credit events or interest-rate shocks. These tables would likely list different counterparties as being exposed to the stress scenario, since it is unlikely that the counterparty with the most exposure to an equity crash is the same as the counterparty with the most exposure to a shock in interest rates.

Table 4.1 Current exposure stress test: equity crash

Scenario: Equity market down 25%					
($MM)	**Rating**	**MtM**	**Collateral**	**Current Exposure**	**Stressed Current Exposure**
Counterparty A	A	0.5	0	0.5	303
Counterparty B	AA	100	0	100	220
Counterparty C	AA	35	0	35	119
Counterparty D	BBB	20	20	0	76
Counterparty E	BBB	600	600	0	75
Counterparty F	A	-5	0	0	68
Counterparty G	A	-10	0	0	50
Counterparty H	BB	-50	0	0	24
Counterparty I	A	35	20	15	17
Counterparty J	BB	24	24	0	11

This type of stress testing is quite useful, and financial institutions have been conducting it for some time. It allows the bank to identify which counterparties would be of concern in such a stress event, and also how much the counterparty would owe the financial institution under the scenario. However, stress tests of current exposure has a few problems. First, aggregation of the results is problematic, and, second, it does not account for the credit quality of the counterparties. Also, it provides no information on wrong-way risk.

While the individual counterparty results are meaningful, there is no meaningful way to aggregate these stress exposures without incorporating further information. If we were to sum the exposures to arrive at an aggregate stress exposure, this would represent the loss that would occur if every counterparty defaulted in the stress scenario. Unless the scenario were the Apocalypse, this would clearly be an exaggeration of the losses. Other attempts to aggregate these results are also flawed. For example, running the stressed current exposure through a portfolio credit risk model would also be incorrect, since expected exposures, not current exposures, should go through a portfolio credit risk model (Canabarro, Picoult, Wilde 2003). Table 4.1 does not provide an aggregate stressed amount as a result.

The stressed current exposures also do not take into account the credit quality of the counterparty. This should be clear from the outset, since it accounts only for the value of the trades with the counterparty and not the counterparty's willingness or ability to pay. This is an important deficiency since a US$200 million exposure to a start-up hedge fund is very different from a US$200 million exposure to an AAA corporate. While we could imagine a limit structure for stressed current exposure that takes into account the credit quality of the counterparty, most financial institutions have not gone down this path for stressed current exposure. The degree of difficulty involved in doing this for each scenario and each rating category is daunting, mostly because the statistical measures such peak exposure provide a more consistent way to limit exposure by counterparties who may be exposed to different scenarios. From Table 4.1, it is unclear whether the CCR manager should be more concerned about Counterparty C or Counterparty D in the stress event. While Counterparty C has a larger stressed current exposure than Counterparty D, Counterparty C has a better credit quality.

Last, stress tests of current exposure provide little insight into wrong-way risk. As a measure of exposure that omits the credit quality of the counterparty, these stress tests without additional information cannot provide any insight into the correlation of exposure with credit quality. Stresses of current exposure are useful for monitoring exposures to individual counterparties, but do not provide either a portfolio outlook or incorporate a credit quality.

STRESS TESTING THE LOAN EQUIVALENT

To stress-test in the credit framework for CCR, we first have to describe a typical stress test that would be performed on a loan portfolio. The typical framework for loans is to analyse how expected losses would change under a stress.

For credit provisioning, we might look at an unconditional expected loss across a pool of loan counterparties. Expected loss for any one counterparty is the product of the probability of default, p_i, where this may depend on other variables, exposure at default, ead_i, and loss-given default, lgd_i. The expected loss for the pool of loan counterparties is:

$$EL = \sum_{i=1}^{N} p_i \cdot ead_i \cdot lgd_i$$

A stress test could take exposure at default and loss-given default as deterministic and focus on stresses where the probability of default is subject to a stress. In this case, the probability of default is taken to be a function of other variables; these variables may represent an important exchange rate or an unemployment rate, for example. In this case, the stressed expected loss is calculated conditional on some of the variables affecting the probability of default being set to their stressed values; the stressed probability of default is denoted p_i^s; and the stressed expected loss is:

$$EL_s = \sum_{i=1}^{N} p_i^s \cdot ead_i \cdot lgd_i$$

The stress loss for the loan portfolio is EL_s-EL. A financial institution can generate stress tests in this framework rather easily. It can simply increase the probability of defaults, or it can stress the variables that these probabilities of defaults depend on. These variables are typically macroeconomic variables or balance-sheet items for the counterparty. The stress losses can be generated for individual loan counterparties as well as at an aggregate level.

This framework can be adapted for CCR treated as a credit risk. In this case the probability of default and loss-given default of the counterparty are treated the same, but now exposure at default is stochastic and depends on the levels of market variables. EPE multiplied by an alpha factor (Picoult 2005; Wilde 2005) is the value that allows CCR exposures to be placed in a portfolio credit model along with loans and arrive at a high-percentile loss for the portfolio of exposures (both loan and derivatives).[4] The same procedure is applied here and EPE is used in an expected-loss model. In this case expected loss and expected loss conditional on a stress for derivatives counterparties are:

$$EL = \sum_{i=1}^{N} p_i \cdot \alpha \cdot epe_i \cdot lgd_i$$

$$EL_s = \sum_{i=1}^{N} p_i^s \cdot \alpha \cdot epe_i^s \cdot lgd_i$$

Stress losses on the derivatives portfolio can be calculated similarly to the loan portfolio case. A financial institution can stress the probability of default similarly to the loan case by stressing probability of default or the variables that affect probability of default, including company balance-sheet values, macroeconomic indicators and values of financial instruments. It can also combine the stress losses on the loan portfolio and the stress losses on its derivatives portfolio by adding these stress losses together.

Table 4.2 shows the results of a typical stress test that could be run that would shock the probability of default of counterparties in a derivatives portfolio. The stress test might parallel the increase in PD by industry after the dotcom crash in 2001–2. The expected loss, stressed expected loss and the stress loss may all be aggregated and even combined with similar values from the loan portfolio.

In addition, a financial institution has a new set of variables to stress. Exposure, as measured by EPE, depends on market variables such as equity prices and swap rates. A financial institution can stress these market variables and see their impact. It should be noted that it is not clear whether a stress will, in aggregate, increase or decrease expected losses. This will depend on a whole host of factors, including the directional bias of the bank's portfolio, which counterparties are margined and which have excess margin. This is in marked contrast to the case where stresses of the probabilities of default are considered. Stresses to the variables affecting the probability of default generally have similar effects and the effects are in the same direction across counterparties. When conducting stresses to EPE, a bank need not consider aggregation with its loan portfolio.[5] Loans are insensitive to the market variables and thus will not have any change in exposure due to changes in market variables.

There are a whole host of stresses that can be considered. Typically a financial institution will use an instantaneous shock of market variables, these are often the same current exposure shocks from the previous section. In principle, we could shock these variables at some future point in their evolution or create a series of shocks over time. This is not common, however, and shocks to current exposure are the norm. In the performance of these instantaneous shocks, the initial market value of the derivatives is shocked prior to running the simulation to calculate EPE. How this shock affects EPE depends on the degree of collateralisation and the "moneyness" of the portfolio, among other things.

Table 4.3 shows how a financial institution might reconsider its stress test of current exposure in an expected-loss framework. Now, in addition to considering just current exposure, the financial institution must consider including the probability of default over the time horizon and the expected positive exposure in its stress-test framework. In this case we are looking at changes to current exposures and thus EPE. We hold the PD constant here. The expected loss, even under stress, is small and measured in thousands. This is due to the rather small probabilities of default that we are considering. We are able to aggregate expected losses and stress losses by simply adding them up.

A financial institution can consider joint stresses of credit quality and market variables as well. Conceptually, this is a straightforward exercise, but, in practice, deciding how changes in macroeconomic variables or balance-sheet variables are consistent with changes in market variables can be daunting. There is very little that necessarily connects these variables. Equity-based approaches (Merton 1974; Kealhofer 2003) come close to providing a link; however, it remains unclear how to link an instantaneous shock of exposure to the equity-based probability of default. While exposure can and should react immediately, it is unclear whether equity-based probabilities of default should react so quickly.

Table 4.2 PD stress: dotcom crash

	PD (%)	EPE (US$m)	LGD (%)	EL (US$m)	Stressed PD (%)	Stressed EL (US$m)	Stress loss (US$m)
Counterparty AA	0.05	213.00	0.70	0.08	0.50	0.77	0.69
Counterparty BB	0.03	202.50	0.60	0.04	0.30	0.38	0.34
Counterparty CC	0.45	75.00	0.70	0.24	0.62	0.34	0.09
Counterparty DD	0.90	30.00	0.65	0.18	1.20	0.24	0.06
Counterparty EE	1.05	10.00	0.75	0.08	1.40	0.11	0.03
Counterparty FF	0.09	157.00	0.50	0.07	0.12	0.10	0.02
Counterparty GG	0.98	68.00	0.70	0.48	1.02	0.50	0.02
Counterparty HH	2.17	3.00	0.34	0.02	3.00	0.03	0.01
Counterparty II	0.03	150.00	0.20	0.01	0.05	0.02	0.01
Counterparty JJ	0.50	50.00	0.60	0.15	0.50	0.15	0.00
Aggregate				**1.36**		**2.63**	**1.27**

Table 4.3 Expected-loss stress test in a credit framework

	Scenario: Equity market down 25%								
	PD (%)	**MtM (US$m)**	**Collateral (US$m)**	**CE (US$m)**	**EPE (US$m)**	**EL (US$000)**	**stress EPE (US$m)**	**stress EL (US$000)**	**stress loss (US$000)**
Counterparty A	0.03	0.5	0	0.5	4.37	0.09	303.00	6.09	6.00
Counterparty B	0.02	100	0	100	100.00	1.34	220.00	2.95	1.61
Counterparty C	0.02	35	0	35	35.16	0.47	119.00	1.59	1.12
Counterparty D	0.18	20	20	0	3.99	0.48	76.00	9.16	8.68
Counterparty E	0.18	600	600	0	3.99	0.48	75.00	9.04	8.56
Counterparty F	0.03	-5	0	0	2.86	0.06	68.00	1.37	1.31
Counterparty G	0.03	-10	0	0	1.98	0.04	50.04	1.00	0.96
Counterparty H	1.2	-50	0	0	0.02	0.02	25.12	19.73	19.72
Counterparty I	0.03	35	20	15	16.31	0.33	19.20	0.36	0.04
Counterparty J	0.12	24	24	0	3.99	0.32	14.66	1.03	0.71
aggregate						**3.62**		**52.32**	**48.70**

This leads to another drawback: the difficulty of capturing the connection between the probability of default and exposure that is often of concern in CCR. There are many attempts to capture the wrong-way risk, but most are ad hoc. At present the best approach to identifying wrong-way risk in the credit framework is to stress the current exposure, identify those counterparties that are most exposed to the stress and then carefully consider whether the counterparty is also subject to wrong-way risk.

Stress tests of CCR as a credit risk allow a financial institution to advance beyond simple stresses of current exposure. They allow aggregation of losses with loan portfolios, and also allow consideration of the quality of the counterparty. These are important improvements that allow a financial institution to better manage its portfolio of derivatives. Treating CCR as a market risk allows further improvements (notably, the probability of default will be inferred from market variables), and it will be easier to consider joint stresses of credit quality and exposure.

STRESS TESTING CVA

When stress testing CCR in a market risk context, we are usually concerned with the market value of the counterparty credit risk and the losses that could result due to changes in market variables, including the credit spread of the counterparty. In many cases a financial institution will consider its unilateral CVA for stress testing. Here, the financial institution is concerned with the fact that its counterparties could default under various market scenarios. In addition, we might consider not only that a financial institution's counterparty could default, but also that the financial institution in question could default to its counterparty. In this case, the financial institution is considering its bilateral CVA. Initially we just consider stress testing the unilateral CVA.

First we use a common simplified formula for CVA to a counterparty that omits wrong-way risk (Gregory 2010).

$$CVA_n = LGD_n^* \cdot \sum_{j=1}^{T} EE_n^*(t_j) \cdot q_n^*(t_{j-1}, t_j)$$

Where:

$EE_n^*(t_j)$ is the discounted expected exposure during the *j*th time period calculated under a risk-neutral measure for counterparty n.

$q_n^*\ (t_{j-1}, t_j)$ is the risk-neutral marginal default probability for counterparty *n* in the time interval from t_{j-1} to t_j and *T* is the final maturity.

LGD_n^* is the risk-neutral loss-given default for counterparty *n*.

Aggregating across N counterparties:

$$CVA = \sum_{n=1}^{N} LGD_n^* \cdot \sum_{j=1}^{T} EE_n^*(t_j) \cdot q_n^*(\,t_{j-1}, t_j)$$

Implicit in this description is that the key components all depend on values of market variables. $q_n^*\ (t_{j-1}, t_j)$ is derived from credit spreads of the counterparty, LGD_n^* is generally set by convention or from market spreads and $EE_n^*(t_j)$ depends on the values of derivative transactions with the counterparty. To calculate a stressed CVA we would apply an instantaneous shock to some of these market variables. The stresses could affect $EE_n^*(t_j)$ or $q_n^*(t_{j-1}, t_j)$.

Stressed CVA is given by:

$$CVA^s = \sum_{n=1}^{N} LGD_n^* \cdot \sum_{j=1}^{T} EE_n^s(t_j) \cdot q_n^s(\,t_{j-1}, t_j)$$

And the stress loss is CVA^s-CVA.

Stressing current exposure, as described previously, has similar effects. An instantaneous shock will have some impact on the expected exposure calculated in later time periods, so all of the expected exposures will have to be recalculated. Stresses to the marginal probability of default are usually derived from credit spread shocks.

Similarities can be seen between stress testing CCR in a credit risk framework and doing so in market risk framework. There is a reliance in both cases on expected losses being the product of loss-given default, exposure and the probability of default. However, these values will be quite different, depending on the view of CCR as a market risk or credit risk. The reasons for the differences are many, and the use of risk-neutral values for CVA as opposed to physical values for expected losses is the most prominent. In addition, CVA uses expected losses over the life of the transactions, whereas expected losses use a specified time horizon, and the model for determining the probability of default is market-based in CVA.

Using a market-based measure for the probability of default provides some benefits. It is possible in these circumstances to incorporate a correlation between the probability of default and the exposure. Hull and White (2012) describe methods to do this. They also demonstrate an important stress test that is available, a stress of the correlation between exposure and the probability of default. They show that the correlation can have an important effect on the measured CVA. Since there is likely to be a high degree of uncertainty around the correlation, a financial institution should run stress tests to determine the impact on profit and loss if the correlation is wrong.

To capture the full impact of various scenarios on CVA profit and loss, a financial institution should include the liability side effects in the stress as well. This part of the bilateral CVA (BCVA), often called DVA, captures the value of the financial institution's option to default on its counterparties. The formula for DVA is similar to the formula for CVA except for two changes. First, instead of expected exposure, we have to calculate the negative expected exposure (NEE). This is expected exposure calculated from the point of view of the counterparty. Second, the value of the option to default for the financial institution is dependent on the survival of the counterparty, so the probability that the counterparty has survived must enter into the calculation as S_I. A similar change must be made to the CVA portion, since the loss due to the counterparty defaulting now depends on the financial institution not defaulting first. The bilateral CVA formula is (Gregory 2010):

$$BCVA = \sum_{n=1}^{N} LGD_n^* \cdot \sum_{j=1}^{T} EE_n^*(t_j) \cdot q_n^*(t_{j-1}, t_j) \cdot S_I^*(t_{j-1})$$

$$- \sum_{n=1}^{N} LGD_I^* \cdot \sum_{j=1}^{T} EE_n^*(t_j) \cdot q_I^*(t_{j-1}, t_j) \cdot S_n^*(t_{j-1})$$

The subscript I refers to the financial institution. Notable in this formulation is that the survival probabilities also depend on CDS spreads and now the losses depend on the firm's own credit spread. This may lead to counterintuitive results such as losses occurring because the firm's own credit quality improves. When looking at stress tests from a bilateral perspective, the financial institution will also have to consider how its own credit spread is correlated with its counterparties' credit spread. Stress losses can be calculated in a similar way as for CVA losses by calculating a stress BCVA and subtracting the current BCVA.

BCVA allows CCR to be treated as a market risk. This means CCR can be incorporated into market risk stress testing in a coherent manner. The gains or losses from the BCVA stress loss can be added to the firm's stress tests from market risk. As long as the same shocks to market variables are applied to the trading portfolio and to the BCVA results, they can be aggregated by simple addition.

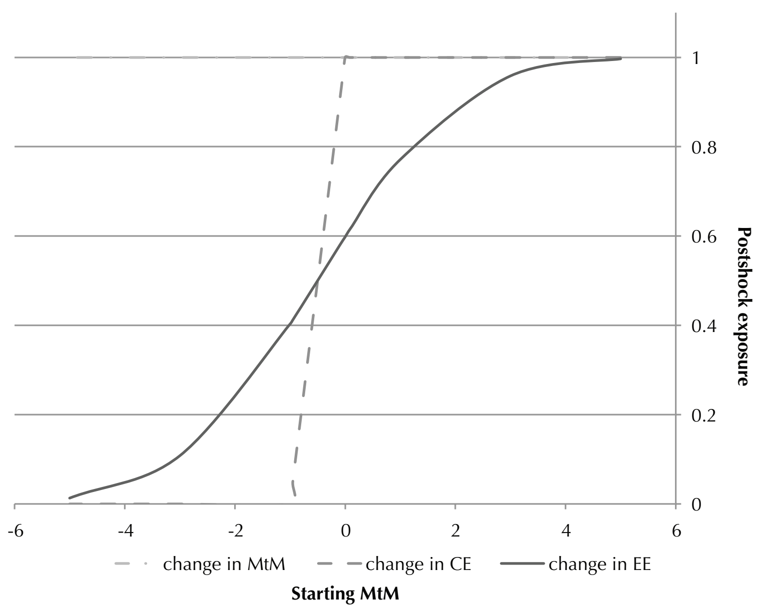
COMMON PITFALLS IN STRESS TESTING CCR

Financial institutions are only beginning to conduct a level of stress-testing beyond stressing current exposure. The methodologies to conduct these tests are only just being developed. It is also rare for CCR to be aggregated with either stress tests of the loan portfolio or with trading-position stress testing results in a consistent framework. With better modelling of CCR exposures and CVA, it is possible to begin aggregating stress tests of CCR with either the loan portfolio or trading positions.

Since most financial institutions will do some form of stressing current exposure, it is tempting to use those stresses of current exposure when combining the losses with loans or trading positions. The analysis above shows that expected exposure or expected positive exposure should be used as the exposure amount, and that using current exposure instead would be a mistake.

In fact, the use of current exposure instead of expected exposure can lead to substantial errors. This can be shown using a normal approximation (Gregory 2010) to expected exposures, which is accurate for linear derivatives with no intermediate payments. Figure 4.1 plots current exposure and expected exposure after a million-dollar shock to the market value of the derivative. For at-the-money exposures, the difference between current exposure and expected exposure is almost half the value of the shock.

Figure 4.1 Current exposure and expected exposure after US$1m shock



Use of delta sensitivities to calculate changes in exposures is also especially problematic for CCR, since it is highly nonlinear. While this can save on computational resources, the errors introduced are not obvious and the linearisation can be highly misleading. At-the-money portfolios with large price moves applied to the portfolio are especially prone to errors from using delta approximations.

CONCLUSION

A counterparty credit risk manager now has a multiplicity of stress tests to consider. Too many stress tests can hide the risk of a portfolio, but a fair number of stresses is important to develop a comprehensive view of the risks in the portfolio. Both the credit risk and market risk views are important since both fair-value losses and default losses can occur no matter how a financial institution manages its CCR. More integrated stress tests can be generated by combining the credit risk view with the loan portfolio, or the market risk view of CCR can be combined with the trading book. The true difficulty remains combining the default stresses and the fair-value stresses to get a single comprehensive stress test. This difficulty aside, counterparty credit risk managers now have more tools at their disposal to measure and manage CCR. The irony is that regulators have begun to move derivative transactions to central clearing to reduce the counterparty credit risk problem just as the ability to manage counterparty credit risk is making major advances.

The views expressed in this article are the author's own and do not represent the views of the Board of Governors of the Federal Reserve System or its staff.

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1 The stresses are run for each counterparty and at the aggregate portfolio level. The stress may also be run for various subportfolios, divided by region or industry, for example. These would have to be run in both a credit and market risk context.
2 It might increase even more since there are multiple risk measures of importance in CCR.
3 This is included in regulatory guidance on stress testing for counterparty credit risk, for example in SR 11-10 (Federal Reserve Board 2011).
4 Alpha typically depends on the quantile at which we measure economic capital. In this case it would be the alpha calculated at the expected loss. For this reason it may differ from the alpha used for economic or regulatory capital calculations.
5 Although exposure for loans is insensitive to market variables for the most part, there can still be some increase in expected losses if probabilities of default are correlated with market variables. Furthermore, loan commitments and some other loan products can have a stochastic exposure.

5

Operational Risk: An Overview of Stress-Testing Methodologies

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Numerous international regulatory standards require the implementation of stress testing as a risk-management tool. The Basel Committee on Banking Supervision (2009) (henceforth BCBS), a key international regulatory guidance on stress testing, recommends including stress tests in a bank's overall risk-management toolkit. The document broadly refers to stress tests as "the evaluation of a bank's financial position under a severe but plausible scenario". It provides general principles for stress testing practices, while allowing banks ample discretion in choosing stress-test methodologies. However, the document refrains from prescribing any particular stress-testing approach, thereby leaving banking institutions with broad discretion in choosing stress-testing methodologies.

The purpose of stress testing is often viewed by regulatory bodies and financial institutions as a means to determine how a financial institution's capital or financial position would be impacted on by an adverse scenario. In most applications, this requires modelling a link between a macroeconomic event or series of macroeconomic events and the performance of a bank's portfolio of assets. In the context of credit and market portfolios, this is often an extension of the models banks already have in place to model and manage the risk of these portfolios because they often have factor models in place.

The state-of-the-art operational risk models, however, do not readily lend themselves to similar stress-testing applications because they tend to be less risk-sensitive compared with most other types of risk models. In other words, correlations between operational risk losses and the macroeconomic or internal business environment variables are generally not explicitly modelled. This poses obvious challenges for stress testing operational risk. As we expand on below, the primary reasons for this include the relatively short history of operational risk modelling, limited historical loss data and the fact that most operational risk models have been developed with the explicit purpose of capital modelling.[1]

In this chapter, we begin with a brief description of the evolution of operational risk models to provide the reader with a better understanding of the unique challenges inherent to modelling and thus stress testing operational risk. We then describe the implications of these unique challenges to stress testing and provide several potential solutions.

MODELLING OPERATIONAL RISK

Although modelling operational risk is a relatively new discipline for banks, it is an important part of the Basel Final Rule (2007). The Final Rule allows banks to use internally developed, risk-based approaches to measure credit and operational risk. For operational risk, the Rule allows banks to follow an Advanced Measurement Approach (AMA) and states the following (Final Rule 2007, p. 69294):

> Given the complexities involved in measuring operational risk, the AMA provides banks with substantial flexibility and, therefore, does not require a bank to use specific methodologies or distributional assumptions. Nevertheless, a bank using the AMA must demonstrate to the satisfaction of its primary Federal supervisor that its systems for managing and measuring operational risk meet established standards, including producing an estimate of operational risk exposure that meets a one-year, 99.9th percentile soundness standard.

The Rule also specifies that banks incorporate four elements into the capital quantification model: (1) internal loss data, (2) external loss data, (3) scenario analysis and (4) business environment and internal control factors (BEICFs). Despite the fact that the Final Rule effectively does not specify how banks must measure or model exposure to operational risk, most large US banks have settled on the loss-distributional approach (LDA) as the primary quantification methodology. Given this widespread use of the LDA across the industry, we now describe the basic approach.

The loss-distribution approach

The goal of the LDA is to model an aggregate loss distribution in a value-at-risk (VaR) framework. The aggregate loss distribution is defined as the total dollar amount of operational risk losses over a given time horizon. Banks typically use historical loss data to separately model severity and frequency distributions and then calculate the aggregate loss distribution through a convolution of these two distributions. In a VaR application, the bank would define a capital charge as a high percentile of this distribution. As an example, the Final Rule (2007) defines the 99.9th percentile of the aggregate loss distribution over a one-year horizon as the minimum regulatory capital requirement.

Because of the complexity of operational risk and the various types of loss events that are defined as operational losses, banks tend to use the LDA to model operational risk for various risk cells, which are commonly referred to as units of measure. Each unit of measure is meant to capture the operational risk losses stemming from a homogeneous data-generating process. Although the specific unit-of-measure definitions vary across banks, most define units of measure along business lines and event types. In the Final Rule, BCBS (pages 69314–15) explicitly defines seven event types:

1. INTERNAL FRAUD: Operational losses resulting from an act involving at least one internal party of a type intended to defraud, misappropriate property or circumvent regulations, the law or company policy, excluding diversity and discrimination.
2. EXTERNAL FRAUD: Operational losses resulting from an act by a third party of a type intended to defraud, misappropriate property or circumvent the law.
3. EMPLOYMENT PRACTICES AND WORKPLACE SAFETY: Operational losses resulting from an act inconsistent with employment, health or safety laws or agreements, payment of personal injury claims or payment arising from diversity or discrimination events.

4. CLIENTS, PRODUCTS, AND BUSINESS PRACTICES: Operational losses resulting from the nature or design of a product or from an unintentional or negligent failure to meet a professional obligation to specific clients (including fiduciary and suitability requirements).
5. DAMAGE TO PHYSICAL ASSETS: Operational losses resulting from the loss of or damage to physical assets from natural disasters or other events.
6. BUSINESS DISRUPTION AND SYSTEM FAILURES: Operational losses resulting from disruption of business or system failures.
7. EXECUTION, DELIVER AND PROCESS MANAGEMENT: Operational losses resulting from failed transaction processing or process management or losses arising from relationships with trade parties or vendors.

In practice, banks have anywhere from a handful to the order of several dozen units of measure. Even with a careful choice of units of measure, a bank may not be able to fully achieve the homogeneity within each unit. The main reasons for the remaining heterogeneity include data limitations and the size and scope of the bank. Regardless of the number of units of measure, banks are adopting the LDA approach independently to model each risk cell.

Because it is a common belief that losses of different units of measure might exhibit certain levels of dependence, a bank's overall capital charge should be aggregated from individual capital charges of its units of measure through, for example, the use of a copula. Copulas are designed to capture various dependence structures within marginal distributions (ie, the aggregate loss distributions of individual units of measure) of a continuous multivariate distribution (ie, the overall aggregate loss distribution at the bank level). Once an appropriate dependence structure is established with the use of copulas, the operational risk capital charge would then be equivalent to the 99.9th percentile of the overall aggregated loss distribution in the case of the Basel Final Rule.

While the LDA may be an appropriate framework for modelling operational risk capital, especially at the high percentile the Final Rule requires, it is often criticised for its lack of sensitivity to risk factors. Furthermore, since the standard LDA framework does not explicitly model the link between macroeconomic variables and operational risk losses, it poses obvious challenges for macro stress-testing operational risk. Without going into the details of these criticisms, suffice it to say at this point that the general framework poses several challenges for stress testing operational risk, which we expand on below.

Challenges to modelling operational risk

Regardless of the methodology used, practitioners are faced with significant challenges when modelling operational risk. Several of these challenges are unique to operational risk because of the nature of operational losses, and many are due to the relatively short history of modelling operational risk. In any case, each of the following challenges impacts on how we can stress-test operational risk.

The prevailing majority of risk models employed in measuring operational risk are statistical models that are static in nature. Dynamic factor models that are supposed to link operational risk with its drivers are still, at the time of writing, under development. Since static statistical models are extreme simplifications of real-world relationships, they are not capable of capturing the true nature of risk. Below, we list several reasons why dynamic models are still in the development phase and, in doing so, outline the challenges of modelling operational risk in general.

First, banks have a limited amount of operational risk data, especially large-tail events that tend to drive operational risk capital. This creates challenges, as even the largest US institutions have been collecting reliable and comprehensive operational risk data only since about 2000. Adding even more complexity is the fact that most banks collect detailed operational loss data only above a certain collection threshold and thus are left with censored data, which makes fitting severity distributions all the more challenging.

Second, because the LDA approach originated in the insurance and actuarial industries, it was developed with the explicit intent of modelling maximum exposure or worst-case scenarios. Similarly, in operational risk applications, the LDA approach is commonly used for capital-modelling purposes and thus the goal is to fit the tail of the distribution. Therefore, modellers tend to focus on higher moments of the distributions. In terms of stress testing, the implication is that there is less focus on fitting the mean of the distribution. Therefore, estimating the base case, or expected loss, is not the primary goal. The implication is that even if operational losses could be linked to risk factors in an LDA framework, it is not clear what would be gained by stressing the expected loss.

Third, the nature of operational risk loss events makes it especially challenging to establish a clear link between macroeconomic events and loss severity. In particular, operational risk exposure tends to be driven by low-frequency, high-severity events generated by fat-tailed, sub-exponential distributions, and, unlike with a portfolio of loans or equity securities, the maximum exposure is essentially unbounded. For example, single events such as rogue trades, class-action lawsuits and natural disasters that cost banks billions of dollars each year are very difficult to model, especially with the relatively small sample sizes available. And it is these large, infrequent losses that tend to drive operational risk exposure. This creates obvious challenges for stress testing because the stress distribution should be realistic enough to assign plausible likelihoods to such losses to ensure a sufficient capital buffer. On the one hand, the stress distribution should ensure a bank has sufficient capital to cover any severe but plausible stress event or a set of events. On the other hand, if not careful, we might end up with a stress distribution assigning unrealistically high probabilities to single events, each individually capable of putting a bank out of business.

Finally, the timing of operational risk events and operational risk losses can be complex. This further complicates estimation of dependence between operational losses and macroeconomic events. Most notably, large losses tend to be legal suits where the control failure that caused the event precedes the legal reserve and settlement or fine by several years. One implication is that it is not clear what date to use in the estimation of the relationship between the macroeconomic events and the operational loss events. On one hand, from a risk-management perspective, it may be best to know the correlation between the timing of control failures and the macroeconomic environment, so managers can prevent future control breakdowns. On the other hand, from a capital-impact perspective, we would wish to model the relationship between the macroeconomic environment and the loss-realisation date.

All of these factors combine to pose significant challenges for stress-testing operational risk. In particular, the LDA approach is not easily amenable to a stress-testing framework. However, despite these challenges, there are several methodologies banks can use to stress-test operational risk, including several within the basic LDA framework. In the remainder of the chapter, we discuss these approaches.

APPROACHES TO STRESS TESTING OPERATIONAL RISK

In this section, we outline several methodologies for stress testing operational risk. We also note that a bank need not use any one methodology in isolation and would likely benefit from implementing a combination of the approaches to better understand its exposure to operational risk.

Stress testing frequency distribution within the LDA

Banks tend to use Poisson or negative binomial distributions to model frequency and some have had success using factor models. If a link between risk factors and operational risk-loss frequency could be established, then stress testing via the frequency distribution would be relatively straightforward. For example, Chernobai, Jorion and Yu (2011) use publicly reported loss data for a large set of financial institutions and develop a Poisson panel regression model for the mean annual frequency of loss arrival. In their model, the Poisson frequency parameter is regressed against a set of firm-specific and macroeconomic variables.

Such a model could be used to stress-test operational risk. Namely, by supplying the model with stressed values of the macroeconomic and firm-specific variables we could extrapolate stressed frequency values and use them to calculate estimated stress values of capital. Stressed values of macroeconomic and firm-specific variables could be generated in an integrated framework under different historic or hypothetical scenarios affecting both sets of variables simultaneously. One caveat to this approach is that it assumes that estimated relationships between the frequency and the explanatory variables of the model as well as the loss severity distribution are not affected by stressed conditions.

An important downside to this approach is that operational risk exposure tends to be driven by low-frequency, high-severity losses.

Consequently, the impact of stressing the frequency distribution on the overall operational risk exposure is small compared with stressing severity.

Stress testing severity distribution within the LDA

Stress testing via the severity distributions in the LDA approach is challenging for the opposite reasons to stressing the frequency distribution. While the shape of the severity distribution is extremely important for measuring operational risk exposure, it is all the more difficult to establish a link between operational risk and macroeconomic risk factors.

In addition to the heavy-tailed nature of the losses, the timing between the events and realisation of losses also makes this challenging. More research needs to be done in this direction. We do not foresee that stress testing severity distributions without bringing any additional information about the tail behaviour (ie, information going beyond what is contained in historically observed losses) is the most fruitful way of approaching stress testing of operational risk exposure.

Stress testing using scenarios

The Final Supervisory Guidance (2012), which was developed to provide a guidance on stress testing for large banks in the US, recommends that the banks consider using several stress-testing approaches, one of which is scenario analysis. In addition to this regulatory document, there are several risk-specific regulatory documents related to stress-testing requirements. For example, the Final Rule (2007) requires Basel II financial institutions to incorporate scenario analysis into their operational risk assessment and quantification systems. Scenario analysis refers to the application of a broad range of historical and/or hypothetical scenarios to various levels of the banking organisations, in order to assess their vulnerability to adverse circumstances.

Perhaps Kupiec (1998) is among the earliest papers focusing on stress testing VaR models through the use of scenarios. While Kupiec uses historical scenarios to stress-test risk models, we could also use hypothetical expert-generated scenarios. In the context of stress testing market risk models, Berkowitz (2000) proposes a mixture approach to stress testing VaR models in which a probability distribution and a probability of occurrence are assigned to each scenario. The stressed VaR model is derived as a probability mixture of the original VaR model and the set of identified scenarios. Taking into account well-known drawbacks of VaR as a risk measure, Aragones, Blanco and Dowd (2001) propose to complement Bertkowitz's framework by estimating expected tail loss (ETL), an alternative to VaR. Although ETL possess superior properties relative to VaR (Artzner *et al* 1999), one important drawback of ETL is that it does not exist if the loss distribution does not have finite first moment. VaR can still be calculated for such distributions. In addition, quantifying the ETL involves integration, which makes it more difficult to estimate than the VaR. Also, regulatory rules require the use of the VaR measure to quantify risk. For these reasons, we focus on VaR in this chapter.

Incorporating scenarios in a mixture framework for the purpose of stress testing an operational risk model is difficult, at least for the following reason. In operational risk, capital is determined by the VaR risk measure as a fixed and prespecified level of VaR (ie, the 99.9th percentile), which is in the far tail of the loss distribution. Therefore, the effect of each scenario on the original VaR is not always obvious under the mixture framework. Scenario realisations exceeding the original VaR might lead to a higher stress VaR measure conforming with the main purpose of stress testing, while those falling short of the original VaR may even reduce the stress VaR. The net effect is not clear. If line-of-business managers are responsible for generating operational loss scenarios, they might avoid generating a reasonable number of scenario losses from the far tail if doing so will negatively affect their performance. If, as a result, too few scenarios have been generated from the far tail relative to the rest of the severity distribution's domain, then this situation might lead to a reduction in capital. Furthermore, whether the reduction in capital happened due to expert opinions or simply because of a disproportionately lower number of far-tail scenarios is not clear. In other words, the mixture approach, in its original form, does not possess a built-in protection against producing stress risk VaR measures that fall short of the original risk measures.

To address the above-described shortcoming of the mixture approach, Ergashev (2012) proposes an alternative theoretical framework for incorporating scenario losses into operational risk modelling. The basis of this framework is the idea that we need to focus on worst-case scenarios, because only those scenarios contain valuable information about the tail behaviour of operational losses. A simple rule for identifying the worst-case scenarios from the pool of all scenarios is proposed. Only the information contained in the worst-case scenarios enters the quantification process in the form of lower bound constraints on the specific quantile levels of the severity distribution. Therefore, the stress VaR values never fall below the original VaR values. This framework could be used to stress-test the original severity distribution without any need for re-estimating the stress severity distribution, because the last distribution is explicitly derived during the process of incorporating the worst-case scenarios.

Converting the macroeconomic scenario into a 1-in-N-year event

As discussed above, the most significant challenge in terms of stress testing operational risk is that, to date, the relationship between operational losses and macroeconomic factors has not been clearly modelled. Regardless of the reason for this, it poses challenges for managers trying to use macroeconomic scenarios to stress operational risk exposure. Ideally, we could resolve these issues and develop risk-sensitive operational risk models. We also need to consider the possibility that the industry and academic literature have not had much success in modelling these relationships because they might not exist.

Since it is difficult to establish a modelled relationship between macroeconomic factors and operational risk losses, in this section we simply assume that there is a one-to-one correspondence between quantiles of both distributions. To the extent that this assumption is true, we could convert the macroeconomic scenario to a 1-in-N-year event and simply compute the $1 - 1/N$ quantile of the aggregate operational loss distribution as the corresponding stress event. More specifically, we assume that, if a specific macroeconomic scenario corresponds to 1-in-N-year event in the historically observed distribution of the macroeconomic variable(s), then this scenario would trigger 1-in-N-year loss event in the operational loss distribution as well.

This is an appealing approach to stressing operational risk capital for banks that already have an established AMA model based on the LDA approach simply because it would not require any additional model development.

One downside of this approach, however, is that the link between operational risk exposure and the specific scenario is established only through the likelihood of the scenario occurring. The implication is that stress testing operational risk in this setting does not allow us to distinguish between banks with different characteristics.[2] Therefore, it is essentially equivalent to the BCBS Final Rule (although the percentiles and time horizon may be different). Another potential drawback relates to our above discussion regarding the challenges associated with using LDA to estimate expected losses, and specifically the fact that LDA is designed to model the tail of the loss distribution. Of course, this concern could be mitigated to a certain extent by estimating the LDA model with a focus on the percentile of interest.

Stress testing the dependence structure

Another potential way of stress testing in the LDA framework is to stress the dependence structure. The idea is that, during stressed periods, internal controls may be more prone to breakdown and the link between losses across units of measure may intensify. As discussed above, banks generally model the aggregate loss distribution for each unit of measure and then combine the units of measure using a copula-based approach.

There are two basic parts to the dependence model which could be stressed: (1) the choice of copula and (2) the dependence structure embedded in a particular copula modelling the dependence between units of measure. Either, or both simultaneously, could be stressed.

The appealing aspect of stress testing the dependence model is that most experts agree that dependency structures across financial assets tend to change in periods of stress. The financial crisis of 2007–9 also highlighted the importance of taking into account possible changes in dependence structure. However, we should also emphasise that stress-testing dependence is among the most difficult approaches to stress testing. First, justifying the copula choice is not an easy task with a limited number of observed losses. Second, the embedded dependence structure is difficult to estimate. Copulas involve a substantial number of parameters to estimate, which is difficult to accomplish given the fact that the sample sizes of observed losses are not large in practical applications. Third, as per the above discussion regarding the timing of operational loss event dates, the calibration of even a simple correlation between events is not straightforward.

Stress testing and model risk

Model risk is present in all financial models. In the case of operational risk, it is especially relevant for reasons including those discussed above and the fact that the field is still in its infancy.[3] This makes stress testing even more important in operational risk than in the other risk area. However, stress testing a model with a potentially substantial model risk is not an easy task. Here, sensitivity analysis, as a special case of stress testing, can be used in conjunction with the above approaches to demonstrate that a model is not overly sensitive to certain reasonable changes to the parameter values or the assumptions of the model.

CONCLUSION

We began this chapter by providing the reader with a high-level background to state-of-the-art operational risk modelling. Within this discussion, we have made explicit reference to the challenges inherent in modelling operational risk. While data limitations are at or near the top of the list of challenges, there are several areas where simply increasing the quality and quantity of operational loss data alone will likely not be sufficient. In other words, these challenges are not going away any time soon, and further research is needed to advance the field.

In terms of stress testing operational risk, the challenges are magnified. Most of them arise from the fact that operational risk exposure tends to be driven by infrequent large events. For example, modelling the aggregate loss distribution accurately requires additional loss data, especially in the tail of the distribution. Stress testing insufficiently accurate static models could amplify the model risk. Modelling dependence with the macroeconomic environment is equally challenging due to the lack of strong supportive evidence.

Despite these challenges and limitations associated with operational risk modelling, we have laid out several potentially fruitful methodologies for banks to stress-test their operational risk exposure. While some appear more promising than others, each of the methodologies is still in its infancy and more research is needed to decide on the appropriateness of any one method. Therefore, we recommend a bank to use a variety of alternative models to estimate the impact of a stress scenario on operational risk capital.

The views expressed in this chapter are those of the authors and do not necessarily reflect the position of the Federal Reserve Bank of Richmond, the Office of the Comptroller of Currency, the US Department of the Treasury or the Federal Reserve System. Bakhodir Ergashev is at the Federal Reserve Bank of Richmond, Charlotte Office, 530 East Trade Street, Charlotte, NC 28202; email: Bakhodir.Ergashev@rich.frb.org. Brian Clark is at the Enterprise Risk Analysis Division of the Office of the Comptroller of Currency, 400 7th Street SW, Washington, DC 20219; email: Brian.Clark@occ.treas.gov.

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1 Hence, the focus is on the tail of the loss distributions as opposed to credit and market risk models that have been developed with the purpose of modelling expected losses.

2 For example, consider the case of a housing price shock as the stress scenario. In this case, a bank with no exposure to mortgages would be subject to the same level of stressing its operational risk capital as a bank with a significant amount of exposure to mortgages.

3 Model Risk Management Guidance (2011) defines model risk as "the potential for adverse consequences from decisions based on incorrect or misused model outputs and reports".

6

Stress Testing of Bank Loan Portfolios as a Diagnostic Tool

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In the aftermath of the financial crisis and its attendant government interventions to stabilise financial markets, stress testing of bank capital adequacy has taken on a prominent role in monitoring risk and capital adequacy at large banking organisations.[1] The stress tests are designed to provide a comprehensive view of bank risk exposure, including exposure to balance-sheet loan losses; revenue declines; counterparty credit risk; trading and market risk; and operational risk.

In February 2009, the federal banking agencies – led by the Federal Reserve – created a stress test and required the nation's 19 largest bank holding companies to apply it as part of the Supervisory Capital Assessment Program (SCAP).[2] The immediate motivation for the 2009 stress test was to determine how much additional capital a bank holding company would need to ensure that it would remain a viable financial intermediary even in the adverse scenario, with the Treasury Department prepared to provide capital to any bank that could not raise the required amount from private sources.[3] The SCAP experience demonstrated the value of a simultaneous, forward-looking projection of potential losses and revenue effects based on each bank's own portfolio and circumstances.

In November 2011, the Federal Reserve issued a new regulation requiring banking organisations with consolidated assets of US$50 billion or more to submit an annual capital plan. Under the rule, the Federal Reserve annually evaluates each institution's capital adequacy, internal capital adequacy assessment processes and their plans to make capital distributions such as dividend payments or stock repurchases. This annual exercise, named the Comprehensive Capital Analysis and Review (CCAR), is designed to ensure that institutions have robust, forward-looking capital planning processes that account for their unique risks, and sufficient capital to continue operations throughout times of economic and financial stress. Company-run and supervisory stress tests are a critical part of this annual capital review. They are used to determine whether a firm's capital distribution plans are consistent with remaining a viable financial intermediary even in an adverse scenario.[4]

Congress drew on the lessons of the 2009 exercise by including a requirement for stress testing in the 2010 Dodd–Frank Wall Street Reform and Consumer Protection Act. Bank holding companies with total consolidated assets of US$50 billion or more and non-bank financial companies that the Financial Stability Oversight Council has designated for supervision by the Federal Reserve began annual supervisory stress testing and semi-annual company-run stress testing under DFA rules in 2012; these also serve the purpose of CCAR stress testing.[5] Bank holding companies with total consolidated assets between US$10 billion and US$50 billion and savings and loan holding companies and state member banks with total consolidated assets of more than US$10 billion will also undergo annual company-run stress tests. Stress tests for these firms were slated to begin in 2013.

In May 2012, the regulatory agencies published a "Supervisory Guidance on Stress Testing for Banking Organizations with More Than $10 Billion in Total Consolidated Assets". As defined by the guidance, stress testing consists of "exercises to conduct a forward-looking assessment of the potential impact of various adverse events and circumstances". This guidance covers a much wider application of stress testing than those conducted for CCAR and DFA.

An important component of the CCAR and DFA stress tests is exposure to credit losses from commercial and consumer loans held on balance sheet, particularly losses from high-risk residential and commercial mortgage lending. These have figured prominently in overall stress projections due to the lingering impacts of high-risk mortgage lending and to the positing of stress scenarios involving a further steep decline in house prices and rise in unemployment. Discussion in this chapter is two-tiered. It includes high-level discussion of principles applicable to bank capital stress tests generally, concerning objectives and limitations of stress testing, design of appropriate scenarios, and the role of models. Where the discussion turns to particular issues related to model estimation, however, we narrow the discussion to modelling of balance sheet loan loss, which is our particular area of experience.

A balance-sheet loan-loss stress projection is distinguished by quantification of losses arising directly from a borrower's failure to repay a loan held on the bank's books. Generally, banks have access to historical data on the repayment performance of commercial and retail credits from which statistical inferences can be obtained regarding borrower performance under varying economic conditions. A loan-loss stress test, however, is based on modelling of borrower repayment performance under conditions at the extremes, generally outside the scope of historical experience. As such, it entails major modelling challenges.

In this chapter we propose a framework for bank capital stress-testing based on recognising inherent limitations of the process; setting objectives appropriate to these limitations; designing appropriate scenarios; and applying credible models. The discussion emphasises that, despite the challenges and limitations, bank capital stress testing in 2012 provides a useful diagnostic analysis of a banking institution's sensitivity to adverse shocks impacting on the loan portfolio. Stress testing can help pinpoint sources of risk; rank order institutions according to risk; indicate improvement or deterioration in a bank's risk position over time; and provide benchmarks for evaluating an institution's risk-management processes and capital adequacy.

The chapter is organised as follows. The next section discusses the purposes and limitations of stress testing and suggests a set of suitable objectives. The following section describes appropriate scenario design and the elements of a credible model estimation process. We then conclude.

DEFINING AND ACHIEVING STRESS-TEST GOALS

Ideally, the goal of bank capital sheet stress tests is to alert the bank or bank regulator to an unacceptable level of insolvency risk. Of course, the level of risk that is unacceptable is subjective, and judgements about it are likely to differ among investors, bank management and the regulators. But, even with a specified a level of risk, this goal, while simple to state, is difficult to operationalise for several reasons.

First, the connection to stress scenarios is not straightforward. Risk is multidimensional. The translation of a particular type of risk into a scenario seems feasible, but risks are correlated, so isolating a single type of risk may simplify the scenario unrealistically. However, designing a scenario based on correlations among types of risk poses implementation challenges and complicates the interpretation of stress-test results. If risks are best represented by a multivariate probability distribution, this seems to imply that no single scenario or small number of scenarios can adequately represent the tails of the distribution. And, if correlations are not accurately known, there can be little assurance that selected scenarios adequately represent tail risks.

Second, stress tests rely on models or constructs that may generate erroneous predictions. In other words, they are subject to substantial model risk and statistical uncertainty. Stress-test models of necessity are simplified representations of reality. They are generally based on past experience as embodied in historical data, which may not be relevant to the next stress event. Moreover, historical data typically covers relatively short periods and are often incomplete, lacking information on important predictors of loss. Even with a correctly specified model and adequate data, estimation of model parameters is subject to statistical error. Finally, because bank balance sheets, financial activities and operational structures are complex, stress-loss predictions depend on combinations of models, making it exceedingly difficult to measure the estimation error for aggregate losses.

Despite these problems, we maintain the view that bank capital stress tests can provide valuable information to bank managers and regulators. We also believe, however, that, while the information obtainable from stress tests is useful, it is inherently limited. The practical value of stress tests depends first and foremost on recognising their limitations and defining appropriate objectives.

Limitations of stress tests

As described above, stress testing is fraught with limitations if approached with the goal of accurately forecasting losses or precisely quantifying risk. To succeed at this level, analysts would need to work out the underlying causes of default as applicable to unprecedented or evolving conditions, rather than just find historical correlations. Statistical techniques and even economic theory may provide little guidance here.

Precision is unattainable with respect to both assignment of probabilities to any particular scenario and estimation of credit losses conditional on assigned scenarios. The question of scenario design is addressed in some detail below; for now, suffice it to say that scenario selection is critical to the information content of a stress test. Scenarios that are too mild could lead to failure to identify at-risk banks; those that are too harsh may generate excessive concerns and will not differentiate risk levels among banks.

Model risk and statistical uncertainty impede predictive accuracy of stress-test models. Model risk arises when the circumstances or scenarios of the stress test diverge from the historical experience on which the model is based, or when data limitations preclude consideration of relevant predictors of credit loss. Statistical uncertainty arises even in the extraordinary case of a fully and correctly specified empirical model, because model coefficient estimates will have a range of uncertainty (confidence interval) around them.

Balance-sheet loan-loss models being built for stress testing surely benefit from the availability of data from the credit crisis and subsequent recession and housing-value decline in 2007 through 2009. Models built with data covering a narrower range of economic conditions cannot be expected to extrapolate as well. Models built with data from the much wider range of economic conditions should do better in deriving estimates based on past experience. However, they remain vulnerable to error when extrapolated beyond their range of economic conditions, to unprecedented situations such as a "double-dip" housing recession.

The CCAR exercise conducted at the end of 2011 to evaluate banks' ability to absorb stress losses during 2012 through 2013 illustrates this aspect of model risk. The unemployment scenario selected for this exercise has the national unemployment rate rising above 13%, well outside the realm of recent historical experience regarding both level and one-year change. Thus, determining the impact of the unemployment scenario on retail and wholesale balance-sheet losses requires a significant degree of extrapolation of fitted historical relationships. Moreover, the CCAR loan-loss models are based on previously observed relationships between borrower repayment performance and macroeconomic variables, which may not generalise to the next downturn.

Future relationships may diverge from those implied by a balance-sheet loan-loss model due to inadequacies of historical data or limits to our understanding of behavioural aspects of repayment. Borrower behaviour around "turning points" in the economic environment or in response to adverse economic events is particularly difficult to accurately predict. For example, credit performance on first-lien mortgages as reflected in first-time delinquency has been improving somewhat faster than models generally predict; see, for instance, Goodman *et al* 2012. The moderating delinquency is partly explained by macroeconomic variables and observable dimensions of borrower credit quality. However, given the large percentage of borrowers who continue to have little or no equity in their homes, and the modest pace of economic recovery, models have tended to predict somewhat slower improvement in mortgage repayment performance. Thus, unobservable factors appear to be at play.[6] The impact of reversion to an adverse housing market and unemployment situation, as would be posited for a stress test, similarly could depend on such unobservable factors, implying substantial uncertainty around predictions of mortgage credit performance for the stress test.

When statistical models are estimated using large datasets, the amount of uncertainty around coefficient estimates generally is small, so that statistical uncertainty tends to be less of a concern than model risk. Even within large datasets, however, statistical uncertainty is aggravated when the number of observations available for inferring the impact of a key risk driver of the stress test is small, or when important variables are measured with error. For example, within the population of mortgage borrowers with negative equity in 2012, the number of observations thins out at higher levels of negative equity, leading to uncertainty around the impact of a further, large decline in home values on this population of borrowers.

An additional, potential limitation of bank capital stress tests pertains to the context in which they are implemented, as distinct from any inherent statistical or methodological weaknesses. Stress-test implementation carries a potential for excessive focus on model-building and model application, at the expense of gathering and analysing other relevant information or of recognising risks that lie outside the bounds of the model. A related problem is the potential for excessive focus on process and methodology, whereby the stress test becomes a mechanical or rigid process of risk assessment, displacing relevant qualitative analysis and impeding modeller creativity. Indeed, there may be circumstances where, due to the available data or the nature of the emerging risk, back-of-the-envelope-type calculations based on plausible assumptions may provide better insight than a statistical model.[7]

Practical objectives for stress tests

Given the major limitations around predictive accuracy of stress-test models, what constitutes reasonable objectives for a stress-test exercise? We believe that the following are practical and effective uses of bank capital stress testing:

- establishing a standard for an acceptable level of post-loss capital;
- differentiating banks by relative risk to identify and remediate banks that lie outside of an acceptable range;
- providing benchmarks for evaluating other quantitative loss models;
- probing the risk-sensitivity of the loan portfolio or other bank portfolios to relevant economic variables;
- probing the risk composition of the loan portfolio or other bank portfolios; and
- delineating the bounds of statistical modelling – highlighting risks outside the realm of historical data.

In establishing a standard for capital adequacy, the stress test would be applied on a pass/not pass basis. In this context, the stress test would be based on a single stress scenario or a small set of scenarios that represent an appropriate level of risk.

This use of the stress test may seem somewhat arbitrary, given the limitations of stress-test models, although no less arbitrary than other regulatory capital standards and offering the advantage of a relatively strong empirical basis for quantifying risk. The decision rule can be made less arbitrary by combining the stress-test results with other relevant information by experienced managers or regulators to reach conclusions about the level of risk and the actions that may be needed to reduce risk.

Using stress tests to rank banks according to risk potentially allows greater flexibility around scenario design, because this does not involve identifying the single, specific stress threshold that corresponds to an appropriate capital standard. While scenarios would need to be plausible, the range of admissible scenarios is determined by what would be informative about relative risk exposures across banks.

This use of stress tests clearly would be confined to bank regulators. However, an analogous, internal use of bank stress tests would be to evaluate relative risk across exposure categories or credit products.

Benchmarking is a natural application of stress tests. For instance, supervisory stress tests can be used as benchmarks for assessing banks' internal loss estimates, while banks' models can provide benchmarks for assessing the reasonableness of loss reserving or economic capital models.

Probing the risk sensitivity and risk composition of bank loan, investment, trading or other portfolios is also a very natural application. Analysis of bank performance under a variety of stresses can reveal weaknesses and anticipate developments likely to raise the bank's level of risk. The goal of probing risk composition is to identify at-risk portfolios or exposure categories.

These objectives pertain to use of a stress-test model to directly quantify risk. Stress-testing exercises can also be informative to the extent that they focus attention on the distinction between risks that are modelled and those not amenable to modelling. Thus, indirectly, the stress-testing process can help identify emerging risks, such as those arising from product innovation or loan origination channels or technologies, outside the bounds of the historical data and current stress-test models.

For the sake of brevity, we forgo more extended discussion of these objectives. It should be self-evident that they are consistent with effective risk management or supervision of banking institutions and that model risk is not an impediment to their implementation. They depend only on the design of appropriate scenarios and the development of logically and statistically sound and reasonably robust loss models, topics we address next.

SCENARIO DESIGN AND MODEL ESTIMATION

After specifying an appropriate objective, the next step is to design stress scenarios that are consistent with the objective. The ability to achieve the objective additionally depends on adequacy and credibility of the models and the model-estimation process.

Scenario design

The choice of stress scenarios potentially introduces error distinct from model risk or statistical uncertainty: it may illuminate the wrong region of the risk distribution, leaving the region that should be the focus of bank supervision unobserved. One step towards a better process should be to describe explicitly the goal of the stress-testing exercise, and the way in which stress-test results will be used.

At its most basic, stress-test design depends on the type of stress it aims to measure. For instance, the Supervisory Capital Assessment Program (SCAP) and Comprehensive Capital Analysis and Review (CCAR) exercises aimed at measuring classic financial stress for systemically important banks – are there sets of plausible if unlikely events that would produce credit losses on a bank's assets, and suppress its future income to the extent that its capital level would fall to a dangerous level? Such a focus on individual bank risk ignores network effects – the risk that one bank's capital will fall to an inadequate level because of the failure of another systemically important bank. It also ignores risk of adverse liquidity events such as depositor runs or collapse of a loan sale or securitisation market.

The scenarios that the Federal Reserve employed for SCAP and CCAR represent one way that financial stress can be created: through a serious recession. These scenarios take the existing economic conditions as a starting point and then hypothesise an immediate sharp global decline in economic activity, represented through forecast time series on a few fundamental domestic and international macroeconomic drivers. These include GDP and disposable-income growth, unemployment, inflation and interest rates, and stock, commercial real-estate and house prices for the US, plus a more limited set of drivers for major international trading partners.

The Federal Reserve scenarios from the latest round of CCAR certainly represent a stressful episode for banks, but does forecast performance under these scenarios provide all the information needed to asses banks' systemic risk? In particular, are there important dimensions of risk that are being overlooked? Are there plausible scenarios along other dimensions that would produce a different pattern of capital impacts across banks than the dimensions included in the Federal Reserve scenarios?

Certainly if Bank A were well capitalised in Scenario 1, and Bank B were undercapitalised, but in equally likely Scenario 2 the results were reversed, then regulators should be aware of both results. Finding whether other plausible scenarios besides a sharp recession would produce distinctly different patterns of outcomes would require loss forecasts under a large number of scenarios, a potentially daunting task.

If stresses that are different in kind represent one source of additional information, then what about stresses of varying severity? The answer to this question would seem to depend on the objective of the stress test. If the objective is a single pass/fail rule, then a single, specific severity threshold is necessary. However, if banks will be ranked, with decisions about capital adequacy made based not only on stress-test results but also on additional factors such as quality of risk management, then a wide range of scenario severities could provide additional information and a more nuanced view of capital adequacy. For instance, an institution viewed as particularly well managed might be subjected to less severe scenarios for determining capital adequacy.

The Dodd–Frank Act requires banks to model at least three scenarios, including baseline and adverse scenarios as well as a severely adverse scenario all provided by the Federal Reserve. The severely adverse scenario is used to assess the adequacy of bank capital. The baseline and adverse scenarios provide additional information about the sensitivity of bank performance to stress and may be useful for more general risk assessment, but are not used to assess capital adequacy at the time of writing.

Creating and forecasting an even more severe version of the Federal Reserve's severely adverse scenario would be relatively straightforward, but would it provide additional useful information? Is there something to be learned from a scenario in which many or all banks become undercapitalised? Potentially, the answer is yes. If increasing the severity of the scenario substantially lowered a bank's ranking among its peers, it could indicate a risk exposure not indicated in less severe scenarios. However, the scope for more adverse scenarios should be limited to those with a non-negligible likelihood of occurring.

If stress testing is to be used as a tool to explore the risk structure of the systemically important banks, then stress scenarios focused on specific types of exposures could be useful. For example, if the regulator wants to identify banks particularly exposed to losses in commercial real estate, then a scenario simulating distress in that particular market will more precisely identify at-risk banks than a general recession scenario that includes a downturn in commercial real estate among several stressors.

Careful exploration of targeted stress scenarios is likely to give the regulator a useful picture of the sources and distribution of risk, but, again, carrying out such an analysis would be a large task. It would also generate multiple views of the riskiness of individual banks, which then must be synthesised into an overall view of the adequacy of the bank's capital plan. Too great a proliferation of stress-test results could just make that task harder, rather than increase its accuracy.

In the discussion to this point, scenarios appear as completely exogenous events. However, the entire rationale for stress testing systemically important banks is that they have the capacity to feed the stress they receive back into the economy. So scenario analysis as described above implicitly assumes either that there are no feedbacks or that the scenario in some sense represents the impact of both the initial economic stress and the net effect of all the feedbacks from systemically important banks. If, as a result of regulation based on the stress test, systemically important banks remain well capitalised through the stress scenario, then an assumption of no feedbacks may be reasonable. However, if feedbacks are expected, then the stress scenario must become dynamic. Initial economic stress impacts the large banks, is distributed within their network, and then feeds back to the economy as a whole, which then determines the economic stress for the next period. A structure like this, incorporating all potential feedbacks, is much more complex than anything so far attempted.

A final issue relating to stress scenarios relates to their variability through time. As with any type of capital regulation, the use of stress testing implicitly assigns capital weights to asset classes and off-balance-sheet exposures. These can reasonably be expected to affect future bank asset choices. Assuming that loss modelling will never become an exact science, bank optimisation with respect to implicit stress test risk weights could increase risk in ways difficult to detect *a priori*. With this concern in mind a case might be made for some variation in stress scenarios over time simply to avoid over reliance on a single view of bank risk, and thereby reduce unmeasured risk in the banking system.

Model estimation

Models are the means of translating economic scenarios into loss forecasts. The goals of stress testing articulated above require that the model provide an accurate representation of historical variation of losses in relation to economic conditions (dynamic relationships). The model also should provide credible projections of future losses under severely adverse economic conditions. In addition, the model should accurately capture relevant (cross-sectional) relationships across different types of exposures within a portfolio, such as between loan and borrower characteristics and credit risk in the case of balance-sheet loan-loss models. Finally, the model should incorporate conservatism in choice of model structure and variable specification as a counterweight to the inevitable data limitations and model risk.

At the same time, practical considerations dictate that the models be as simple and transparent as possible. For instance, in the case of supervisory models, the models must be amenable to relatively quick application to the portfolios of multiple institutions during the annual stress-testing cycle. They must also be conducive to annual updating and validation and submission to some level of public scrutiny.

Accuracy in capturing historical variation requires testing alternative model specifications with the aim of improving the model's fit over the economic cycle. Similarly, accuracy in capturing cross-sectional relationships requires investigating alternative model specifications. Specification testing, of course, is limited by the set of variables within the historical, development database and by the set of economic variables for which scenarios are obtainable.

In building balance-sheet loan-loss models for stress tests, there tend to be more rapidly diminishing returns to specification testing compared with other activities, for two reasons. First, the objectives of stress testing are relatively broad. Assessing the bank's ability to withstand a severe economic downturn generally requires less granular attention to individual borrower characteristics than other applications such as credit scoring, for example, where the focus is on each borrower's marginal contribution to credit risk. Second, the marginal improvements in a model's fit that might be achieved through extensive specification testing will do little to offset the substantial model risk inherent in a stress-testing exercise.

In stress testing, as in modelling generally, improving a model's fit historically does not necessarily improve the accuracy of predictions. One potential complication is "overfitting" of historical relationships, whereby a model produces estimates based on temporary or spurious correlations rather than stable causal relationships. An overfitted model may match historical variation but at the expense of eroding the model's predictive accuracy, reducing its transparency or weakening its theoretical or intuitive foundation.

In stress testing, this concern is exacerbated by the possibility that improving the model's accuracy in capturing historical variation may involve weakening estimated relationships to economic variables. This could lead to less conservative stress-loss predictions, diminishing the credibility of the stress test. For example, in a time series or dynamic panel-type loan loss model, inclusion of a lagged loss rate may substantially improve the historical fit of the model as well as the accuracy of short-term forecasts. However the autoregressive term might partly capture the impact of economic conditions, causing weaker estimated economic relationships and less conservative stress-loss forecasts.

One way to limit the potential for overfitting is to apply economic theory to guide the selection of variables for the model. A second is to be guided by the dictum "less can be more": improvements to historical fit accorded by increasing the complexity of a model or number of included variables should be balanced against the increased potential for overfitting. Particular caution should be applied with respect to inclusion of potentially endogenous variables that improve the fit to historical data but weaken the estimated relationship between default and macroeconomic variables.

Another potential problem is that a model may be robust in-sample but not with respect to loss prediction under stress scenarios. In other words, minor alterations may have little impact on model goodness of fit but imply substantially different losses under stress scenarios. The preferred specification should be robust not only with respect to in-sample fit but also robust or at least conservative (in the sense of providing an upper bound on loss estimates) with respect to stress-loss prediction.

Even out-of-sample testing or backfitting is of more limited value in the stress testing arena compared with other modelling contexts, and should be interpreted with caution. A model may predict well out-of-sample under non-stress conditions, but have limited credibility for stress-loss prediction. Thus, for example, a balance-sheet loan-loss model that is predicting higher-than-observed delinquency rates during a favourable or improving economic environment may be preferable to one that has been re-estimated to provide a better fit. While it is important to monitor the performance of a statistical prediction model, including a stress-test model, through backtesting missing the mark is not necessarily an indication of a need to re-estimate. Rather, especially in the context of a stress test, off-the-mark prediction is an issue to investigate and seek to understand, with the goal of improving the model as needed.

In the realm of stress testing, the goal for the development and validation of balance-sheet loan-loss models is not forecast accuracy *per se*. Rather, the goal is to provide credible loss forecasts under the assumption that borrowers' responses to the stress scenarios will resemble historical performance under broadly comparable conditions. There can be no assurance either that future behaviour under stress conditions will resemble past performance, or that the historical data incorporate a sufficiently diverse range of economic conditions to guarantee accuracy of the prediction. Moreover, the stress scenarios are unlikely to actually materialise (hopefully they will not), ruling out a true backtest of the model. Hence, robustness of stress-loss predictions and appropriate conservatism of model assumptions are equal if not more important considerations than model performance in backtesting.

CONCLUSIONS

Bank capital sheet stress testing is a potentially useful tool for bank risk management and supervisory risk assessment. However, loss predictions under stress scenarios necessarily represent extrapolations of experience and knowledge and should be considered as such. Model risk and statistical uncertainty impede predictive accuracy of stress-test models. Thus, a bank capital stress test can provide a benchmark, but not a forecast.

As such, stress testing can be used to establish a standard for capital adequacy; to identify and remediate banks that lie outside of an acceptable range of exposure to credit loss; and to provide benchmarks for evaluating other quantitative loss models. Stress testing is also potentially useful as an analytical tool to probe the risk sensitivity or risk composition of the loan portfolio. Somewhat paradoxically, it is also useful for illuminating the limits of statistical modelling; that is, for highlighting risks outside the realm of historical data.

While using stress-test results in a pass/not-pass mode is straightforward, well-executed stress tests should be able to support a more nuanced view of bank risk. For example, stress tests could highlight specific activities that make a disproportionate contribution to overall risk for the institution and deserve deeper review. However, stress testing can potentially produce very large amounts of information. To be used effectively, stress-test results must be conveyed in a form that can be effectively understood and acted on by bank managements and regulators.

The design of both individual stress scenarios and an effective set of scenarios for a stress test are problems that are ripe for further research and development. For example, the Federal Reserve scenarios from the 2011 CCAR represent a stressful episode for banks, yet it is still important to consider whether the forecast performance under these scenarios provides all the information needed to assess banks' systemic risk.

To achieve effective stress tests, institutions must recognise the specific demands of forecasting for stress scenarios, and design their model development process appropriately. Loss modelling for stress testing puts a premium on ability to extrapolate reasonably. The preferred modelling approach or model specification should be robust not only with respect to in-sample fit but also robust or at least conservative with respect to stress-loss prediction.

With respect to balance-sheet loan-loss models in particular, there tend to be more rapidly diminishing returns to specification testing and out-of-sample validation efforts in stress testing compared with other modelling contexts. Pursuing marginal gains in model fit will do little to offset the substantial model risk inherent in the stress-testing exercise, but may lead to overfitting, which will reduce a model's reliability.

Likewise, a loan-loss model may predict well out-of-sample under non-stress conditions, but have limited credibility for stress-loss prediction. Robustness of stress-loss predictions and appropriate conservatism of model assumptions are equally important to consider along with model performance in backtesting

When implementing a bank capital stress-test process, it is important to be mindful of the potential for the process to promote inefficient use of resources and impede creativity in assessing risk. Excessive focus on methodological issues in model-building and model application can divert attention from gathering and analysing other relevant information. Likewise, excessive focus on process and methodology may cause the stress test to become a mechanical risk assessment exercise, impeding creativity and hampering recognition of emerging risks.

If undertaken without a clear sense of the limitations, and without clear objectives or a context for judging model effectiveness, bank capital stress testing can end up becoming an open-ended activity and drain on resources with no satisfactory conclusion. Effective and efficient application of bank capital stress tests requires acknowledging the limitations of the exercise; setting feasible objectives; designing scenarios consistent with the articulated goals; and developing loss models subject to sensible and cost-effective robustness criteria.

The views expressed in this chapter are those of the authors and do not reflect the views of the Federal Reserve Bank of Philadelphia, Federal Reserve System or Office of the Comptroller of the Currency. We thank William Lang and Amy Jordan for many helpful comments.

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1 For additional historical perspective, see the speech "Developing Tools for Dynamic Capital Supervision" by Federal Reserve Governor Daniel K. Tarullo at the Federal Reserve Bank of Chicago Annual Risk Conference, April 10, 2012.

2 The test involved two scenarios – one based on the consensus forecast of professional forecasters and the other based on a severe, but plausible, economic situation – with specified macroeconomic variables such as GDP growth, employment and house prices. Each participating institution was asked to supply, in a standardised format, detailed information on portfolio risk factors and revenue drivers that supervisors could use to estimate losses and revenues over a two-year period conditional on these scenarios.

3 The Federal Reserve's decision to disclose the results of the test on a firm-specific basis served a second purpose: to provide investors, and markets more generally, with information that would help them form their own judgements on the condition of US banking institutions.

4 In the first quarter of 2011, the Federal Reserve had conducted a similar review of the 19 firms that had participated in the SCAP. As part of the CCAR, the Federal Reserve evaluates institutions' capital adequacy, internal capital adequacy assessment processes, and their plans to make capital distributions, such as dividend payments or stock repurchases. The stress test is only one of several essential components of the capital review. The Federal Reserve may object to a capital plan because of significant deficiencies in the capital planning process, as well as because one or more relevant capital ratios would fall below required levels under the assumptions of stress and planned capital distributions.

5 There are two sets of instructions: one for the 19 firms that participated in the CCAR in 2011, the other for 12 additional firms with at least US$50 billion in assets that have not previously participated in a supervisory stress-test exercise. The level of detail and analysis expected in each institution's capital plan will vary based on the company's size, complexity, risk profile and scope of operations. The instructions include a supervisory stress scenario that will be used by all of the firms and the Federal Reserve to analyse firms' capital needs to withstand such a scenario while continuing to act as a financial intermediary. For the 19 firms that participated in the CCAR in 2011, the Federal Reserve will also conduct a supervisory stress test using internally developed models to generate loss estimates and post-stress capital ratios.

6 In short, several years of high default rates on mortgages may have filtered out higher-risk borrowers, including along unmeasured dimensions of credit quality. Unobserved heterogeneity may be tied to the household's overall balance-sheet composition and vulnerability to income or wealth shocks.

7 For an example of such a rough calculation or scenario-based analysis that provided warning as early as 2006 of the potential impact of payment shocks from hybrid ARM resets, see http://www.loanperformance.com/infocenter/whitepaper/FARES_resets_whitepaper_021406.pdf

7

Stress-Test Modelling for Loan Losses and Reserves

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The widespread use of macroeconomic and financial factors in the quantitative models that banks use to forecast their credit losses has been an important development. The financial crisis of 2007–9, and the associated severe recession, underscored the need for banks to incorporate economic and market conditions into their retail and wholesale credit risk models in order to produce credible stress loan-loss estimates. Prior to the crisis, banks were unable to estimate, and apparently uninterested in estimating, the credit losses that would result from a recession, probably because a generation of bank executives had never experienced a severe recession. This left banks unprepared for the severe loan losses that occurred between 2008 and 2010. In onsite supervision of national banks' credit-risk management systems during the past several years, the authors have observed that bank executives at the larger banks, in response to the 2007–9 crisis, have determined that models capable of estimating credit losses conditional on stress economic scenarios were necessary for enterprise-wide capital planning and stress testing, and so directed their staffs to begin model-development efforts.

Several recent supervisory and regulatory developments probably also have accentuated this trend. First, the largest US banks that are subject to the Advanced Internal Ratings Based (AIRB) approach of Basel II (and Basel III) are required to conduct a cyclicality stress test in Pillar I and a forward-looking stress test of credit risk as part of the Internal Capital Adequacy Assessment

Process in Pillar II. Second, the Basel Committee on Banking Supervision issued a consultative paper in January 2009 that recommended that banks use enterprise-wide stress tests to provide a forward-looking assessment of their risk profile and capital adequacy (Basel Committee 2009). Third, in an attempt to quell rapidly escalating fears about the solvency of the US banking system during the 2007-9 crisis, the Federal Reserve conducted its Supervisory Capital Analysis Program (SCAP) in spring 2009. The SCAP, a macroprudential supervisory bank stress test, used a stressful macroeconomic scenario to assess the capital adequacy of the 19 largest US bank holding companies.[1] Building on the success of the SCAP exercise, the Federal Reserve conducted its Comprehensive Capital Analysis and Review (CCAR) bank stress tests in 2011, 2012 and 2013 using macroeconomic stress scenarios that involved a much larger number of macroeconomic and financial factors than were used in the SCAP.[2]

Finally, the Dodd–Frank Wall Street Reform and Consumer Protection Act of 2010 required certain financial companies with total consolidated assets of more than US$10 billion to conduct annual stress tests using a minimum of three macroeconomic scenarios (baseline, adverse and severely adverse) provided by the company's primary federal regulator. As a result, enterprise-wide stress testing (and an associated formal capital-planning process) has become a regulatory requirement for all banks and federal savings associations with more than US$10 billion in total assets.

Since 2008, substantial work has been conducted to develop macro-forecasting models for retail and wholesale credit risk, especially at the largest banks. In this chapter, some of the internal modelling practices that the authors have observed at national banks, where macroeconomic and financial risk drivers have been incorporated into the quantitative models used to generate retail and wholesale credit loss forecasts and loan-loss reserve estimates, are discussed. Some of the strengths and weaknesses of the various modelling approaches are also presented. Finally, several econometric specification and estimation issues the authors have observed that need to be addressed by banks in developing their macroeconomic-based credit risk stress-testing models are discussed.

BANK MODELS FOR LOAN LOSSES AND RESERVES

Most of the risk-assessment models needed for enterprise-wide stress tests (eg, trading risk and banking-book interest-rate risk models) have been in place at banks for quite some time. Therefore, the major modelling challenge has involved the development of credit-risk models that incorporate macroeconomic and financial variables. Prior to the crisis of 2007–9, banks had relied on a variety of quantitative and expert-judgement approaches in their credit-risk modelling. For retail credit risk, banks relied on credit and behavioural scoring models, matrix models, roll-rate and Markovian-chain models, and vintage models.[3] With very few exceptions, none of these models incorporated macroeconomic conditions, but instead rank-ordered credit applicants by their unconditional probability of default (PD). While most of the models can be used to generate a borrower-specific PD, the relationship between macroeconomic factors and defaults rates was, for the most part, not taken into account.

For wholesale credit risk, loan officers' expert judgement was used in credit-grading systems to assign each borrower a risk grade. Similar to retail credit risk, historical data can be used to provide estimates of the PD for each risk grade. However, macroeconomic factors were not used prior to the financial crisis of 2007–9, except perhaps indirectly, since economic conditions were viewed by banks as tending to unduly influence the loan officers' credit-risk judgement.

ALLOWANCE FOR LOAN AND LEASE LOSS MODELS

All banks subject to credit risk must establish an adequate allowance for loan and lease losses (ALLL), which is intended to cover expected credit losses (measured in the form of charge-offs) over a given horizon.[4] The ALLL is a stock and recorded as a contra-asset (ie, an asset with a negative balance) on the bank's balance sheet. In the financial reports banks issue each quarter, changes in the ALLL are referred to as loan-loss provisions, and included in non-interest expense and deducted from net income. When banks take charge-offs, the amount is subtracted from the ALLL. Although net loan-loss provisions and net charge-offs (ie, gross charge-offs less recoveries) can be negative, this typically happens infrequently. Under the uniform capital standards of US federal banking regulators, loan-loss reserves up to a value of 1.25% of risk-weighted assets are included in Tier 2 regulatory capital.

While accounting standards are vague on the issue, the horizon used for charge-off forecasts in setting loan-loss reserves is typically one year for retail loans, and one or two years for wholesale loans. At smaller banks, the method used for determining the ALLL is typically based on expert judgement. At larger banks, a combination of quantitative models and expert judgement is used in determining reserves.

The total ALLL consists of a quantitative reserve component and a qualitative reserve component. The quantitative component is based on historical charge-offs, while the qualitative component typically has reflected an expert-judgement-based adjustment that captured factors such as changes in lending policies and procedures and changes in international, national and local economic and business conditions that are not reflected in historical charge-offs. Since 2008, however, the ALLL has become more quantitative and forward looking, at least at larger banks, many of which now use statistical and econometric methods to capture the sensitivity of charge-offs to changes in macroeconomic and financial variables. For example, ALLL qualitative models may have a macroeconomic modelling component with two or three macroeconomic variables lagged several quarters up to a year. Moreover, many banks have begun to conduct stress tests of the qualitative component of their loan-loss reserves using multiple macroeconomic scenarios (Pocock 2012).

The overall aggregate predictive accuracy of banks' ALLL models can be evaluated by comparing the ratio of the subsequent year's charge-offs to the beginning-of-year loan-loss reserves. Table 7.1 presents data taken from the December 31 financial statements over the period 2005–11.

Table 7.1 Charge-offs as a percentage of beginning of year ALLL, commercial banks, 2005–11 (unweighted means)

Year	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**
15 largest banks	22%	36%	48%	108%	103%	79%	56%
All banks	19%	18%	25%	48%	73%	58%	50%

As shown in Table 7.1, assuming the typical one-year charge-off coverage target for reserves, banks dramatically overstated their reserves in the boom years that ended in 2007. This result shows the near-total lack of a relation between ALLL and charge-offs during the good years, suggesting banks perhaps had motives other than credit losses in setting their loan-loss reserves such as income smoothing, regulatory capital management and private information signalling.[5] In sharp contrast, the largest 15 banks understated their reserves in 2008 and 2009, a period that covered the height of the 2007–9 crisis, and the associated recession, which was the worst since the Great Depression.

The authors' loan-loss reserve results for the 15 largest banks reported in Table 7.1 are consistent with those of Furlong and Knight (2010), who have argued that the unusually low levels of reserves compared with eventual loan losses in 2008 and 2009 reflected two underlying causes. First, accounting standards limit banks' ability to set aside provisions for loans that are performing, but that might become delinquent in the future, without evidence that charge-offs would increase. Second, banks' forecasts of the severity of recessions and subsequent future loan losses are characterised by large errors. Given the extreme severity of the 2007–9 crisis, and the unprecedented decline in real-estate values, it was not surprising that the largest banks substantially underreserved in 2008 and 2009. As such, then, banks that forecast losses and set provisions based on past experience would have severely underestimated the credit losses that eventually occurred during the crisis of 2007–9.

POOL-LEVEL LOSS MODELS

Pool-level models are top-down models used by banks to forecast charge-off rates by retail and wholesale loan type as a function of macroeconomic and financial variables. The typical pool-level model has defined the loan type broadly. For example, all commercial real-estate (CRE) loans may be defined as the pool, or, alternatively, CRE loans may be divided into their major subtypes, eg, industrial, hospitality, retail. For the large banks subject to the CCAR stress test, the level of granularity for the portfolios has reflected the granularity requested in the CCAR reporting templates. At some banks, the charge-off time series might extend back five years, while at other banks the charge-off history might extend back twenty years – a period that would capture the past three US recessions. Even at the pool level, however, many banks have found it difficult to create internal datasets for charge-offs that are long enough for credible estimation. Those banks that cannot create sufficiently long time series usually resort to having an external vendor create the charge-off time-series datasets.

The charge-off rates used by banks in their top-down regression models are measured quarterly, which means that a five-year time series contains only 20 observations, and a 20-year time series has only 80 observations. This paucity of data creates a premium on parsimony in model development. Therefore, most banks use only from one to four macroeconomic and financial risk drivers as explanatory variables, to preserve degrees of freedom in their regression-based forecasting models. At most banks, the macroeconomic and financial variables that are considered for use in the charge-off regressions are usually determined by an executive-level committee that has been assigned to specify the various economic scenarios. Banks' modellers then use a combination of statistical significance tests and management's expert judgement to arrive at the final set of macroeconomic and financial variables that are used in the regressions for each loan type. Some banks have decided to use the same set of variables for each loan type, sometimes sacrificing predictive accuracy for the sake of consistency.

The primary advantage of pool-level models has been the focus on the charge-off rate instead of loan-loss reserves.[6] While still an estimate, charge-offs are taken by banks at a time that more closely aligns with the actual realised losses, and thus are much more accurate and closer to the specific quantity of interest than are reserves. The primary disadvantage of pool-level models is that borrower-specific characteristics are generally not used as explanatory variables, except at the aggregate level using pool averages. For example, for first-lien residential mortgage loans, defaults are extremely rare on loans for which the loan-to-value (LTV) ratio is less than 100%, but rise at an increasing rate as the current LTV ratio goes above 100% (Goodman *et al* 2010; UBS 2005). This asymmetry means that the pool average LTV ratio generally has not helped to predict mortgage defaults. To illustrate, assume a mortgage pool for which half of the mortgages have an LTV ratio of 50% and the other half have an LTV ratio of 130%. Given such a mortgage pool, the average LTV ratio would be 90%, and a zero default rate would probably be predicted, even though borrowers whose loans have an LTV ratio of 130% would default at a high rate.

Banks typically have used single-equation, reduced-form regression models to forecast the annualised net charge-off rate quarterly for each loan-type portfolio. For the most part, these regression models are dynamic and specified as autoregressive models of order p, where p lags of the charge-off rate (the dependent variable in these regressions) are used as explanatory variables to account for the substantial autocorrelation displayed by charge-off rates. Besides the reduced-form autoregressive econometric models, a small number of banks have been developing and using simple error-correction models to forecast annualised net charge-off rates (Crook and Banasik 2012; Assouan 2012). For all top-down models, quarterly net charge-offs are derived by multiplying the net charge-off rate forecasts by balance forecasts provided by the banks' corporate treasuries.

A potential concern associated with banks' use of autoregressive forecasting models is the significant correlation between the macroeconomic and financial risk drivers. This multicollinearity can serve to mute the effect of shocks to the macroeconomic and financial variables on the charge-off forecasts. This is an important issue in conducting effective and meaningful stress tests, since it may not be possible to quantify the full impact of macrofinancial shocks on credit losses when there is significant correlation among the macroeconomic and financial variables, as well as between these variables and lagged values of the charge-off rate. Also, the use of an autoregressive model may prevent the charge-off rate (the dependent variable) from responding quickly to a shock in the macroeconomic and financial variables due to including lags of the charge-off rate as explanatory variables.

As far as the development of the top-down charge-off models is concerned, smaller mid-size banks (those close to the $10 billion asset threshold for banks required to conduct enterprise-wide stress testing under the Dodd–Frank Act) may not have the financial resources necessary to attract skilled statisticians and econometricians. For these banks, then, an attraction of the pool-level models is that ordinary least squares (OLS) estimation typically can be used.

LOAN-LEVEL LOSS MODELS

Loan-level models are bottom-up models used by banks to forecast the expected loss by retail and wholesale loan type for each loan. The expected loss is calculated for each loan. In these loan-level models, the sum of expected losses across all loans provides an estimate of portfolio losses.

The large US banks that are subject to the AIRB approach typically have used the Pillar I definition of default in calculating PD, loss-given default (LGD), and exposure at default (EAD) in the bottom-up models. For the most part, account-level PDs are estimated using logistic regressions that include both internal borrower-specific characteristics and macroeconomic and financial variables as predictors. In contrast, LGDs are usually estimated using a regression model at the portfolio level that includes macroeconomic and financial risk drivers. Finally, EAD for term loans equals the principal balance at default, including currently undrawn commitments. In order to capture the larger positive correlation between PD and LGD during periods of stress, many banks use the same macroeconomic risk drivers in their PD and LGD regression models. (Technically, AIRB models use pools of loans, but Basel II specifies that the loans in each pool must be essentially identical to each other in terms of credit risk, so the AIRB models are defined as loan-level here.)

In contrast to the relative simplicity of top-down charge-off models, there are a variety of loan-level methodologies that can be used, but these models are much more complex to specify and estimate. Loan-level methodologies generally require more sophisticated econometric and simulation techniques. Also, the macroeconomic and financial risk drivers are often correlated with borrower-specific characteristics, and similar to the pool-level autoregressive models discussed above, the multicollinearity among the regressors serves to mute the effect of shocks to the macroeconomic and financial variables on expected losses. This is an important issue in conducting effective and meaningful stress tests, since it may not be possible to quantify the full impact of macrofinancial shocks on credit losses.

For many banks, loan-level models require data that are not available, particularly as long historical time series. US banks that are subject to the AIRB approach of Basel II have been maintaining detailed data on borrower-specific characteristics since the early 2000s. However, other banks generally find it to be a big challenge to create historical data on borrower-specific characteristics. As noted above, some banks have resorted to using vendors to provide pool-level charge-off data. However, vendors may not be able to provide borrower-specific data at a reasonable cost for these banks. As a result, apart from the Basel II AIRB banks, the authors generally have observed historical loan-level data at other banks of at most five years in length.

In principle, loan-level models would appear to be superior to pool-level models in terms of forecast accuracy, since they use both macroeconomic factors and loan-specific characteristics as predictors of expected losses. However, the forecasting superiority of loan-level models remains to be adequately demonstrated by out-of-sample backtesting. Hughes and Stewart (2008) empirically addressed the issue of whether aggregate models of credit risk yielded better forecasts of portfolio aggregates than loan-level models. Using simulation techniques, they found that pool-level models performed better than loan-level models.

Credit and behavioural scoring models with macroeconomic factors

A simple model used by banks combines credit scores, such as the Vantage or FICO score, and macroeconomic factors to predict defaults or severe delinquencies, and then produces default probabilities at the loan level. These loan-level estimates are then aggregated to produce a pool-level default rate. An example of this approach was provided by Hughes (2009), who showed that macroeconomic factors had predictive power for defaults and delinquencies. Other work also has documented the importance of macroeconomic factors as predictors of loan-level defaults, deliquencies and credit scores (Hughes 2008; Thomas 2000; Bellotti and Crook 2009).

Credit migration analyses

Many banks' stress-testing models use credit-migration or roll-rate analysis. Migration in this context refers to the movement of a loan through a transition matrix of some kind, where the rows indicate some measure of current credit quality, and the columns indicate the next period's credit quality.

Retail migration matrices are usually based on delinquency status. For each loan type, the bank defines the number of days delinquent, at which point the loan is deemed to be in default. The matrix is typically terminated at that point, although it can include a column that shows the loan to have been converted to collateral. A stylised migration matrix for first-lien residential mortgages is shown in Table 7.2.

The transition of a loan from current to 1–30 days past due is probably the most important metric for measuring the sensitivity to macroeconomic factors. However, at least for retail credit, 1–30-day delinquencies are very volatile. They display a significant seasonal component, and consist of payments that are missed accidentally, but then quickly cured, and so-called "rolling 30s", where the borrower has missed one payment that is never made up. As a result, few, if any, banks use this delinquency bucket in their retail credit modelling.

Table 7.2 A stylised retail transition matrix

To From	Current	30–60 days past due	60–90 days past due	Default (90+ days past due or real-estate-owned)
Current	98%	2%	0	0
30–60 DPD	40%	20%	40%	0
60–90 DPD	20%	20%	20%	40%
Default	2%	4%	8%	20%

Note: The last row does not add to 100% due to the conversion of REO to cash.

The time-and-state invariant transition probabilities assumed for the typical first-order Markovian transition matrix used by banks are restrictive and not the most realistic default-modelling approach (van Deventer 2009; Kiefer and Larson 2004). However, most banks interpret the conditions loosely and calculate the PD as the product of adverse credit migrations. In Table 7.2, assuming static transition probabilities, the PD of a current loan at the 90-day horizon is (0.02*0.4*0.4), reflecting the probability of transition from "current" (actually 1–30 days past due) to 30–60 days past due multiplied by the probability of transitioning from 30–60 to 60–90 days past due multiplied by the probability of transitioning from that bucket to default. Similarly, the default probability of a 30-day delinquent loan at the 90-day horizon is (0.2*0.4*0.4)+(0.4*0.4), ie, the probability that the borrower makes a payment but then misses the next two payments plus the probability that it misses the next two payments, and so on. There are several ways to convert the 90-day default rate to the 12-month default rate typically used for retail loans.

The transition-matrix approach produces only the probabilities of default, and not the LGD. As a result, modellers must estimate the LGD separately. For most types of retail loans, the LGDs are close to 100%, with the exception of first-lien residential mortgages, where substantial recoveries are typically expected. Prior to the housing bubble of the 2000s, the rule of thumb was an LGD of 20% to 30% for prime residential mortgages (Qi and Yang 2009) and an LGD of 40% to 50% for subprime mortgages.[7] In the aftermath of the crisis of 2007–9, however, that rule of thumb has become too simplistic to apply. The alternative approach has been to calculate the LGD of a loan as a function of the loan-to-value ratio at the time of default plus an add-on for recovery costs. Frequently, the loan-to-value ratio is modelled as a function of a scenario-specific home-price index.

Wholesale credit migration matrices are usually based on the credit ratings assigned to the obligors by the bank. Banks typically have assigned 10 to 20 grades to wholesale debtors, rank-ordering them in terms of their PD. For each rating grade, the PD at any horizon can be calculated as a historical average. Usually, the internal ratings are based on the expert judgement of the loan officers, although quantitative models are increasingly being used to supplement the expert judgements.

Unlike for retail loans, most wholesale loans keep the same grade from month to month. While most of the stability in ratings is probably real, some is undoubtedly due to inertia on the part of the loan officers. Moreover, banks probably vary considerably in the diligence of their loan officers in keeping the internal credit ratings up to date.

For a given relationship between internal loan grade and default rating, the stress-testing challenge for banks has been to estimate how changes in economic conditions correlate with changes in loan grade. In the first years after 2008, the impact of changing economic conditions tended to be based on the expert judgement of the loan officers, but there has been movement towards the use of macroeconomic-based models. Since the macroeconomic models require a history of internal loan-grade migrations, the macroeconomic sensitivities of these migrations can be affected by the loan officers' diligence and ability in maintaining up-to-date loan ratings.

For wholesale LGDs, many banks assign a rating analogous to the PD ratings. Some banks combine the PD and LGD ratings into one rating, which effectively produces an expected-loss rating. Other banks simply assign a historical-average LGD, which could be model-based. Unlike retail LGDs, wholesale LGDs are highly sensitive to macroeconomic and financial factors (Frye and Jacobs 2012).

In order to account for the changing risk profile of both retail and wholesale portfolios at the loan level, the authors have observed some banks using dynamic credit transition matrices that are conditional on stressed economic scenarios (Bangia *et al* 2002). Retail transition matrices are based on delinquency status, while wholesale transition matrices are based on internal risk ratings. These dynamic transition matrices, which are conditional on macroeconomic and financial variables, require nonstationary Markov chains (Grimshaw and Alexander 2011).

There are several different econometric approaches for estimating transition probabilities that the authors have observed. The simplest was to estimate the relationship between macroeconomic and financial variables and the PD using OLS. Technically, this is not a valid approach, since the migration probabilities are bounded by zero and one, while OLS assumes an unbounded distribution. However, for most of the intermediate cells in a transition matrix, probabilities are reasonably close to 50%, so the boundary issue is less of an issue. However, the transition from current to 30-days past due is close to a zero probability, while transitions from the late delinquency buckets to default are close to a probability of one.

There are two possible solutions to this problem. One approach is to find an alternative method for estimating initial and late-stage transitions, but the authors have not seen such an approach implemented by banks. A second method would be to standardise the transition probabilities (ie, characterise observations by the number of standard deviations from the mean), thereby converting the transition probabilities from a bounded to an unbounded distribution. The authors have seen this approach implemented, but, as of late 2012, there has not been sufficient time for banks to compare forecasts with actual results.

The preferred econometric approach is to use a logistic regression to combine borrower-specific characteristics with macroeconomic variables to predict credit migration as a loan-level binary outcome. Chen *et al* (2011) used this approach, and showed that macroeconomic variables appeared to outperform borrower characteristics in predicting credit migrations. They also found that generalised maximum entropy outperformed a multinomial logit model. However, as with the other models discussed here, they did not include a substantial out-of-sample comparison of forecasts with actual results.

A variant on the use of migration matrices

In this approach, the modeller predicts the proportion of loans in each migration bucket as a function of macroeconomic and financial variables, rather than using the transition probabilities as the dependent variable. In other respects, such as estimating LGDs and draws on unfunded commitments, the approach is the same as for migration analyses. An alternative implementation would use a multinomial logit or ordered probit regression model.

Charge-off rates across loan types

Since economic risk factors change at the same time for all banks, it would be convenient for modellers if charge-offs for different loan types responded with the same lag to changes in macroeconomic and financial variables. Table 7.3 shows charge-off rates across loan types, by year.

Table 7.3 shows that CRE charge-off rates tend to lag other lending types, such as C&I, Consumer and HELOC loans, by about one year. Otherwise, charge-off rates for all loan types increased for the most part much in tandem. For example, charge-off rates for both C&I and residential construction loans have peaked at the same time.

Table 7.3 Annual percentage charge-off rates, by loan type, industry aggregates (weighted means)

	C&I	Consumer	Credit card	HELOC	Res. const.	Owner-Occ. CRE	CRE	2nd-lien, closed-end residential	1st-lien residential
2005	0.7	1.8	5.9	0.1	0.0	0.1	0.1	0.3	0.1
2006	0.6	1.5	4.3	0.2	0.1	0.1	0.1	0.4	0.1
2007	0.8	2.0	5.0	0.5	0.5	0.1	0.2	0.7	0.2
2008	1.4	2.7	6.3	1.9	4.2	0.1	0.5	3.1	0.9
2009	3.1	3.6	10.2	3.0	7.6	0.6	1.5	5.8	1.4
2010	2.4	2.7	10.9	2.8	7.8	0.9	2.4	5.2	1.4
2011	1.3	2.4	6.7	2.2	5.2	0.8	1.8	4.5	1.1
2012 (1H)	0.9	2.0	5.2	2.0	2.9	0.6	1.2	4.5	0.9
Qrtly peak	2009 Q4, 4.0	2009 Q2, 3.6+	2010 Q1, 14.5	2009 Q4, 2010 Q1, 3.3	2009 Q4, 9.9	2010 Q4, 1.2	2010 Q4, 2.7	2009 Q4, 6.6	2009 Q4, 1.9

Source: Call Reports. The charge-off rates for 2012 are through June 30. The peak in credit-card charge-off rates was probably artificial, as FAS-167 required banks to put revolving-trust securitisations back onto the balance sheet, with a resulting charge-off surge

ECONOMETRIC MODELLING ISSUES

In conducting onsite supervisory review during the past several years, the authors have observed a common set of econometric issues that arise when model developers incorporate macroeconomic and financial variables into regression-based forecasting models. These issues have generally fallen into those related to regression specification and those related to estimation. Potential remedies for the econometric issues identified below can be found in many econometrics textbooks.

Specification issues

First, in choosing the set of macroeconomic and financial variables to be included as explanatory variables in the regression models, model developers have frequently used pairwise Pearson correlation coefficients between the dependent variable, eg, charge-off rates, and the various macroeconomic and financial explanatory variables to determine the subset of economic variables considered for the final econometric models. Typically, the correlation coefficients are rank-ordered and the three or four economic variables with the largest correlation coefficients are considered for use in the regression specification. This is a rather narrow approach to selecting the final explanatory variables. It is well known, for example, that Pearson correlation coefficients can only detect linear association between variables, and they do not capture significant dynamic nonlinear relationships that could be present. They are also likely to pick up spurious relationships that are driven by a third common variable that is omitted from consideration.

Second, the lag lengths for the macroeconomic and financial variables are typically chosen in an ad hoc manner. Although there are optimal lag-length search procedures that could be used in specifying the lag lengths, these very often are not used. This issue would also apply to the choice of lag length for the dependent variable used in autoregressive models. The choice of lag length for the macroeconomic variables is important, since the use of lags that are too short results in changes to the dependent variable that do not capture the full impact of a macroeconomic shock.

Third, modellers typically have not engaged in a careful and well-documented, empirically-based approach to the choice between levels, log-levels or first differences of the charge-off rate variables and the macroeconomic and financial variables in the top-down regression models. This issue has also been observed for bottom-up loan-level models. Generally, it would be preferable to test the sensitivity of stress-test results to the choice of functional form and variable transformations.

Fourth, there generally has been little or no attention paid to the difference between trend-stationary series and difference-stationary series (ie, those time series with a unit root or stochastic trend). This is considered to be an important specification issue for time-series regression modelling. For most banks, it appeared that only the possibility of difference-stationary data was considered in specifying the regression models. Spurious autocorrelations can easily be induced in a time series showing trend, either by mistakenly removing a deterministic trend from difference-stationary data or by differencing trend-stationary data. Because of this, careful attention should be paid to the type of non-stationarity characterised by the time-series data.

Fifth, the regression models used are for the most part specified as being linear in the macroeconomic and financial variables. The assumption of linearity can impose important restrictions on the responses of the dependent variable for stress-testing analysis. For example, the linearity restriction imposes the following severe properties: symmetry, ie, the magnitude of the responses is the same regardless of whether the macro shock is positive or negative; proportionality, ie, responses are proportional to the change in the macro factor; and history independence, ie, the shape of responses is independent of initial conditions of the macroeconomic variables (Misina and Tessier 2008).

Sixth, the potential for a significant seasonal component in the dependent and predictor variables has been typically ignored. For example, charge-off rates display significant quarterly variation that could be taken into account by including quarterly dummy variables in the top-down regression specifications.

Estimation issues

First, there has been a lack of comprehensive diagnostics to assess the validity of the estimated regression models, including functional form, variable selection and lag-length choice. For example, there has typically been inadequate attention paid to the properties of the regression residuals, such as serial correlation and heteroscedasticity, and the presence of outliers, influential observations and structural breaks. Also problematic has been the use of the Durbin–Watson (DW) statistic to test for serial correlation when lagged dependent variables are used as regressors. The DW test is biased towards accepting the null hypothesis of no serial correlation in such cases, and therefore should not be used.

Second, outlier observations are frequently deleted from the datasets used for estimation. Instead of doing so, robust estimation techniques such as median regression should be explored to address the issue.

Even when model development is sound and robust, the most important test of a model comes when out-of-sample forecasts are compared to actual values in evaluating a model's predictive accuracy.

CONCLUSION

The financial crisis of 2007–9, and the associated severe recession, underscored the need for banks to incorporate economic and market conditions into their retail and wholesale credit risk models in order to produce credible stress loan-loss forecasts. While substantial work has been conducted to develop macro-forecasting models for retail and wholesale credit risk, especially at the largest banks, the industry has not yet established what could be viewed as best modelling practices. In this chapter, some of the internal modelling practices that the authors have observed at national banks, where macroeconomic and financial risk drivers have been incorporated into the quantitative models used to generate retail and wholesale credit loss forecasts and loan-loss reserve estimates, have been discussed. Some of the strengths and weaknesses of the various modelling approaches have also been presented.

The views in this chapter are those of the authors and do not necessarily represent the views of the Office of the Comptroller of the Currency.

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1 Macroprudential bank stress tests are used to assess the key vulnerabilities of the banking system as a whole to macroeconomic and financial shocks. See Foglia (2009), BCBS (2012) and Schuermann (2012) for details.

2 The 2009 SCAP used three macroeconomic variables in its state space for the banking-book stress test: GDP growth, unemployment and house price index. The CCAR bank stress tests in 2011, 2012 and 2013 focused on estimates of projected revenues, losses, reserves and pro forma capital levels under a baseline, a severe and an adversely severe stress economic scenarios. See Schuermann (2012) for a more detailed discussion.

3 Henderson (2009) discussed banks' retail credit risk models, their features and how the models performed during the financial crisis of 2007–9.

4 See SFAS 5, SFAS 11, SFAS 112, and SFAS 114. While those in the industry still referred to these as "FAS-5" and "FAS-114", SFAS 5 has become ASC 450 and SFAS 114 has become ASC 310. The primary components of a bank's ALLL consist of loans collectively evaluated for impairment (the FAS 5 part), loans individually evaluated for impairment (the FAS 114 part) and loans acquired by the bank with decreased credit quality (the SOP 03-3 part). See Thornton (2012) for a detailed discussion.

5 The academic literature has distinguished between non-discretionary and discretionary factors used by banks in setting their loan-loss provisions and reserves. Non-discretionary factors refer to those related to changes in loan credit quality and economic conditions, while discretionary factors refer to those related to income smoothing, regulatory capital management and private information signalling. Floro (2010) conducted an empirical study of the two sets of factors used by banks in setting their loan-loss reserves.

6 For nearly all the types of models discussed here, many model developers have used the Pillar I convention of Basel II and have modelled exposure at default, LGD and probability of default separately in estimating expected losses. These models are more complex and less parsimonious than those that forecast charge-offs directly and, therefore, subject to a higher degree of modelling uncertainty. Despite the loss of parsimony, however, there is evidence that the pool-level charge-off models perform no worse than those using a more granular expected loss approach (Frye and Jacobs 2012).

7 The latter is based on the authors' conversations with industry experts in residential-mortgage recoveries.

8

A Framework for Stress Testing Banks' Corporate Credit Portfolio

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Since the financial crisis of 2007 and beyond, which drew unprecedented attention to the stress testing of financial institutions, stress-tests exercises have become a central risk-management tool to assess the potential impact of extreme events on banks' P&L and balance-sheet structures.

Stress tests are viewed as complementary to traditional risk-measurement metrics such as value-at-risk (VaR), as they are an important mechanism for detecting weaknesses of both a single financial institution and threats to financial stability. Nowadays, financial institutions are required to perform regular exercises within Pillar II of the regulatory framework of the Basel Accord in order to assess the global impact of adverse events or changes in market conditions on banks' capital adequacy. Supervisory authorities as well are used to leading such exercises: the International Monetary Fund (IMF) with its regular Financial Sector Assessment Program, the European Banking Authority (EBA) with its European "bottom-up" stress tests, including a disclosure step, and national supervisory authorities, which all have built dedicated tools, especially for regular top-down exercises. The scope of stress testing includes traditional credit risks, market risks, operational risks, interest-rate risks and, since the financial crisis, liquidity risks.

Stress testing corporate credit risk, also known as "wholesale credit risk", is a key component of stress testing for global institutions. Credit risk in itself (including retail credit risk) is indeed one of the major sources of risk for banks, judging by the extent of banks' credit risk-weighted assets (RWAs),[1] and, accordingly, may have a major impact on the solvency of financial institutions. The subprime crisis has highlighted the need for stress testing banks' portfolios as numerous credit institutions incurred major losses and write-downs from structured US subprime related assets since mid-2007.

This chapter examines stress testing for credit risk, focusing on risks arising from corporate loans and other credit exposures.[2] It aims at introducing a Basel II-type modelling framework to perform credit stress-test scenarios through credit migration matrices (or transition matrices), which has been implemented by French authorities and is currently used as a tool for top-down stress-test exercises. This approach is still relevant under the Basel III framework, since nothing new has been introduced in the Basel III framework with respect to the assessment of credit risks of banks' corporate portfolios.

The chapter is organised as follows: the first section briefly depicts the model our stress-test framework rests on, which is largely based on the Merton model; then we introduce the way this framework is implemented to conduct top-down stress-test exercises; finally, we comment on a few outputs of the stress tests.

THE MODEL SPECIFICATION

Several models are available for quantifying credit risk, this risk stemming either directly from actual defaults of credit exposures, or indirectly from migrations of credit ratings, taking into account their prudential treatment.[3] These models may be either structural (modelling of firms' value and capital structure) or reduced forms, where credit events are exogenous to the firms. Here we rely on the latter approach, with credit events triggered by macroeconomic shocks, and focus on credit migrations (see ECB, 2007, for alternative industry credit models).

The model we introduce in this section relies on the basic idea that the evolution of rating transitions can easily be linked to a synthetic credit indicator.[4] The main hypothesis is that the underlying asset value of a firm evolves over time, through a simple diffusion process, and that default is triggered by a drop in firm's asset value below the value of its callable liabilities. In the Merton framework, shareholders actually hold a call option on the firm, while debtholders hold a put option.

General specification

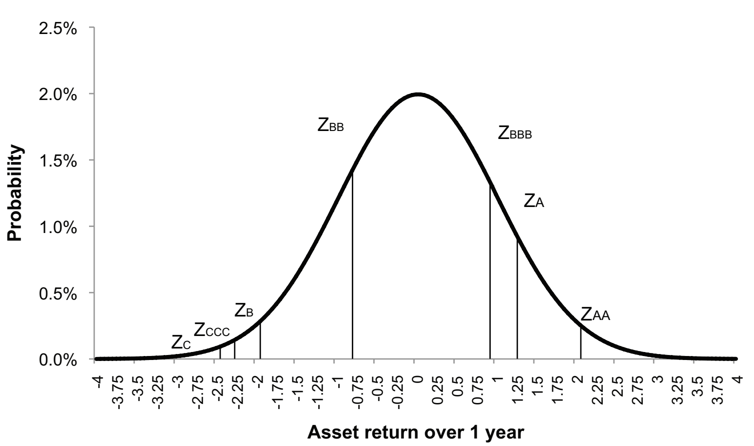
Based on the assumption that changes in the logarithm of the firm's asset value ($\Delta \log A_i$) can be related to both a systemic factor (Z, the credit index) and an idiosyncratic factor (ε_i) via a factor model, the specification is the following for firm *i*:

$$\Delta logA_{i,t} = -\sqrt{\rho}Zt + \sqrt{1-\rho}\varepsilon_{i,t} + c_i$$

where c_i is the long-run growth of firm i's asset value and ρ is the asset correlation between any two firms in the portfolio. All firms are supposed to have identical characteristics (eg, their correlation to *Z*) with respect to their credit rating, which then leads us to identify i as a credit class rather than an entity.

Assuming, then, that changes in asset value are normally distributed (*Z* and ε_i are mutually standard normal variables and mutually independent), the default probability may be expressed as the probability of a standard normal variable falling below a critical value, defined as the different ratings (with a total of n classes, with n=8). Similarly, thresholds can be set up for rating migrations, as graphically represented in Figure 8.1.

Figure 8. 1 Asset return distribution with rating thresholds for BBB issuers



This framework, on which is also based the Basel II Asymptotic Single Risk Factor (ASRF) model, results in the following relations with respect to default probabilities:

$$PD_i \,|\, \{Z_t = \Phi^{-1}(\alpha)\} = \Phi\left[\frac{\Phi^{-1}(\overline{p}_i) + \sqrt{\rho}\,\Phi^{-1}(\alpha)}{\sqrt{1-\rho}}\right]$$

where PD_i |{...} is the (conditional) default probability in state Z, Φ is the Gaussian cumulative distribution function, $\overline{p}_i$ is the long term average probability of default (PD) of class i (i=1,…n) (or unconditional PD) and α is the probability that the value Z (or below) occurs. The closer α is to 0, the less frequent is the crisis and the greater its severity. In the Basel II framework, α is equal to 0.1% (this corresponds to the regulatory confidence level of 99.9%, which is the required confidence level to compute regulatory capital requirements under Basel II & III frameworks). In our application we use n=8 risk classes, where class 8 stands for the default class. Default probabilities along with rating migrations depend on a sole parameter (Z_t, the credit latent index discussed below), meaning that migrations matrices can be modelled through one macro factor (ASRF: Asymptotic Single Risk Factor).

This formula, expanded to every component of the nxn (here 8x8) transition matrix, is:

$$P_{ijt} = \Phi\left[\frac{\Phi^{-1}(\overline{P}_{i8} + \ldots + \overline{P}_{ij} \;+ \sqrt{\rho}\, Z_t}{\sqrt{1-\rho}}\right] - P_{i8t} - \ldots - P_{i,j+1,t}$$

This approach, which aims at representing transition matrices by a single parameter, was studied by Belkin, B., Forest, L. R. Jr and Suchower, S. J. (1998). They follow the CreditMetrics framework proposed by Gupton, Finger and Bhatia (1997).

Estimation of the correlation factor

The correlation factor ρ between the obligor i and the general state of the economy (in the ASRF model, all obligors are linked to each other by this single risk factor Z, which reflects the general state of the economy) has been estimated in order to obtain the best possible fit of historical data by the model, under the hypothesis that the correlation is the same for all obligors (and thus rating classes).

THE STRESS-TESTING FRAMEWORK

The following framework is based on a relationship between the latent credit index and the macroeconomic situation. This link is indeed fundamental, since most stress-test exercises start with the choice of a set of macroeconomic stress scenarios. Those stress scenarios are then linked to risk parameters – default rates (DRs), loss rates, regulatory PDs, regulatory LGDs, transition matrices – which will, in the end, affect banks' solvency.

Our approach is based on an intermediary variable, namely the aggregate DR. First, we measure the link between GDP (or the macroeconomic scenario) and the DR, then between the DR and the latent credit index, in order to compute the stressed transition matrix.

The different steps described here are based on relationships uncovered for France, in particular regarding the link between credit risk and the macroeconomy, but we explain how they may be replicated for other institutions / countries.

The data

Adequate data is of course necessary for calibrating the model. While specific information on the loan portfolios of institutions are essential, we show how to rely on S&P transition matrices,[5] a method that can be to some extent transferable to other institutions / countries as long as they have a similar global portfolio of corporate loans.

Prudential Common Reporting

Our framework basically requires information on the structure of banks' portfolios by types of rating. They are available from banks' Prudential Common Reporting (COREP).[6] COREP is a set of European harmonised data on solvency issues (own-funds adequacy, credit RWAs, market RWAs, operational RWAs) handled by the EBA. It intends to enhance the level of harmonisation of the supervisory reporting. A specific COREP template is dedicated to the credit risk of IRB corporate portfolios, in which the regulatory PDs for each class of risk are reported to the French authorities by banks in the quarterly prudential COREP templates.

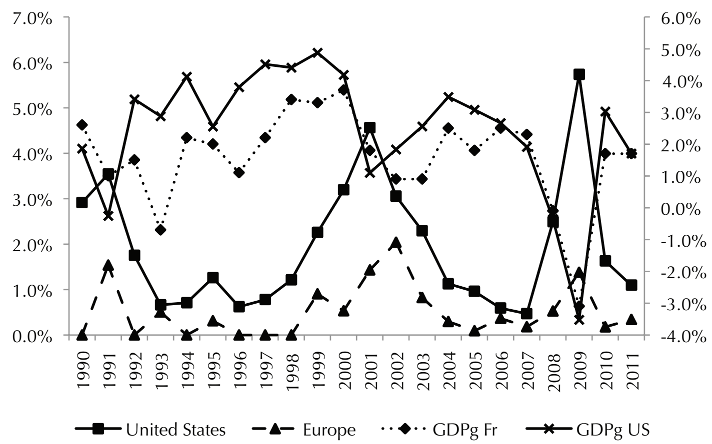
This information is actually combined with mappings (provided by the onsite-inspections division) that convert the internal rating system of each bank into the S&P rating scale. This step is facilitated by the fact that most banks use such a conversion scale to compute, when possible, a distance between their internal rating and agency ratings, as an indicator for assessing the performance of their internal models. This is a necessary step in order to stress banks' portfolios by using S&P transition matrices.

The S&P transition matrices

Our framework takes advantage of the S&P CreditPro database, which contains issuer ratings history for 15,726 obligors over the 1981–2011 period, of which 2,127 ended in default. The obligors are mainly large corporate institutions – sovereigns and municipals are excluded – and pools include both US and non-US industrials, utilities, insurance companies, banks and other financial institutions, and real-estate companies.[7]

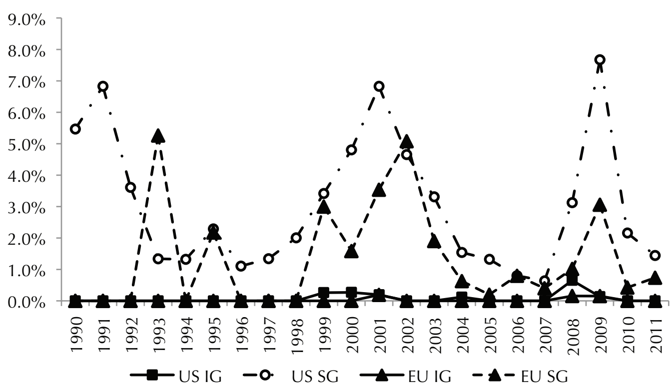
Over the past two decades from 1990 to 2011, three major business cycles can be distinguished: (i) the recession that took place in the wake of the First Gulf war at the beginning of the 1990s (GDP growth dropped to −0.3% in 1991 in the US and to −0,7% in 1993 in France); (ii) the burst of the Internet bubble (GDP growth dropped in the US to 1.1% in 2001 from over 4% from 1998 to 2000, while in France GDP growth declined to 0,9% in 2002 and 2003 from over 3.5% in 2000); and (iii) the 2007-and-beyond subprime crisis (both American and French GDP growth dropped to less than −3% in 2009).

Figure 8.2 Default rate according to S&P (left scale) and GDP growth (right scale) over the 1990–2011 period



During each of these periods, DRs surged both in Europe and the US (see Figure 8.2). It is especially striking after the burst of the Internet bubble, during which (i) the DR of American corporates reached the level of 4.5% (2% in Europe) and (ii) the total amount of debt-defaulting was historically high due to failures of major companies (Enron, WorldCom, Parmalat and so on). DRs during the subprime crisis surged even higher in the US (5.70% in 2009).

Figure 8.3 Default rate according to S&P over the 1990-2011 period for both speculative-grade (SG) and investment-grade (IG) obligors



If DRs, and, more globally, credit migrations, are therefore clearly linked to the economic context, it turns out that default events mainly involve speculative-grade obligors (rated BBB and below). Investment-grade obligors are much less sensitive to the business cycle, underlining two different dynamics for investment-grade corporates on the one hand, and for speculative-grade (which is actually the main driver of the global DR) on the other hand (see figure 8.3).

In Table 8.1, annual S&P transition matrices displaying probabilities to migrate from one rating to another are based on a "static pool approach". Credit-migration rates are computed by comparing ratings on the first and last days of the year to construct the migration rates. Rating movements within the year are accordingly not counted. This estimation approach, based on average behaviour, does not actually capture rare events such as back-and-forth transitions or series of consecutive downgrades within the year. Default is considered to be an absorbing risk class: if a recovery from default may be observed, it is extremely rare. Usually, firms having defaulted are excluded from the pool the following year, which prevents the recovery trajectory to ever be caught in a one year transition matrix.

Table 8.1 S&P average credit rating transition matrix (1990–2011)

	AAA	**AA**	**A**	**BBB**	**BB**	**B**	**CCC, CC, C**	**D**
AAA	90.2%	8.9%	0.5%	0.2%	0.0%	0.0%	0.2%	0.0%
AA	0.3%	89.3%	9.8%	0.6%	0.0%	0.0%	0.0%	0.0%
A	0.0%	2.1%	92.3%	5.1%	0.2%	0.1%	0.0%	0.0%
BBB	0.0%	0.1%	4.2%	91.2%	3.4%	0.7%	0.1%	0.2%
BB	0.0%	0.1%	0.4%	5.1%	86.9%	6.4%	0.5%	0.6%
B	0.0%	0.0%	0.2%	0.5%	7.1%	82.7%	4.8%	4.7%
CCC, CC, C	0.0%	0.0%	0.3%	0.6%	1.1%	13.0%	58.1%	27.1%
D	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%

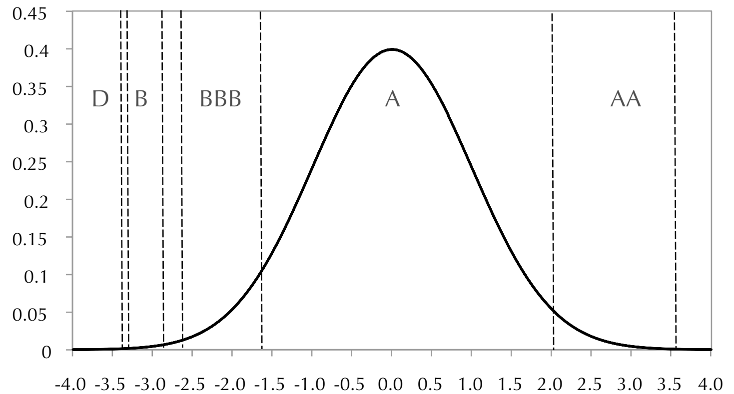
As we have seen, migration matrices may be driven by a standard normal distribution – (almost) without losing any information. Migrations are then not depicted by migration rates but through a set of thresholds that depend on the latent variable Z.

As an example, we suppose that an issuer is currently rated A. Table 8.2 and Figure 8.4 show the migration probability from the current A rating to any of the other eight ratings, together with the corresponding threshold from a standard normal distribution.

Table 8.2 Migration rates and scores for an A-rated issuer (1990–2011)

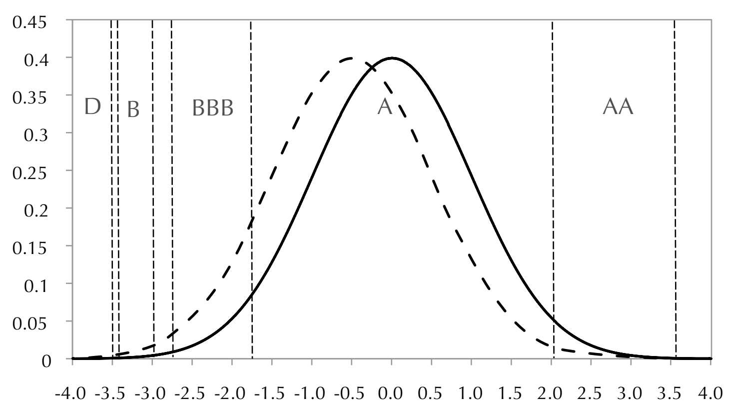
	AAA	**AA**	**A**	**BBB**	**BB**	**B**	**CCC, CC, C**	**D**
Migration rates	0.0%	2.1%	92.3%	5.1%	0.2%	0.1%	10.0%	0.0%
Score bins	]3.61 ; +∞[	]2.03 ; 3.61]	]-1.60 ; 2.03]	]-2.64 ; -1.60]	]-2.88 ; -2.64]	]-3.25 ; -2.88]	]-3.30 ; -3.25]	]-∞ ; -3.30]

Figure 8.4 Rating thresholds and transition probability distribution for an A-rated issuer



Under adverse economic conditions, the normal distribution of rating migration would shift to the left, implying worse ratings levels (see figure 8.5), meaning that the probability of downgrade and default increases. As the whole credit-migration matrices are driven by a single-parameter Z, which depicts the average financial health of corporate institutions (credit index), this shift corresponds to a simple change in the value of Z.

Figure 8.5 Rating thresholds and transition probability distribution for an A-rated issuer after a shift to the left (–0.5)



The economic situation: linking GDP to the aggregate default rate

In order to calibrate the model, we need to measure the link between the macroeconomic environment and defaults. The results presented here are specific to the French situation, hence would need to be re-estimated to implement it inn other countries. However, the method is quite general and can be replicated, following the same steps. This implies:

- ❑ defining an economic situation scale, as a percentage deviation from maximum defaults;
- ❑ linking defaults to (national) macroeconomic determinants; and
- ❑ mapping the aggregate DR into the latent credit index, and we offer a numerical method for doing that.

The model we present is mainly designed to compute RWAs, through PDs linked to the macroeconomic environment. The impact of stressed scenarios on P&Ls, including credit losses, is computed through another model (Coffinet, Lin, Martin, 2009; Coffinet and Lin, 2010).

The economic situation scale

Our economic situation index is the DR since this is both highly correlated to macro-variables like the GDP and directly linked to the situation of corporate institutions.

In our stress-test framework, the state of the economy is accordingly measured on the following scale:

$$\lambda_t = \frac{\widehat{DR_t} - \overline{DR}}{DR_{crisis} - \overline{\overline{DR}}}$$

where $\widehat{DR_t}$ is the DR forecast at t and $\overline{DR}$ is the average DR over the sample period and DR_{crisis} is the DR reached during the worst crisis observed over the period under observation (in our example, this is computed as a mean of yearly DR for the years 1991, 2001, 2002, 2009). λ_t equals 0 on average over the business cycle, 1 when the reference crisis is reached. If λ_t equals 0.33 for example, the economic situation would be one-third of the maximum historical deviation from the average DR.[8] This scale is unbounded so as to suit stress scenarios which never occurred previously.

Forecasting the default rate in a stress-testing exercise

The link between the DR and the macroeconomic environment may obviously be subjected to more discussions than those presented below. We aim through this couple of equations to provide some alternative specifications for the link between the DR and the economic situation, using different macroeconomic variables. These equation can be used in order to project the DR over the simulation horizon of the stress tests (each scenario would consist of time series of GDP, inflation, interest rates and so forth) that would be fed into the equation to get a DR scenario. The equations are estimated by Ordinary Least Squares. These equations should be re-estimated for implementing our model to other countries.

$$\begin{cases} DR_t = \underset{(0.0003)}{2.565}^{***} + \underset{(0.0038)}{0.579}^{***} DR_{t-1} - \underset{(0.0010)}{0.379}^{***} GDPg_t - \underset{(0.0021)}{0.887}^{***} INFL_{t-1} \\ R^2 = 0.67, DW = 2.17 \end{cases} \tag{8.1}$$

Where DR is the default rate, GDPg is GDP growth, INFL is the inflation

$$\begin{cases} DR_t = \underset{(0.0019)}{2.673}^{***} - \underset{(0.0077)}{0.372}^{***} GDPg_t - \underset{(0.0345)}{0.705}^{**} INFL_{t-1} \\ R^2 = 0.39, DW = 1.05 \end{cases} \tag{8.2}$$

$$\begin{cases} DR_t = \underset{(0.0077)}{3.584}^{***} + \underset{(0.0286)}{0.478}^{**} DR_{t-1} - \underset{(0.0032)}{0.348}^{***} GDPg_t - \underset{(0.0074)}{0.798}^{***} INFL_{t-1} - \underset{(0.3278)}{0.125} UR_t \\ R^2 = 0.70, DW = 2.15 \end{cases} \tag{8.3}$$

Where URt stand for the unemployment rate at t.

$$\begin{cases} DR_t = \underset{(0.0012)}{2.4512}^{***} + \underset{(0.0055)}{0.5718}^{***} DR_{t-1} - \underset{(0.0017)}{0.3744}^{***} GDPg_t - \underset{(0.0050)}{0.8508}^{***} INFL_{t-1} + \underset{(0.6097)}{0.0507} SPREAD \\ R^2 = 0.68, DW = 2.12 \end{cases} \tag{8.4}$$

Where SPREAD is the spread between the interest rates on the ten-year French Treasury note and the three-month Euribor.

Among the prominent points highlighted by these equations are as follows.

- THE INERTIA OF THE DR: The DR inertia, ie, the autoregressive coefficient in equations (1), (3) and (4), is both strong and significant: past values of the DR provide good forecasting results.

- THE INDICATORS OF THE STATE OF THE ECONOMY: According to the range of econometric tests, led by the ACP, the most relevant economic variables with respect to DR forecasting are GDP growth and the unemployment rate.
- THE FINANCIAL ENVIRONMENT. The spread between long-term interest rates (10y) and short-term ones (3m) used in equation (4) is both classical and relevant. However, its impact is often mild and positive.[9]

In addition, it might be interesting to integrate feedback effects between defaults and the business cycle (Bruneau, de Bandt and El Amri 2012).

The "conversion" function: mapping the aggregate default rate into the latent credit index to generate the stressed transition matrix

The final step is to map our time series of defaults (more precisely of our economic situation scale, which is a simple transformation of defaults, as indicated earlier) into our latent macroeconomic systemic factor on which the transition matrices are based. We provide here a numerical method for doing that, which could be easily replicated. We thus define a second conversion scale in order to convert the crisis percentage into the corresponding stressed transition matrix.

For that purpose, we consider the actual transition matrix observed when the economy enters into the recession periods mentioned above (namely in 1991, 2001–2 and 2009).[10] We compare that matrix to the unconditional transition matrix over the sample period. The latter matrix can be viewed as a through-the-cycle transition matrix.

More precisely, we define a scale based on the couple $Z_{0\%crisis}$ and $Z_{100\%crisis}$, which are the two credit indexes that respectively best fit (i) the through-the-cycle transition matrix (TM_{TTC}) as the average of transition matrices observed over the period and (ii) the "crisis" transition matrix (TM_{crisis}) as an average of the transition matrices observed in 1991, 2001, 2002 and 2009. Note that we chose a simple average transition matrix conditional on exceeding the probability of 82% (which would be equivalent to the 4 worst observations in a 22-year sample). However, we could have used variable weights over time to compute an average transition matrix highlighting different crisis episodes (banking- or industry-related crisis).

From the comparison of the observed and asymptotic single-risk-factor (ASRF) transition matrices we derive the value of the latent macroeconomic systemic factor corresponding, respectively, to "normal times" and "crisis":

$$\begin{cases} \hat{Z}_{0\% crisis} = \arg\min_{Z_t} \left| TM_{TTC} - TM(Z_t) \right| \\ \hat{Z}_{100\% crisis} = \arg\min_{Z_t} \left| TM_{crisis} - TM(Z_t) \right| \end{cases}$$

Several kinds of matricial norms can be used: we chose the Euclidian norm, typically used in linear optimisation problems. Assuming the relationships $Z_t = Z_{0\%} \Leftrightarrow \lambda_t = 0$ and $Z_t = Z_{100\%} \Leftrightarrow \lambda_t = 1$ between the state of the economy and the credit index, the final step is to compute the value of the macroeconomic systemic risk, which comes from the following "conversion" function:

$$Z_t = [(Z_{100\% crisis} - Z_{0\% crisis}) \times \lambda_t + Z_{0\% crisis}]$$

where λ_t depends on the spread between the long-term average DR and the one forecast over the stress horizon. The stressed transition matrix is then used to compute the level of RWAs (under the large corporate parameters of the Basel II formula, using regulatory PDs).

We should mention that, in our stress-test framework, the transition matrices do not depend on one parameter Z but on two parameters ($Z_{investment\ grade}$; $Z_{speculative\ grade}$) in order (i) to stick to a simple approach – we could have as many credit indexes as notches within S&P transition matrices – and (ii) to reflect the two distinct regimes followed by investment-grade and speculative-grade obligors. Indeed, as depicted earlier in this chapter, global DRs are largely driven by the credit quality of speculative-grade counterparties, so that the identified crisis periods are periods of crisis for speculative-grade obligors, rather than for investment-grade ones. Practically, this means that two sets of parameters ($Z_{0\% crisis}$, $Z_{100\% crisis}$) have been estimated, one on the investment sub-part of the TTC and crisis matrices, and one on the speculative sub-part.

NUMERICAL APPLICATION

We present now a few outputs of the model for stress testing. First, we provide more detailed information on necessary inputs, namely banks' exposures. We then use the model presented in the section "The stress-testing framework" above to compute ratings migration on banks' portfolios, hence to compute the level of RWAs under stress. We present the aggregate results for our sample of five of the largest French banks in a baseline and a stressed scenario.

Composition of French large banks' corporate credit portfolio and evolution over time of exposures at default

An initial portfolio is made up of corporate credit exposures of the five largest French banks. Information on exposures and risk profile[11] is available in COREP reports. Banks' portfolios are relatively diversified in terms of sectors. Most exposures are investment-grade and are mainly located in Europe and North America.

Based on this information, we need to compute the evolution over time of exposures at default (EAD).

Let us assume that the horizon of the following exercise is two years, so, starting from end-year 0, the stress test ends Year 2.

Starting with a portfolio of assets in different rating categories, we compute how the portfolio changes over time following a shock. This implies computing a stressed transition (or migration) matrix with the probability of moving from one rating category to another. Technically, this is a Markov chain matrix, assuming that all information at time t+1 is contained at time t.

Furthermore, banks' balance sheets are supposed to be static (as opposed to dynamic), meaning that the total non-defaulted exposures remain stable over the stress period. The assumptions made in our example could very well be modified.

Calculation of risk-weighted assets and capital requirements for credit risk.

Formally, considering an initial portfolio with a given risk structure $EAD0,i$ at time 0 with $i=AAA, AA,\ldots,D$, the dynamic behaviour of the portfolio has the following form:

$$EAD_{t,i}=EAD_{t-1,i}[TM_t^{stress}(Z_{IG};Z_{SG})+\Delta EAD_t]$$

The portfolio risk structure depends on the credit migration matrix, which is a function of macroeconomic and financial factors . $\Delta EADt$ is the growth of new loans; it is adjusted so as to comply with the static balance-sheet constraint. Regulatory capital requirements are then calculated according to the Basel II formula.

We consider the two hypothetical following scenarios:

- a baseline scenario based on GDP growth projections from the IMF's World Economic Outlook (WEO); and
- an adverse scenario that is supposed to lead to a maximum cumulated deviation from baseline of two standard deviations of GDP growth for 2012–13.

Table 8.3 shows the main key macroeconomic factors that drive our two scenarios.

Table 8.3 Macroeconomic variables' forecast used for a stress-test simulation

	Baseline		Adverse	
	2012	**2013**	**2012**	**2013**
Inflation (%)	1.7	1.5	1.3	0.2
GDP real growth (%)	0.5	1.0	–1.9	0.0

The main outcomes under these two scenarios, in terms of risk parameters (regulatory PDs) and capital requirements (RWA levels), which are the main final output of our stress-testing framework, are displayed in Table 8.4. Changes in RWAs in the table are computed as the sum of changes in RWAs over five of the largest French banks.

Table 8.4 Main outcomes under the baseline and adverse scenarios

	Baseline		Adverse	
	2012	**2013**	**2012**	**2013**
Stressed regulatory PDs (annual rate of change)	+2%	+12%	+15%	+11%
RWAs (annual rate of change)	+2.6%	+5.3%	+12.9%	+5.9%

Table 8.4 shows the outcome of this sensitivity analysis in which regulatory PDs[12] and migration rates were stressed over the 2012–13 period. It is worth noticing that other regulatory parameters, such as LGD and correlations, have not been stressed in this particular exercise. The results in Table 8.4 illustrate the existence of a smoothing effect of the stressed scenario on RWAs, due to the negative relationship between regulatory PDs and the correlation with the credit index (ρ), as assumed in the internal-ratings-based (IRB) model.

The outcome of this simulation shows that the sensitivity of IRB minimum capital requirements to increases in regulatory PDs and credit migrations is significant. Indeed, an increase of PD by 15% in 2012 (resp. 13% in 2013) in the adverse scenario raises capital requirements by about 11% (resp. 5.9% in 2013). Moreover, the initial shock, a deep recession in 2012, raises both risk parameters and capital requirements at least up to 2013. This is consistent with our expectations, since Basel II formulas rely on through-the-cycle PDs, which tend to smooth the impact of the shock at the very beginning of the stress but makes it last longer.

CONCLUSION

Credit risk remains one of the most important risks faced by commercial banks. This chapter provides a stress-testing framework for banks' corporate credit portfolios, a framework that is currently used by French authorities to perform biannual top-down exercises.

This framework is therefore appropriate for data available at a supervisory authority level and aims to achieve the best trade-off between simplicity and robustness. Our stress-test framework takes advantage of the quarterly prudential COREP templates and of the S&P CreditPro database, which provides statistics over the previous two decades regarding credit migration of more than 10,000 American and European companies.

The calibrations proposed – namely AR models for observed DRs, which assume stationary explanatory variables as well as mean reversion dynamics – are consistent with the Basel II framework, which relies on through-the-cycle risk parameters (PDs). This framework is therefore fully relevant for benchmarking bottom-up exercises. Furthermore, from a regulatory point of view, this framework is a realistic approach to how banks compute their RWAs: regulatory parameters, such as PDs and LGDs, are estimated as through-the-cycle parameters, possibly with an add-on coefficient for prudence (taking into account downturn economic conditions for LGD). As a consequence, they tend to become less and less sensitive to a given stress period, given that they are based on ever-increasing historical datasets. It is indeed important in our view that the stress-testing framework be as close as possible to the actual regulation governing the computation of RWAs.

Views expressed do not necessarily correspond to those of the Autorité de Contrôle Prudentiel.

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1 In the case of France, credit-risk RWAs represents more than 75% of total RWAs.

2 Exposures from structured credit products or from over-the-counter (OTC) derivatives exposures are not covered here.

3 Prudential filters may sometimes dampen the effect of marked-to-market gains or losses.

4 See Dumontaux and Médée, 2009.

5 See Standard and Poor's (2012) and Standard and Poor's (2007).

6 For any further information, see http://www.eba.europa.eu/Supervisory-Reporting/COREP.aspx

7 The structure of the corporate portfolio of French banks, dominated by international groups, allows the use of such a reference sample to calibrate their stress-testing framework. It could therefore be extended to other global banks, once we are ready to assume that all global banks tap the same markets, in terms of risk characteristics, but differ in terms of portfolio composition.

8 Actually, it is one-third of the deviation between the average default rate and DRcrisis (the mean of yearly DRs for the years 1991, 2001, 2002, 2009).

9 There is a vast literature on the forecasting properties of the slope of the yield curve.

10 Notice that we consider the recession dates in the US since the database we used is based on a sample of US and European firms, also assuming that large corporates are global companies significantly affected by the US business cycle. In the practical implementation of stress tests, however, we assume that this calibration also holds for the portfolio of corporate assets held by French banking groups. Such an assumption is imposed by the data constraints (ratings on corporate assets as provided in the Banque de France FIBEN database are available only with a lag, preventing their use in real-time stress testing).

11 The breakdown by rating is given by the S&P equivalent of internal rating.

12 Regulatory PDs, consistent with Basel II regulations, are estimated as a long-term moving average of observed default rates; a stressed default rate, which is produced by our model, is therefore included in the new time window at the end of each year, thus yielding a stressed regulatory PD.

9

EU-Wide Stress Test: The Experience of the EBA

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In the midst of the financial crisis, the European Banking Authority (EBA) was established on January 1, 2011, with a broad remit that included safeguarding the stability of the EU financial system.[1] According to its founding regulation,[2] the EBA is required, in cooperation with the European Systemic Risk Board (ESRB), to initiate and coordinate EU-wide stress tests to assess the resilience of financial institutions to adverse market developments. While the stress test is a key component of the EBA's toolkit, it is only one of a range of supervisory tools used by the EBA for assessing the resilience of individual institutions as well as the overall resilience of the European banking system.

The first EU-wide stress test of 22 banks was performed by the Committee of European Banking Supervisors (CEBS), the EBA's predecessor, in 2009. The individual results of the stress test were kept confidential. Only a press release was published with the key results. Some details of the macroeconomic scenario were published (GDP, unemployment and property prices). Furthermore, the results were published in a very concise manner:

> Under such adverse scenario, the potential credit and trading losses over the years 2009–2010 could amount to almost €400 bn. However, the financial position and expected results of banks are sufficient to maintain an adequate level of capital also under such negative circumstances. Notably, the aggregate Tier 1 ratio for the banks in the sample would remain above 8% and no bank would see its Tier 1 ratio falling under 6% as a result of the adverse scenario.[3]

In 2010, CEBS performed another EU-wide stress test among 91 banks; an aggregate report was published as well as individual bank results. The individual bank results consisted of a single page with the level of Tier 1 capital, risk-weighted assets (RWAs), losses and loss rates for both scenarios (baseline and adverse).

Building on the experience of two previous EU-wide stress tests undertaken by CEBS, the EBA conducted a stress test among 91 banks in 2011. This exercise was undertaken in coordination with National Supervisory Authorities (NSAs), the ESRB, the European Central Bank (ECB) and the European Commission (EC).

The exercise was conducted on a bank-by-bank basis, on the highest level of consolidation of the banking group. The objective of the stress test was to assess the resilience of the EU banking system, and the specific solvency of individual institutions, to hypothetical stress events under certain severe scenarios decided on by supervisors in conjunction with the ESRB/ECB. It was a microprudential stress test focused primarily on assessing banks in a bottom-up manner in a way that is conservative and consistent across the EU.

In this chapter we describe the EBA's experience in carrying out the EU-wide stress test, with a focus on 2011, and provide some insights into the design, organisation and management of such a complex exercise. After a first, introductory section, we move to the summary of the main findings of the stress test and conclude with our views on the lessons learnt from the 2011 exercise.

KEY CHARACTERISTICS OF THE EBA 2011 STRESS-TEST EXERCISE[4]

The 2011 EU-wide stress-test exercise was characterised as a constrained bottom-up stress test. While banks are required to use their internal models for estimating possible losses in a stress scenario, the EBA identified common minimum methodological assumptions, imposed a single adverse scenario and carried out an in-depth quality-assurance process. This is probably the most important feature of the EBA's stress test, a precondition for ensuring comparability of the results across institutions from different countries and a level playing field in the implementation of supervisory measures following the stress test.

Therefore, the organisation of an EU-wide stress test requires complex preparatory work, involving both methodological and procedural aspects. For the 2011 exercise, the preparatory phase started in September 2010, and 10 months later the bank-by-bank results were published.

The first step in running an EU-wide stress-test exercise was to define the sample of banks to be involved and objective of the exercise. As for the former, the 2011 exercise was carried out among 91 banks at consolidated bank group level. The selection of the sample was based on representativeness (50% of national banking sector and 65% of the European banking sector), with the possibility for NSAs to add additional banks when deemed relevant from a financial stability perspective. The objective was to assess the overall resilience of the EU banking system and to identify possible capital needs at specific institutions.

In fact, the EU stress test has been – like similar exercises carried out in other countries during the financial crisis – a pass/fail test: banks that proved to be not able to maintain enough capital in the adverse scenario have been requested to raise new capital or to activate mitigating measures, if available.

The second step in the process is developing the macro scenario. The baseline scenario was based on the European Commission forecasts, while the adverse scenario has been developed by the ECB in cooperation with the ESRB. The stress-test horizon was set at two years, as in many regulatory stress tests. The adverse scenario was composed of three elements: (1) a set of EU-shocks mostly tied to the persistence of the sovereign debt crisis, (2) a global negative demand shock originating in the US and (3) a USD depreciation vis-à-vis all currencies. In the adverse scenario the cumulative GDP drop in the EU was 4%, with a fall of the residential house price by 15% at EU level. Besides the macro scenario for positions in the banking book, market-risk shocks were designed for stress testing the positions in the trading book as well. The market-risk shocks were aligned with the macro scenario. For example, share prices within Europe decreased by 15% instantaneously in the adverse scenario. Furthermore, a specific stress scenario was applied for securitisation positions in the banking and trading book. To that end, predefined migration matrices for the baseline and adverse scenario were used, based on historical experience.

The third step in the process is designing the stress-test methodology. As mentioned above, the EBA 2011 stress-test exercise was carried out by following a constrained bottom-up approach. A bottom-up stress test is a microprudential test that relies on specific idiosyncratic data and approaches (for example, banks used their internal models – where available – to calculate the impact of the stress test on the balance sheets and the profit-and-loss accounts). But the exercise was constrained by a series of EBA-prescribed restrictive assumptions and a common macro scenario. The design of the methodology was a challenging task aimed at striking the right balance between realism and conservatism, respecting the banks' specificities and ensuring consistency of treatment and comparability of the results. While this is common to different system-wide exercises, the EU setting required extra effort in order to ensure consistency across banks belonging to different jurisdictions and subject to not-fully harmonised rules and supervisory practices.

In general, the methodology was designed in respect of the existing and forthcoming prudential and accounting rules applicable in the time horizon of the exercise, notably the International Accounting Standards (IAS) and the Capital Requirement Directive (CRD) and amendments. Two main features were thus the application of the prudential filters and the application of the amortised cost for the assets booked in the held-to-maturity portfolio (EBA 2011a).

Another important element for the credibility of the entire exercise was to define the capital threshold in terms of Core Tier 1 ratio (CT1). Notwithstanding the lack of a consistent definition of CT1 capital in the pre-Basel III regulation, the EBA decided to deduct hybrid capital instruments from the Tier 1 capital, in order to identify a common definition in line with – even though not equal to – the Basel concept of common equity Tier 1. Government support measures were recognised as eligible CT1 capital. By setting a common definition of CT1 capital, comparability across the banks involved in the exercise was ensured. The threshold was set at 5%, which banks were expected to meet after taking into account the impact of the adverse scenario.

A key assumption designed to ensure consistency in the constrained bottom-up approach, and which had a large impact on the results of the stress test, was considering banks' balance sheets as static over the time horizon of the exercise, ie, no management actions were allowed for mitigating the impact of the adverse scenario (static balance-sheet assumption). In practice, this implied a constant business mix, constant funding mix, a zero growth rate, the rollover of maturing assets and liabilities and no workout of defaulted assets. This approach guaranteed comparability of the results across banks and a level playing field, at the cost of reducing the realism of the exercise (see also the last section).

The methodology also imposed some constraints on the stress test's starting point. In particular, banks were requested to subtract the PL-impact of the market risk shocks on the trading book portfolio from the average net trading income of a bank over the last five years. Since estimating net trading income before stress would have been difficult, using a historical average represented a simple and conservative benchmark. Furthermore in order to incorporate funding risk, the EBA prescribed to a certain extent the evolution in the cost of funding. For example, the interest expenses to be paid for wholesale funding had to increase according to the evolution of the interest rate envisaged in the macroeconomic scenario. Another assumption prescribed was that there is a perfect correlation between the evolution in the sovereign credit spread and that in the bank's credit spread. Furthermore, banks have only been allowed to pass up to 50% of the cost of funding increase to the clients through a potential adjustment to the credit spread on the maturing loans.

The reliability of the results and the comparability across banks were then assured through three lines of defence (EBA 2011c): (i) the banks' own internal controls, (ii) the consistency checks carried out by the national supervisors and (iii) a quality assurance process carried out by the EBA.

This last line of defence was a new aspect of the 2011 stress test, with an ad hoc task force in charge of performing a thorough peer review and assessing the proper application of the common methodology. This level of cooperation, with national experts coming to join EBA staff for a prolonged period in assessing results, was a step forward in stress-test cooperation in the EU. Banks' results, in particular in terms of risk parameters for credit risk, have also been compared and outliers identified. The computation of benchmarks has been performed using the granular data collected by the EBA, including exposures at default (EADs), probabilities of default

(PDs) and loss-given defaults (LGDs) with asset-class and counterparty countries' breakdowns. However, it is worth underlining that no asset quality review was undertaken ahead of or during the stress-test exercise. This is in the remit of national supervisors.

In some cases, banks were required to revise their estimates in order to bring them into a more consistent range. Indeed, although the EBA did not request an automatic application of the benchmarks, banks were asked in some cases to revaluate their initial estimations, providing explanations in case of significant deviation and resubmitting the results if explanations were considered inadequate. As the result of peer review, additional guidance was provided to banks for clarification purposes and in order to obtain consistency across banks. In this additional guidance (see, EBA, 2011), the EBA prescribed for example an approach to determining regulatory risk parameters and thus additional provisions to be held by banks for sovereign and institutional exposures (see Panel 9.1).

PANEL 9.1 TREATMENT OF SOVEREIGN AND FINANCIAL INSTITUTIONS' EXPOSURES IN THE BANKING BOOK

Due to discrepancies between the additional provisions for sovereign and financial institutions across banks, the EBA prescribed the additional provisions to be held by banks by setting the additional provisions equal to the increase in expected loss. The EBA developed an approach based on probabilities of default attributed by rating agencies and assuming downgrades depending on the conditions of the specific countries. The first step was to identify the degree of the downgrade (number of notches), which was linked to the initial rating. For exposures with AAA ratings, no downgrade was needed. For AA exposures a two-notch downgraded needed to be applied. At last, for exposures with BBB+ rating, a four-notch downgrade was requested (floor at CCC). After the application of the downgrade to the initial rating, this rating after stress needed to be mapped to a PD. For simplicity and consistency purposes, the EBA used the two years' cumulative default rates observed by the three well-known rating agencies Fitch, Moody's and S&P (see Table 9.1). The LGD to be used for the calculation of the impairments was set by the EBA at 40%. The increased provisions amount is equal to the multiplication of the PD after the downgrade and the LGD of 40%.

Further benchmarks were also identified for the computation of the increase in the cost of funding, the impact caused by the transition to the Basel 2.5 framework for market risk capital requirements.

RESULTS AND DISCLOSURE

One interesting point to note is that, from the announcement of the start of the stress test, banks raced to strengthen their capital base in order to ensure they were deemed strong in anticipation of it. To this end, while the EBA, together with NSAs, ECB, ESRB and EC, were preparing for the launch of the EBA 2011 stress-test exercise in March 2011, some banks that were selected to participate in the exercise were already increasing their capital base. In total, the capital base of the banks participating in the exercise increased by €50 billion between January and April 2011.

The average CT1 ratio of the banks decreased from 8.9% to 7.7% after two years of stress. In total, eight banks had a CT1 ratio below 5%, leading to a total capital deficit of €2.5 billion. Table 9.1, published by the EBA (2011c) provides an overview of the results of the EBA 2011 stress test exercise.

In total, eight banks had a CT1 ratio under the adverse scenario below the set 5% benchmark.

Following the publication of the 2011 EU-wide stress test results in July 2011, the EBA issued a recommendation (EBA 2011e) to national supervisory authorities (NSAs) to ensure that appropriate mitigating actions were put in place with respect to (i) banks with a CT1 ratio below 5% in the adverse scenario and (ii) banks with a CT1 ratio close to 5% in the adverse scenario and with sizeable exposures to sovereigns under stress.

Along with the bank-by-bank stress-test results, the EBA also published detailed information about banks' actual exposures. This was part of an unprecedented effort for increasing transparency and reducing uncertainty over EU banks' financial conditions. In total 3,200 data points were published per bank resulting in an unprecedented level of harmonised disclosure of the results and banks' exposure data. In fact, disclosure has represented a complement to the analysis conducted by the EBA itself, allowing market participants to make their own assumptions and possibly testing further scenarios beyond the EBA baseline and adverse scenarios for the banking book and the trading book.

Table 9.1 Results of the 2011 EU-wide stress test – country data

Adverse scenario	2010	2012	< 2%	< 3%	< 4%	< 5%	< 6%	< 7%	< 8%	< 9%	< 10%	> 10%
AT	8.2%	7.6%	0	0	0	1	0	0	1	1	0	0
BE	11.4%	10.2%	0	0	0	0	0	0	0	0	0	2
CY	7.7%	5.7%	0	0	0	0	1	1	0	0	0	0
DE	9.4%	6.8%	0	0	0	0	2	4	2	1	1	2
DK	9.8%	11.9%	0	0	0	0	0	0	0	0	1	3
ES	7.4%	7.3%	0	0	3	2	7	5	1	3	2	2
FI	12.2%	11.6%	0	0	0	0	0	0	0	0	0	1
FR	8.4%	7.5%	0	0	0	0	0	2	1	1	0	0
GB	10.1%	7.6%	0	0	0	0	0	1	2	1	0	0
GR	10.2%	6.1%	1	0	0	1	2	0	2	0	0	0
HU	12.3%	13.6%	0	0	0	0	0	0	0	0	0	1
IE	6.2%	9.8%	0	0	0	0	0	0	1	0	0	2
IT	7.4%	7.3%	0	0	0	0	1	2	1	1	0	0
LU	12.0%	13.3%	0	0	0	0	0	0	0	0	0	1
MT	10.5%	10.4%	0	0	0	0	0	0	0	0	0	1
NL	10.6%	9.4%	0	0	0	0	0	1	0	1	1	1
NO	8.3%	9.0%	0	0	0	0	0	0	0	1	0	0
PL	11.8%	12.2%	0	0	0	0	0	0	0	0	0	1
PT	7.1%	5.7%	0	0	0	0	2	2	0	0	0	0
SE	9.0%	9.5%	0	0	0	0	0	0	0	1	2	1
SI	5.7%	6.0%	0	0	0	0	1	0	0	1	0	0
Total	8.9%	7.7%	1	0	3	4	16	18	11	12	7	18

Source: EBA (2011c)

LESSON LEARNED FROM THE EBA 2011 STRESS TEST

The EBA 2011 stress-test exercise has represented an important step towards an EU-wide forward-looking assessment of risks and vulnerabilities in the European banking sector. The development of a common methodology and its early publication was very well commented on by the different stakeholders. This ensured transparency for market participants as regards the assumptions and the mechanics of the exercise as well as consistency across banks in conducting the stress-test exercise. At the same time, the commitment for future exercises is to further anticipate the publication of the methodology, in order to enhance the interaction with the industry ahead of the launch of the exercise and, ideally, testing the templates for data collection.

Furthermore, the decision to set the capital threshold at CT1, and communicating the capital threshold (5% CT1) in advance of publishing the stress-test results, guaranteed a credible and disclosed capital benchmark. Early disclosure also encouraged banks to strengthen their capital positions ahead of the test by raising €50 billion between January and April 2011.

The quality assurance and peer review were also beneficial and added value in terms of ensuring adequacy in the interpretation of the methodology and the mapping of the macroeconomic scenario into micro-parameters. Looking ahead, further work on the early definitions of benchmarks to be used in this process is needed and would lead to even more robust results.

Last, but not least, the unprecedented level of harmonised disclosure of the results and banks' exposure data disclosure was perceived a significant step in the direction of greater transparency. In particular, disclosure on banks' actual exposures and starting points has added value and contributed to reducing uncertainty about the state of health of the EU banking sector. It also allowed analysts to perform their own assessment and complement the EBA's scenarios with further sensitivities.

Along with significant pros, the EBA stress test has been also challenged. Some criticisms relate to the process and the ongoing fine tuning of templates and benchmarks during the exercise itself as more information became available. The process for future stress tests will attempt to overcome this by road-testing templates and gathering information on benchmarks *ex ante*. However, particular criticism was in terms of the outcome of the exercise and of some of its assumptions.

Market concerns about the EU banking system and the financial stability implications thereof were deemed not to be directly addressed by the stress-test exercise. A first problem was probably linked to the design of the macroeconomic scenario. Indeed, the adverse scenario agreed when the exercise was launched was taken over by later events, with a further deterioration of the economic environment (vis-à-vis an expected modest recovery) and the eruption of the sovereign crisis. In addition, funding problems and, more importantly, liquidity squeeze pointed to the lack of a review of banks' liquidity positions. Finally, increasing pressure on asset quality, especially in some jurisdictions and for some asset classes, reduced the credibility of the results. In particular the capital shortfall has been perceived as far too optimistic, also in relation to the lack of severe sovereign stress for exposures in the banking book. This criticism was, however, partly tackled by the EBA by running a capital exercise in Q4 2011 (see Panel 9.2).

It should be noted, however, that this criticism is only partially grounded. In some cases, observers have not been able to read more carefully the published results and correctly interpret the data disclosed by the EBA. It has been partly a communication problem linked to the misperception of what a stress test can (and cannot) deliver.

It is beyond the purpose of this chapter to analyse this issue in depth, but it is interesting to show a different way of presenting the stress-test results in terms of incremental impact instead of overall level of CT1 ratio.

Figures 9.1 to 9.3, based on data published by the EBA, show for instance the impact of the stress scenario on banks' loss rates for the retail and corporate exposures and represent an intuitive way for identifying banks more affected, also in relation to the country-specific change in GDP.

In Table 9.2, also based on public data for a sub-sample of banks, we ranked banks by impact of the adverse scenario on some P&L flows, capital position and RWAs.

Table 9.2 tells us quite a different story with some banks that dealt with significant problems that the stress test had actually identified as more sensitive (or less resilient) to the EBA's adverse scenario. In our view, the message is clear: the mechanics of the stress test have some shortcomings that cannot be easily avoided, but a more in-depth and imaginative analysis of the results would have provided interesting insights.

Figure 9.1 Multiple Loss rates, retail scenario/Dec 2010

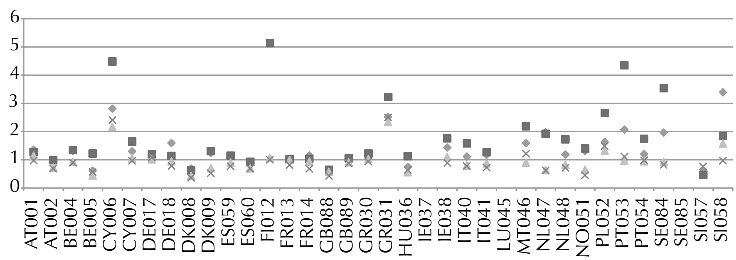


Figure 9.2 Multiple loss rates, corporate scenario/Dec 2010

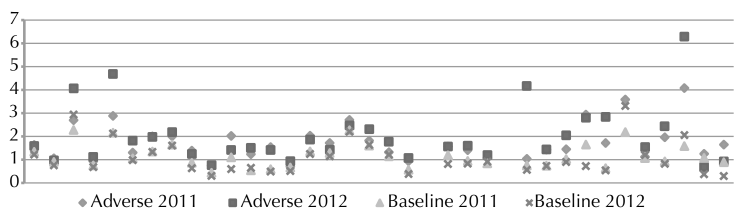
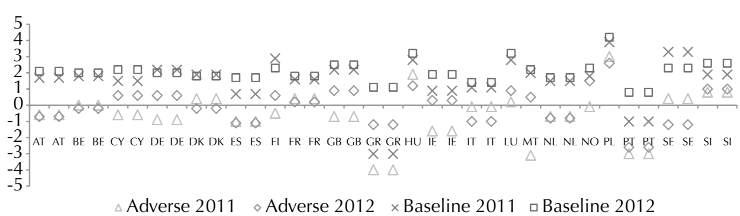


Figure 9.3 Percentage change in GDP in the scenarios (home country banks)



A last point is related to the preparation of future EBA stress tests. An important aspect to manage is the expectations from the market. A stress test is not a forecast of the future: it is just the assessment of what would happen should an event, subject to a probability distribution, materialise. A stress scenario needs to be severe but plausible. The sovereign crisis has broadened the perspective with respect to plausibility and severity. The objective of an EU-wide stress-test exercise needs to be clarified in advance. Moreover, it needs to be communicated what stress testing does and does not do. So for the next EU-wide stress-test exercise, which was planned for 2013, the lesson learned from the EBA 2011 stress-test exercise would be incorporated as much as possible.

Table 9.2 Ranking of banks according to the impact of the 2011 EU-wide stress test

Bank code	Bank name	Operative Income	Trading book	Cost funding	Impairments	RWA	CT1	CT1R Adv-Bas
AT001	Erste Bank Group (EBG)	4	3	5	3	5	3	3
AT002	Raiffeisen Bank International (RBI)	5	4	3	2	4	4	2
BE004	Dexia	7	4	6	6	6	5	5
BE005	KBC Bank	7	7	6	3	7	5	5
CY006	Marfin Popular Bank Public Co Ltd	2	7	2	7	3	7	6
CY007	Bank of Cyprus Public Co Ltd	6	5	3	5	2	6	6
DE017	Deutsche Bank AG	3	6	7	2	7	2	4
DE018	Commerzbank AG	5	6	3	4	7	5	5
DK008	Danske Bank	1	6	4	1	1	2	1
DK009	Jyske Bank	2	3	7	1	4	1	7
ES059	Banco Santander S.A.	1	3	1	3	5	1	2
ES060	Banco Bilbao Vizcaya Argentaria S.A. (BBVA)	2	3	6	3	3	1	4

Table 9.2 (*continued*)

FI012	Op-Pohjola Group	5	5	7	6	5	4	3
FR013	Bnp Paribas	7	2	2	4	6	4	4
FR014	Credit Agricole	6	5	4	4	1	4	2
GB088	Royal Bank of Scotland Group Plc	7	3	7	1	5	6	6
GB089	Hsbc Holdings Plc	6	2	7	2	7	3	5
GR030	Efg Eurobank Ergasias S.A.	4	1	2	5	3	7	7
GR031	National Bank of Greece	1	7	2	7	4	7	7
HU036	Otp Bank Nyrt.	2	4	5	3	3	1	7
IE037	Allied Irish Banks Plc	7	7	1	1	6	7	6
IE038	Bank of Ireland	7	5	2	2	1	7	7
IT040	Intesa Sanpaolo S.P.A	2	1	6	4	4	4	3
IT041	Unicredit S.P.A	3	4	6	4	6	5	2
LU045	Banque et Caisse d'Epargne de l'Etat	4	6	5	7	1	1	1
MT046	Bank of Valletta (Bov)	4	7	7	7	1	5	3

Table 9.2 (*continued*)

NL047	Ing Bank NV	5	4	1	5	7	2	7
NL048	Rabobank Nederland	3	6	3	5	7	2	6
NO051	Dnb Nor Bank ASA	3	1	5	7	1	2	1
PL052	Powszechna Kasa Oszczednosci Bank Polski S.A. (Pko Bank Polski)	1	1	4	6	3	3	1
PT053	Caixa Geral de Depósitos, SA	6	7	5	6	4	6	5
PT054	Banco Comercial Português, SA (BCP Or Millennium Bcp)	6	1	3	5	6	7	4
SE084	Nordea Bank AB (Publ)	5	2	1	6	1	3	1
SE085	Skandinaviska Enskilda Banken AB (Publ) (Seb)	3	2	7	7	5	3	3
SI057	Nova Ljubljanska Banka D.D. (NLB D.D.)	1	2	1	1	2	6	2
SI058	Nova Kreditna Banka Maribor D.d. (NKBM D.D.)	4	5	4	2	2	6	4

PANEL 9.2 EBA 2011 CAPITAL EXERCISE

In December 2011, the EBA launched a capital exercise in order to reassure market participants on the resilience of EU banks to a sovereign shock. This was part of a more general plan to break the link between banks and sovereigns via (i) direct capital injections into banks from EU bodies, (ii) effective EU-wide bank term debt guarantees, and (iii) higher capital buffers across the entire banking system.

In this context, in December 2011 (EBA 2011d), the EBA issued a recommendation that banks raise their CT1 capital to 9% after accounting for an additional buffer against stressed sovereign risk holdings. The capital exercise was not a stress-test exercise, since no stress scenario was prescribed. In the capital exercise banks were required to evaluate, in a prudent manner, their sovereign exposures.

The recommendation requires banks to strengthen their capital positions by building up an exceptional and temporary capital buffer against sovereign debt exposures to reflect market prices as at the end of September 2011. In addition, banks were required to establish an exceptional and temporary buffer such that the Core Tier 1 capital ratio would reach a level of 9% by the end of June 2012.

The buffer requirement was not designed to cover losses in sovereigns, but to provide a reassurance to markets about the banks' ability to withstand a range of shocks and maintain adequate capital levels. The sovereign capital buffer has been clearly established as a one-off measure and not as a permanent requirement.

CONCLUSION

This chapter described the EBA experience in running the EU-wide stress test, focusing on the 2011 exercise. In particular, we tried to highlight what the challenges were – in terms of methodology, governance of the process and communication – of a stress test covering an ample sample of banks from different jurisdictions which are subject to banking regulations that are not fully harmonised.

There are various peculiarities in handling this kind of exercise, but we would like to conclude with three main messages.

The first is that a choice needs to be made between comparability and realism in designing the stress test. The EBA privileged the former and opted for a static balance-sheet assumption and a constrained bottom-up setting. This may be criticised from a theoretical perspective, but it is the only manageable approach in practice and contributes to ensure a level playing field.

Second, the results of the stress test cannot be interpreted in a mechanistic way, but should be read carefully and subject to further sensitivities. In that respect, the disclosure exercise that accompanied the release of the stress-test results greatly contributed to reduce uncertainty on banks' exposures to different sources of risk.

Finally, communication is key and it is important to increase awareness of what a stress test can and cannot deliver. In that respect, managing expectations is part of the preparation for a stress test, particularly if individual results are disclosed. This avoids the spreading of a false sense of security as well as of complacency.

The opinions expressed in this chapter are those of the authors and do not involve the EBA and its Members. Useful comments and suggestions from Piers Haben are gratefully acknowledged.

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1 High Level Group on Financial Supervision in the EU published a report in February 2009, the so-called De Larosière Report. The aim of the report was to lay out a framework to take the EU further in its process of integration, which includes (i) a new regulatory agenda (Basel III), (ii) stronger coordinated supervision (eg, EBA) and (iii) effective crisis-management procedures.

2 Regulation (EU) No. 1093/2010 of the European Parliament and of the Council of November 24, 2010.

3 CEBS's press release on the results of the EU-wide stress testing exercise (2009).

4 This section analyses the results presented in EBA (2011a and 2011b).

10

Stress Testing Across International Exposures and Activities

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Stress testing foreign exposures of internationally active financial institutions presents an array of challenges from developing datasets to understanding and factoring in qualitative factors that may drive loss rates. These factors can be a function of the government or more simply related to developments in lending practices within a given market. Our work to stress test consumer loan portfolios across a group of countries led us to conclude that a stress-test approach for consumer portfolios in Asia is best pursued on an individual-country basis with a stratification of the consumer portfolio by secured and unsecured credits. This chapter describes our work in this area and uses the Korean consumer market as a case study.

CONDUCTING STRESS TESTS OF INTERNATIONAL ACTIVITIES IN AN IDIOSYNCRATIC WORLD

Financial institutions with international business activities, including operations in foreign markets, have a number of questions to consider in designing stress tests that cover these activities, exposures and risks. The first and most important is deciding on the purpose of the stress test, since international risks can overlie a number of different risk types, such as credit, market and operational. International risks can be viewed as an overlay since there are determinants of loss rates to consider that are additional to those in a more standard functional form of a model estimated using data and exposures strictly within a single country. For example, if corporate default rates were simply determined by the economic growth rate within a domestic economy, this function would have to be altered if the corporate obligor was also exposed to risks from government intervention in the provision of foreign exchange.

In foreign markets, banks and borrowers are subject to country risk, which is the risk that economic, social and political conditions and events in a foreign country will affect an institution (OCC 2008). Further, these conditions can manifest themselves in the form of a crisis, such as a sovereign-default, exchange-rate or banking-system crisis. These crises can happen in any combination and in any order and need to be considered in the design of an international stress test. Emerging-market countries have been more prone to these crises, but, as evidenced by Iceland (banking-system and exchange-rate crises), Ireland (banking-system crisis) and Greece (sovereign default, as evidenced by a forced restructuring), developed countries are also vulnerable to these crises. Thus, depending on the purpose and scope of the stress test, factoring the potential for one or more crises into the downside scenario is an important consideration when stress testing international portfolios. Being subject to these types of risks also requires that the stress-testing framework be forward-looking and flexible so that stress tests can be executed should sudden changes in economic, financial, political or social conditions take place.

Given the wide range of risk types and potential crises that a bank is exposed to in foreign markets, the scope of the stress test needs to capture the majority of a bank's foreign exposures, activities and risks. The scope of the stress test can also pre-identify transmission channels for some of the losses, but, as managers and modellers think through the scenario under consideration, additional risk channels may be identified and incorporated into the stress test. For example, a recession scenario may open up a liquidity risk channel if the country is highly indebted, has a low level of international reserves and is reliant on foreign capital inflows to finance its debt. These channels may surface as the scenario, and incorporated shocks in the stress test will be driven by internal or external factors. For example, does the scenario incorporate an internal shock, such as a change in government policies, eg, nationalisation of an industry that triggers a sharp decrease in investment activity, or an external shock where the scenario envisions a sovereign default by a major trading partner? Given the complexities that international activities introduce, there is a much wider range of factors and principles that firms need to account for in the design of the stress test. In particular, firms should check to see if Principles 7–15 of the Basel Committee on Banking Supervision's (BCBS) May 2009 report[1] have been implemented and are guiding the stress test.

One way to consider and track the risks that the firm could be exposed to is through a table, such as Table 10.1.

Table 10.1 Potential risks to factor into stress tests for international activities

Country	**Transfer Risk**[2]	**Nationali-sation**	**Sovereign default**	**Operational risk from civil strife**	**…**	**Bank holiday**	**…**
Argentina		X	X				
…	X			X		X	X
Zambia					X		

A traditional recession-based scenario should be considered a minimum stress test for most foreign-country exposures and activities. The level of complexity of the stress test would vary substantially for a firm with limited exposures in a few countries compared with a firm operating in more than 100 countries using complex products and risk-mitigation strategies. A firm with more complex operations may at the outset of developing its stress-test platform identify a set of countries of highest priority, eg, through the use of a simple calculation of risk-adjusted exposures, known concentrations, or a contagion scenario set of identified countries. The firm may also be able to group countries with similar economic structures (commodity-based, fixed exchange rate) or risks (highly indebted with both current account and fiscal deficits) until the full stress-testing framework can be built. Proceeding in this manner also may help overcome some of the data challenges that the modellers may face, such as generating or obtaining a consistent set of data elements across all of the countries the firm operates in.

Some of the risks are idiosyncratic to individual countries, such as operational risks to the firm from civil strife or imposition of regulatory controls, which imposes challenges to doing a cross-country systemic stress test. However, in the knowledge that these factors are present, the model can control for those elements using various econometric techniques, such as fixed-effects regressions that introduce country dummy variables. These factors can then be tested separately through sensitivity or country-specific stress tests to determine whether material risks were masked by the modelling technique employed. This is likely to involve considerable expert judgement that senior management should be made aware of during the design, testing and reporting on the stress tests.

The final critical elements of the stress test will be the measurement(s) chosen for its objective – capital, earnings, informing bank strategies – and determining a set of potential action points for monitoring and executing risk-mitigation strategies should the scenario materialise. The governance of the stress-testing framework should provide direction for determining these elements; but, at a minimum, the results should be clear, actionable and well supported, and inform decision-making vertically within the firm as well as horizontally across all business lines and functions that manage international activities or would be exposed to those risks.

DATA CHALLENGES IN ESTIMATING INTERNATIONAL STRESS TESTS

The measurement(s) chosen for assessing the international stress test (in accordance with its purpose) will depend in part on the data available for the model estimation – a significant challenge for some countries and variables. Cross-country data has been facilitated by the Basel Committee's efforts to standardise measures for capital; the international accounting standards for capturing key financial indicators for corporations and financial institutions; and the IMF's standardisation of basic macroeconomic data. However, the availability of comparable, cross-country data can diminish significantly depending on the risk type(s) assessed and model strategy chosen, particularly at more granular levels, and may require the financial institution to start building a dataset. Significant data issues will need to be conveyed to senior management, risk managers and business lines, since the interpretation of stress-test results needs to be pragmatic and viewed in light of data limitations relative to home country stress tests.

There are some common public sources for data, including the IMF's international financial statistics and trade data; the World Bank's external debt and governance indicators; and central bank, supervisory and ministry-of-finance websites. Private-sector firms may collect additional elements. The multilateral organisations have worked to make the measurement of the data consistent across countries; however, this may not be the case when collecting individual country data, so it is critical to understand how variables are defined and measured and not assume that, because the name of the variable is similar to that used in other countries, they are indeed identical or consistently measured. Delinquency rates and non-performing loan ratios are good examples of variables that may be defined differently across countries. In Russia, for example, the non-performing assets ratio includes just the past due portion of the loan. Such definitional variations can distort comparisons of portfolio credit quality across countries. This is true whether the data is obtained directly from in-country sources or from vendors that have collected it and packaged it for end-users. The data limitations can be particularly acute and constrain the ability to implement consistent, granular stress-test analyses across countries. However, using proxies, stress tests on a country-by-country basis may be feasible.

There may be a more basic problem when what would normally be considered a standard variable is simply not collected by one or more countries. For example, the unemployment rate is a significant explanatory variable for retail loan performance across countries. However, in India, the government has not collected monthly or quarterly unemployment-rate data across the country, since the logistical difficulties are enormous and the cost prohibitive, or in some countries the unofficial labour market is so large as to render the official unemployment numbers meaningless. Therefore, when a model is being developed, a starting point is to inventory the available data series for each country the bank is exposed to and then consider possible proxies for those data series that cannot be obtained. Some proxies can be developed from what theoretically should be highly correlated variables, such as the level of industrial production and the level of employment, or there is the possibility of obtaining and using proxies from structurally similar economies and banking systems.

There are also some basic data considerations and challenges for banks' internal datasets, including identifying the country of risk, the location of collateral and the reliability of guarantees.

STRESS TESTING INTERNATIONAL RETAIL PORTFOLIOS

A good stress-testing framework employs multiple conceptually sound stress-testing approaches. This is particularly true with international activities, as data limitations may force some programmes to be basic sensitivity analyses while some more advanced banks could do full-scope, enterprise-wide stress tests with multiple scenarios. In this section we will focus on stress testing international retail portfolios to estimate expected losses on bank exposures to foreign consumers. Retail models are more challenging as, to our knowledge, there are no existing comprehensive, comparable cross-country datasets on which to base models. Further, significant variations in laws and culture can affect retail default rates and, due to differences in creditor rights, the level of loss-given default (LGD). This can cause the relationship of economic variables to loss rates to vary from country to country and from product to product. However, on a country-by-country basis for most developed countries and a number of emerging-market countries, data can be gathered on retail loan performance and basic macroeconomic and governance variables.

The loan performance data can be obtained from a bank's own loss history or from the central bank/supervisors, which report aggregated data on loan-loss rates, even possibly segmented by consumer product type. Portfolio segmentation may be necessary when building models for a bank operating across countries or with multiple loan types. For example, within the portfolio of countries that we have modelled, secured portfolios did not yield significant coefficients or meaningful regression equations, while there was success with unsecured lending. An important lesson from our modelling experience was that international retail models are not necessarily the same as modelling home country portfolios or even across countries within a region, eg, Asia, and that basic portfolio diagnostics and more in-depth examination of the country's consumer market was required to develop a sound model.

Segmenting the portfolios within and across countries has the benefit of isolating potential correlations and eliminating noise and offsetting impacts. With so many moving parts in a multiple-country, multiple-product-type model, results can be watered down or rendered insignificant. Indeed, in our modelling work, the assessment of an aggregated portfolio of secured and unsecured products for individual countries did not yield robust results. For example, a retail portfolio in the Eurozone could include Greece and Germany with both credit cards and first-lien home mortgages. If this were the case, then it would seem that the most logical approach for this retail portfolio would be a segmented portfolio approach, ie, one that isolates, to the extent possible, the retail portfolio's various moving parts on both the left and right sides of the equation:

Country X Losses (Mortgages) = f (home prices, interest rates, unemployment)

Country X Losses (Credit Cards) = f (unemployment, inflation, interest rates, credit growth)

It is possible that data diagnostics and evaluation of portfolio characteristics of the retail portfolios reveal that some countries could be grouped into a homogeneous portfolio, barring the presence of idiosyncratic risks as discussed in earlier.

STRUCTURAL AND CYCLICAL ISSUES

For each county, a number of structural and cyclical considerations had to be considered and factored into the models. Structural considerations include the structure of the capital markets and legal framework for the institution's products and services as well as creditor rights, which affect LGD estimates. For emerging markets, there are structural changes occurring to both the economy and banking system (such as financial deepening) that need to be taken into consideration. These structural changes can cause correlations and variable relationships between dependent variables and prospective independent variables to change or break down. The chart in Figure 10.1 showing Brazil's unemployment rate juxtaposed with the percentage of banking system loans to individuals that are past due by 90 days or more highlights this point.

Figure 10.1 Brazil banking system: loans to Individuals 90+ days past due versus unemployment rate

Source: Banco Central do Brasil and Instituto Brasileiro de Geografia e Estatística

As Figure 10.1 indicates, in the years from 2002 to 2012, Brazil has experienced a long-run decline in its unemployment rate, reflecting, in part, a period of structural change and rapid development for the economy. As a result, the predictive power of the unemployment rate for the consumer loan portfolio performance had deteriorated. In fact, the correlation between changes in past due loans and the unemployment rate became negative in 2011, a counterintuitive result. Over this same period, bank lending expanded rapidly with institutions targeting new (and untested) consumers with an array of products from credit cards to payday lending (an example of financial deepening and the evolution of the banking system).

The introduction of new products and other financial innovations is an important consideration when designing stress tests. In such countries as Hungary and Poland during the early 2000s, banks started marketing Swiss-franc-linked mortgage products, which offered interest rates significantly lower than comparable local currency loans. By the summer of 2008, according to the IMF, the foreign-currency share of new house-purchase loans in Hungary hit 70%. The global financial crisis of 2008 and 2009 resulted in a surging value for the Swiss franc, precipitating a repayment crisis for Hungarian homeowners. This underscores the importance of understanding the portfolio characteristics in the design of stress tests.

Not only is segmenting by product type important, but segmenting by classes of borrowers, as well as by loan vintage, could yield meaningful differences in the results of the stress tests. For example, countries with a new generation or economic class of borrowers, loan-loss experience may be difficult to predict, as the loss experience is likely to differ from the loan-loss history for borrowers with longer credit histories. Many countries have established credit bureaus and that can be useful for segmenting different borrower classes (if those registries are made publicly available). The existence and quality of local credit bureaus is a function of the length of their existence, the type of information they collected and the quality controls over the registries. In Australia, the credit bureau contains only negative information. However, "comprehensive credit reporting" will begin in 2014. In 2003, Hong Kong's credit bureau, which was established in the early 1980s, expanded the type of information provided, in the wake of changes to Hong Kong's privacy laws. Modellers need to determine whether there are significant variations in credit registries across countries (eg, some reported only negative information) that can also contribute to bank underwriting decisions and ultimately have a bearing on cross-country loss rates.

Cyclical considerations entail not only debt levels and servicing, but also credit growth relative to the economic cycle, particularly if the real rate of growth for the banking system has been rapid. If the rate of real credit growth is rapid, eg, greater than 10%, then the bank has to consider not only the condition of its own portfolio but the potential condition of the portfolios of its competitors as well, since the possibility of widespread degradation of underwriting standards could lead to regulatory actions if not a full-blown banking crisis. If a crisis is a possibility, then the scenario under consideration may need to be re-scoped or an additional, more severe downside scenario may need to be executed.

FACTORING IN FOREIGN REGULATORY ACTIONS

Regulatory actions complicate the predictive power of past portfolio performance under forward-looking stress tests. Supervisory authorities have implemented a range of macroprudential regulations aimed at controlling loan growth and striving to prevent asset bubbles. Such measures include lowering the maximum loan-to-value (LTV) ratios for mortgage loans as well as implementing requirements on debt service capabilities for consumer loans. Such measures have been widely adopted across Asian consumer lending markets, from Korea to Singapore, though there are significant variations in the stringency of the measures. While largely a positive for loan performance, these measures will potentially affect the performance of loan-loss models.

If the assessment is for possible regulatory actions, then more typical administrative measures such as increasing LTV requirements and lowering debt-to-income measures could affect the revenue stream of the bank, while increased provisioning requirements could affect net income and the market's perception of the bank. As such, not only should these actions be factored into scenarios but models must also account for these actions in bank performance and the wider affect on the macroeconomy.

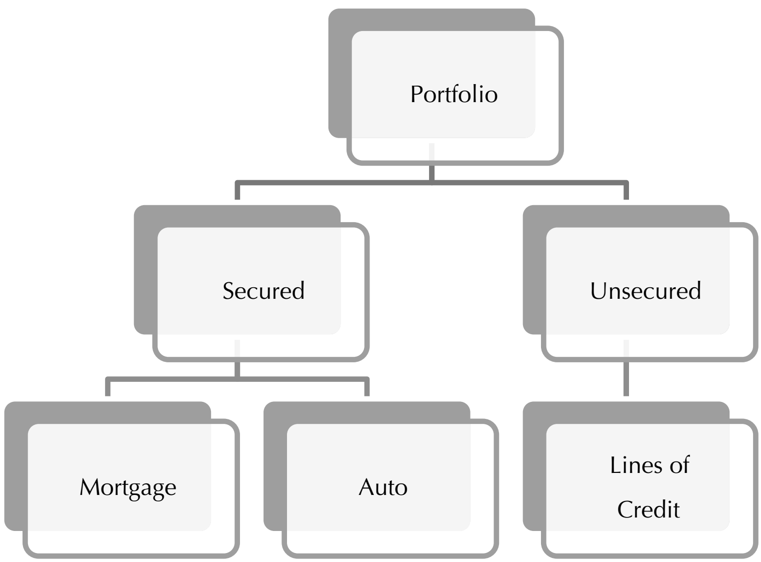
In addition, regulatory actions can have negative impacts on markets through moral hazard and forbearance. Taiwan's experience in 2004–6 is a case in point. During this period, banks aggressively expanded unsecured consumer loans. As charge-off rates spiked, the government responded with restructuring measures offering easier repayment terms that covered 30% of outstanding credit-card balances, according to IMF estimates (Laeven and Laryea 2009). These restructured loans were for the most part reclassified as performing. Such regulatory moves can have a large effect on model performance, which needs to be accounted for in the evaluation of the results and possibly require modification to and re-estimation of the model.

Quantitative proxies can be developed for these seemingly qualitative factors. For example, the potential for a wider range of regulatory actions should be considered in the scenario if the risk of a political backlash from rising defaults is a possibility. In addition, potential changes in regulatory requirements depend on the quality of the regulator, the maturity of the banking sector and validity of the legal system. Quantitative measures for these elements are available and could be factored into the modelling process. For example, the World Bank publishes numerical estimates for six governance indicators, which could then be incorporated into the model directly or transformed into an index.[3]

ASIAN CONSUMER PORTFOLIOS: STRATIFICATION REQUIRED

Stress testing retail portfolios may require stratification between secured and unsecured lending, due to wide variances in loss rates between these two broad types of lending. An analysis of loss rates across Asian countries underscores the need to differentiate between secured and unsecured retail portfolios. As highlighted in Figure 10.2, mortgages and car loans involve collateral and tend to pose lower risk than unsecured lines of credit, such as credit cards. In Singapore for example, Moody's (2009) has an expected loss for housing loans of 0.05% under their base case, compared with 5.3% for other individual loans. The expected loss under the stress case is 2.5% for housing and 17.0% for other loans to individuals.

Figure 10.2 A simple stratification of a retail portfolio



In Asia, historical loss rates on mortgages are extremely low primarily due to conservative underwriting standards that are typical in Asia (for example, low LTV ratios, and lenders typically have full recourse). Even in extreme downside scenarios – such as in the Hong Kong home price collapse during the late 1990s – mortgage loss rates typically do not spike in this region. Stress tests of the mortgage portfolios in Asia confirmed this, as the results did not show material loss rates under a basic recession downside scenario. This does not mean that periodic stress tests for mortgage portfolios are not required or stressed using alternative scenarios – such as a disaster-based scenario – just that other portfolios should receive higher priority until the full enterprise-wide stress-testing framework is operational. In contrast, more meaningful and material results were obtained when assessing unsecured and credit-card lending.

Case study: Korea's credit-card crisis and structural changes in the consumer market

Korea was chosen as a case study since we anticipated collecting a relatively rich dataset, given that Korea experienced three crises in 10 years:

1. 1997–8 Asian crisis;
2. 2002–4 credit card crisis; and
3. 2007–9 global credit crisis.

The Korean credit-card crisis of the early 2000s provided a good cycle to stress-test. The crisis was precipitated by a rapid increase in credit growth and surging consumer debt levels. In particular, the surge in Korean credit-card debt relative to GDP was closely followed by a spike in impaired assets (Kang and Ma 2007). This crisis provided a key ingredient for model development: a time series that included a complete credit cycle to evaluate.

But, even with the Korean crisis providing a useful cycle, many changes have occurred in the Korean consumer credit market since 2003, and these changes had to be taken into account when specifying models for the post-credit-card-crisis period. In particular, the tightening of macroprudential regulations, stronger bank risk management and controls (underwriting), better credit infrastructure and a less crowded, more competitive banking system affected the environment.

Another important change in the Korean credit-card market since the crisis was the change in product composition, from higher-risk cash-advance products to less risky instalment products. According to the Korean Financial Supervisory Service, cash advances accounted for 65% of credit-card loans in 2002, compared with less than 20% by 2011. These changes have contributed to the development of a vastly different Korean consumer credit market, and this structural change needed to be accounted for in the model.

STRUCTURAL BREAKS AND DUMMY VARIABLES

Another potential structural break was from industry consolidation, since a merger between a strong and weak institution can introduce a structural break in the time series data for the combined institution. This poses a decision point for the sample size for the analysis – typically, a longer time series is desirable to ensure the largest possible number of observations, but this must be weighed against the need to control for structural breaks in the data series.

In the Korean estimations, a dummy variable for the credit-card crisis was included in the credit-card model. The dates for the dummy variable were chosen based on the Quandt Andrews Breakpoint test for structural breaks. Breaks were identified at December 2002 and April 2005.

Indeed, there is a broader point at work here, particularly when considering emerging-market economies and other banking systems. The emerging-market banking systems can be dynamic, rapidly evolving systems, with new products being introduced routinely and new borrowers with little to no experience with credit. Depending on the magnitude and the size of the concentration the bank has, these elements can introduce sizeable stress losses for the bank. These factors can also introduce noise into time series data and need to be assessed and potentially addressed within the model specifications.

ESTIMATING LOSSES ON KOREAN CREDIT CARDS AND UNSECURED LOANS

A primary goal in the design of these models was to identify how macroeconomic shocks affect portfolio credit quality. There are at least two approaches for imputing a shock: one would be a straightforward application of a historical shock, while a second approach would be to apply a combination of the most extreme performance, to date, in terms of both depth and duration, for key economic variables from each of the crises. To have this stress – a low-probability but high-impact event – Korea would have to experience internal and external economic, financial market shocks simultaneously. It is important to think through and estimate a wide range of scenarios given the potential for contagion. The focus of the discussion below is on identifying the underlying risk factors that could cause a substantive deterioration in the asset quality of the portfolio.

To capture turning or inflection points in asset quality and provide a larger number of observations, monthly data was favoured over quarterly data. For the credit-card market, bank-level data was used, as the Korean supervisors did not start posting monthly performance data until 2005. In many countries, the regressions will have to be estimated using quarterly data, since that is the only publicly available data, or banks may be able to use internal databases that have higher-frequency data.

A decision on whether to estimate the level of losses or the ratio of losses relative to credit-card receivables was also required in laying out the approach. Additionally, the issue of modelling gross or net losses was considered. The choice between the gross and net losses can have dramatic effects on estimation results as recoveries (the difference between gross and net) can be lumpy on a monthly basis. In addition, the pattern and behaviour of recoveries (and therefore net losses) will vary by product type and country. Bankruptcy laws and other local provisions (recourse versus non-recourse lending) and secured versus unsecured lending (as well as the value of collateral) will all have an impact on recovery assumptions. If using internal data, historical experience with recoveries can typically be extrapolated and evaluated to determine the most appropriate dependent variable.

INDEPENDENT VARIABLES: KOREAN CREDIT CARDS AND UNSECURED LOANS

In general, the performance of the consumer credit markets was assumed to be thus:

To determine the drivers of credit-card loss rates, a large number of variables that could cause cashflow problems and drive delinquencies and defaults were considered:

- ❏ economic growth (GDP) and related measures such as exports, industrial production and the unemployment rate;
- ❏ monetary indicators such as inflation rates, credit growth and interest rates; and
- ❏ wealth measures such as home prices and stock indexes.

Not all contemporaneous measures showed clear predictive power for credit card loss rates

DATA DIAGNOSTICS MAY ALTER THE MODEL SPECIFICATION

As part of data diagnostics, the data was reviewed graphically, and statistical tests were conducted to determine the underlying properties for such things as stationarity. Stationarity, whereby statistical parameters do not change with time, is a required property for time series regressions, which is often obtained by first differencing the variable, ie, subtracting the prior period's observation from the current period's observation. We also checked for correlation among the variables.

Table 10.2 Correlation matrix of Korean macroeconomic factors

	unemployment	**credit growth**	**exports index**	**unemployment (-2)**	**unemployment (-3)**	**credit growth (-3)**	**credit growth (-24)**	**exports index (-6)**
unemployment	1.00							
credit growth	-0.42	1.00						
exports index	0.08	-0.20	1.00					
unemployment (-2)	0.81	-0.50	0.20	1.00				
unemployment (-3)	0.77	-0.51	0.24	0.92	1.00			
credit growth (-3)	-0.29	0.89	-0.09	-0.48	-0.41	1.00		
credit growth (-24)	-0.03	-0.12	-0.48	0.00	0.02	-0.10	1.00	
exports index (-6)	-0.06	-0.19	-0.04	0.00	0.00	-0.21	-0.19	1.00

Numbers in parentheses indicate the lag of that variable

Table 10.2 shows that the unemployment rates are highly correlated with one another (0.81 and 0.77) as is credit growth with the credit growth from three months back (0.89). Any time a variable is highly correlated (0.80 or greater), the model developer should consider dropping one of the two variables.

ESTIMATION RESULTS

Given the likelihood of borrowers drawing on savings to stave off defaulting, different lags of the independent variables were also included in the regressions. Our estimations showed that lag structures can vary dramatically from indicator to indicator across countries. The following variables were important risk factors for Korean credit-card loss rates: the change in the unemployment rate and credit growth with 3-month and 24-month lags. The regressions did incorporate a dummy variable identifying the credit-card crisis and an autoregressive (AR) term. The AR term was used to correct for serial correlation. For unsecured lending, the change in the unemployment rate, credit growth and an export index were significant in the estimation of monthly Korean unsecured loan loss rates over the sample period 2000–10 (using monthly data).

As noted above in the general discussion on structural and cyclical issues, rapid consumer credit growth is frequently a significant factor (with a several-quarter lag) in contributing to future credit losses, particularly if the seasoning of these new credits coincides with an economic event. Various lags for the real credit growth variable were significant but the lag length was purely a function of the data as opposed to a point that would be predicted by theory, ie, 6-, 12-, 18-, 24-month lags were not necessarily significant since the timing of the cycle was not readily apparent. Akaike Information Criterion (AIC) was used to determine the best lags of each independent variable, but this raises the probability that the out-of-sample predictive power of the model will be weak and require further analysis of the model specification.

For example, several consumer credit risk managers have pointed out that, in emerging-market economies, consumer loan performance can be dramatically affected by inflation (food prices, for instance). A key consideration in this regard is the income segment of the institution's portfolio: lower-income borrowers are more vulnerable to rising inflation rates than the more affluent consumers. So the model could possibly be improved if this data were available or could be constructed or proxied.

SUMMARY

Although the modelling of unsecured portfolios proved promising as changes in macroeconomic variables showed a causal relationship in the changes in Korean credit-card loss rates, the truly important element of this work was the required study of the Korean credit cycles, consumer product markets, regulatory actions and economic shocks arising from multiple quarters – both internal and external – and that these factors differed to varying degrees across countries in Asia. This underscored the need to evaluate markets on an individual basis and to proceed with caution when trying to estimate regressions across a region or globally. This is not a small undertaking, but it yields a large benefit by being able to anticipate potential drivers of future portfolio losses.

The views expressed in this chapter are those of the authors and do not necessarily reflect those of the Office of the Comptroller of the Currency or the US Department of the Treasury.

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1 See http://www.bis.org/publ/bcbs155.htm. See also IMF 2012, pp. 19–45, for an alternative formulation of principles.

2 "Transfer risk is the possibility that an asset cannot be serviced in the currency of payment because of a lack of, or restraints on the availability of, needed foreign exchange in the country of the obligor" – "Guide to the Interagency Country Exposure Review Committee Process", 2008, p. 1.

3 The six World Bank indicators are: voice and accountability; political stability/absence of violence; government effectiveness; regulatory quality; rule of law; and control of corruption (see http://info.worldbank.org/governance/wgi/sc_country.asp).

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Liquidity Risk: The Case of the Brazilian Banking System

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Stress tests are already a widely used tool for risk management of financial institutions. Central banks and individual banks run these tests for determining potential risk sources that they might encounter in scenarios of severe change in the macroeconomic situation and assessing their resilience to such events. By testing themselves or the financial system as a whole beyond normal operational capacity, they can quantify vulnerabilities, and the stability of the given system or entity may be studied and pursued more easily (Vazquez, Tabak and Souto 2012).

To design and apply a stress test, many important assumptions should be taken. The first step must be identifying the specific risk and vulnerability of concern. In the literature about stress testing of banking risks, the most common type of risks considered are credit, market and liquidity. The majority of papers have focused on assessing credit risk, since this is the bank's most important risk component. However, liquidity stress testing is getting more visibility and importance.

Although liquidity crises are not so frequent, their impacts are high (low-frequency, high-impact events), especially due to their contagious effects and to the consequences of the interaction between the banking risk factors. After the global financial crisis of 2007–9 there is an increasing interest in studying the vulnerabilities provided by liquidity risks. From this important event many lessons can be taken. The De Larosière Group (2009) points out the key lesson that regulators paid little attention to the system as a whole, while too much focus was given to microprudential supervision of individual institutions.

The crisis served to show weakness in the stress-testing exercises performed on financial institutions and systems around the world (Ong and Čihák 2010). It also showed how the vicious dynamics of liquidity risk can undermine the stability of the financial system (Van den End 2010). To Aikman *et al* (2009), the crisis illustrates the importance of modelling the closure of funding markets to financial institutions and accounting for liquidity feedbacks within any model of systemic risk. In sum, the ongoing crisis serves as an alert to the importance of managing liquidity risk and, therefore, it underscores the need to explicitly take into account liquidity risk in stress-testing frameworks (Van den End 2009).

Once they had understood the importance of stress testing liquidity risk, researchers working for different financial institutions around the world started to develop methods to endogenise liquidity risk in a stress-testing framework. This task is quite complex, since a method has to be developed that has the ability to quantify dependences and interactions between the various types of risk. Wong and Hui (2009) suggest that for banking stability it is important to assess the extent to which a banking system is exposed to the interaction of risks. In their paper, the stress-testing framework explicitly captures the link between default risk and deposit outflows. Not only is the interaction of the risks incorporated but also their contagious effects. The framework presented by Aikman *et al* (2009) also attempts to fully integrate funding risks and solvency risk.

In a framework of stress testing for liquidity risk, two components are important: (i) funding liquidity risk (concerning the bank's balance-sheet liability side: there may be a bank run by depositors or the bank may be unable to rollover liabilities) and (ii) market liquidity risk (asset side: illiquidity in the market for the bank's assets, when the bank needs to sell them). An example of a stress-test model that involves both components is the one presented by Van den End (2009). By considering the first and second rounds (feedback) of shocks, the model presented endogenises market and funding liquidity risks and captures, as second-round effects, the collective response of heterogeneous banks and reputational effects. The IMF originally centred its liquidity tests on the paper of Čihák (2007) using bank balance-sheet data to perform bank-run-type stress tests on a bank-by-bank level. Aikman *et al* (2009), on the other hand, focused on the role of asset-side (market liquidity) feedbacks.

Some papers innovate with their stress-testing models. One topic that motivated some interesting material was the establishment of minimum standards for liquidity risk (Liquidity Coverage Ratio, or LCR, and Net Stable Funding Ratio, or NFSR) by Basel III (BCBS 2010). To study the effects of these new minimum standards, Van den End (2010) developed a stress study that linked funding cost liquidity to regulation and central bank operations. The conclusions from its model outcomes support policy initiatives such as the ones proposed by the Basel Committee (BCBS 2010). By testing scenarios of stress, the paper finds that banks that adjust to the Basel III establishments (such as by holding a higher stock of liquid assets) have substantially lower second-round effects and tail risks. These findings highlight the importance of defining a sufficiently high-quality level of liquid assets to limit the idiosyncratic risks to a bank. The outcomes of the tests also evidence the important role of stronger liquidity profiles in reducing the risk of collective reactions by banks and therefore in preventing second-round effects and instability of the financial system as a whole.

Van den End and Kruidhof (2012) simulate the systemic implications of the LCR using a liquidity stress-testing model. The authors model the LCR as a macroprudential instrument that can be used to moderate the adverse side effects that arise due to interactions of bank behaviour with the regulatory liquidity constraint. The authors applied tests with different switching rules and banking sector structures. By testing the reduction of the minimum LCR requirements, the paper finds that a flexible approach of the LCR in stressed times reduces the number of bank reactions and associated negative side effects. Another rule tested was the widening of the buffer definition, and the measure was found to be effective in limiting the interaction between the minimum requirement and bank reactions. At extreme stress levels, the paper finds that the LCR becomes ineffective as a macroprudential instrument and, in order to maintain the stability of the system, a lender of last resort is requested.

The development of the framework that endogenises liquidity risk into stress tests is an essential stage of the stress-testing exercise. Maybe just as important are the stages of data-collecting, information-processing and numerical analysis. The top-down and bottom-up approaches are the two strategies of information processing that can be applied to stress testing bank risks. The advantage of running a test with the bottom-up approach is the use of more detailed data and less complexity in modelling liquidity shocks. The disadvantage is that, unlike the top-down approach, these tests are less consistent. The advantages of the top-down approach include more consistent results and more flexibility to simulate different scenarios of shocks. According to Čihák (2007), the majority of stress tests presented in financial-stability reports are based on bank-by-bank data. Central banks that are not involved in microprudential supervision and do not have access to more detailed data rely on top-down approaches.

The BCBS (2011) published a document on the progress in implementing macroprudential policy frameworks, gathering information on the subject. Although the document discussed macroprudential policy and systemic risk, many of its considerations can be readily applied to liquidity risks, given their systemic nature. According to the document, risk measures should be able to capture the time and cross-sectional dimensions of risk, which define requirements for metrics to be created and monitored. The main measurement approaches that apply, extracted from a survey conducted by the IMF (2011), includes the following: indicators of imbalances (eg, of bank credit, liquidity and maturity mismatch, and currency risk), indicators of liquidity market conditions, metrics of concentration of risk within the system and stress testing. The metrics of concentration of risk within the system (eg, the network-theory-related measurements, like connectivity and centrality, or the results of default cascade simulations) are related to the cross-sectional dimension of risk, focusing on the channels of contagion and amplification, and could be used to determine the systemically important institutions, while the stress testing is used to evaluate the resilience of individual banks and of the banking system as a whole.

Stress tests for liquidity are not so developed as stress tests for credit and market risks. However, important works have been done by central banks researchers, as the already mentioned Van den End (2010), Wong and Hui (2009), and Aikman *et al* (2009). These models are usually integrated with credit or market risk. This feature is the main difference between these models and the approach for liquidity stress testing at the Central Bank of Brazil.

Despite the importance of liquidity risk stress testing, most central banks do not publish results from liquidity stress tests. This reflects the liquidity-modelling complexity and the need of more detailed and high-frequency data. The Central Bank of Brazil has published liquidity stress test results since 2009. From the side of the banks, a survey with Brazilian banks indicates that their risk-management policies have been improved to account for possible liquidity problems. Many banks have started to run liquidity stress tests after the financial crisis. However, it is not usual to disclose the results.

Given the importance of developing liquidity stress-test models we focus on the Brazilian banking system and how it has been impacted on by the financial crisis, focusing on liquidity issues. We then present the Brazilian banking system, before discussing the impacts of the crisis on the system, employing contagion tests to show that banks may have heterogeneous responses to liquidity shocks. The following section presents a discussion on liquidity stress testing performed by the Central Bank of Brazil, as well as results from a survey of banks that operate in the Brazilian banking system. The last section draws our conclusions.

THE BRAZILIAN BANKING SYSTEM

Banks are financial institutions with a major role in a capitalist economy. Their importance is a consequence of their roles as money creators, as managers of the payments system and as financiers of economic activities. At the same time, as rational agents, banks take actions to maximise their profits. Restrictions can come from the macroeconomic environment and from the banking system microstructure. This condition gives a hint on the risks involving the banking system and why they are potentially dangerous. Fragility in banks' individual accounting and management, combined with macroeconomic shocks, can lead to crises in the system. When such crises happen, the consequences can be great and will include impacts on the economies' credit situation, interest rates and investments, and bring about negative changes in the levels of economic activity. To maintain a solid and healthy banking system, it is essential to establish bank regulations supplemented by constant supervision.

The Brazilian banking system began its trajectory at the beginning of the 19th century, when the Banco do Brasil (Bank of Brazil) was founded and later was partially considered a monetary authority (da Costa, 2012). However, it was only between 1930 and 1945 that the most important banks were founded and the Brazilian banking system effectively began to grow, reaching the total of 644 banks in 1944. Since its start, Brazil's banking system went through various transformations, mainly adaptations to the various changes in national and international politics and economic scenarios. These transformations led to a system with solid regulations, supervised by the Central Bank of Brazil (created in 1964). Based on the Federal Constitution of 1988, some of the Central Bank functions as a monetary authority are the issue of money, the determination of the reserves requirements of banks and controlling liquidity with open market operations.

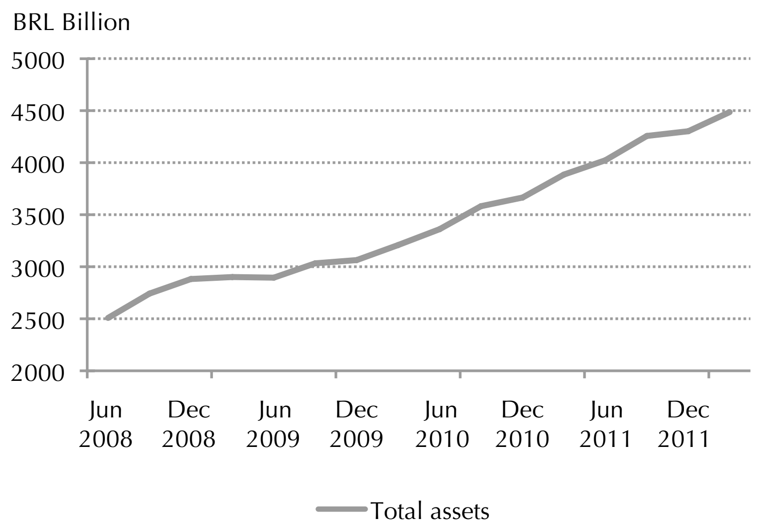
The banking system's condition in the late 20th and early 21st centuries was shaped by important structural transformations that occurred in the early 1990s. These transformations were consequences of the implementation of measures of monetary policy in 1994 and 1995. The 1994 measure is known as "Plano Real", in which the exchange rate between the Brazilian currency (real) and the American dollar was initially set at 1 to 1. This measure was used by the government to stabilise the economy, which had been passing through a long period of high inflation rates initiated in 1964, during the military regime (1964–85). The impact of this plan on the banking system was deep. One of the major changes faced by banks was on their profits' sources. During the high inflation period, banks took advantage of the condition to profit from floating; however, after the currency stabilisation, this kind of revenue vanished. Banks found an alternative source of profit by charging their customers fees for services provided. The demand for credit also increased, given the increase of the predictability horizons allowed by the stabilisation of the economy and the more optimistic associated expectations. The banks' profit with services, which represented only 8% of the GDP in 1990, reached 10.5% in 1993 and 21.5% in 1995.

Important policies were also implemented in 1995. Programmes were created to restructure and fortify the financial system, preventing liquidity crises and stabilising the system. Another relevant measure taken that year were the incentives given to the opening of the Brazilian financial system to foreign capital and banks. The objective of this action was to attract foreign banks to the national system and expand the credit supply. This would increase banks' competition, forcing them to reduce costs by improving their management to become more efficient. To the population and firms, the benefits would be a greater variety of banks and lower interest rates. The measure was indeed effective in attracting more foreign banks, but the concentration increased. This happened because mergers and acquisitions not only involved the new-entrant foreign banks but also were performed by domestic institutions among themselves. During the first four years after the "Plano Real", 104 financial institutions suffered some kind of adjustment. The number of domestic private banks and state-owned banks reduced while the number of foreign-controlled banks increased by less than the reduction in the number of domestic banks. In 1993, foreign-controlled banks owned 7.28% of the total financial system, reaching 25.91% by 1999.

From 1999, Brazilian banks began an innovation process. They developed techniques of fundraising and asset management, increasing their loans-to-reserves ratios. The efficient use of the interbank market can be considered the key innovation (da Costa 2012). The period between 2003 and 2006 was marked by greater access by the population to banks and credit. Between 2001 and 2006, the number of accounts in the banking system increased by 52%. Savings accounts were the most popular service provided and increased 50%, while the growth of current accounts was 37%. The popularisation of banking services became possible due to technological advances, which included the installation of ATMs and credit-card readers in busy areas and retail outlets. These indirect banking facilities increased the supply of banking services without the need for an increase in the number of bank agencies. Popular credit programmes offered by commercial banks also brought about an expansion in the economy's consumption demands.

By 2012, the Brazilian financial system had 2,218 operating financial institutions. In December 2011, the total assets of Brazil's whole financial system exceeded BRL5,135 billion. Its stock of credit operations reached BRL2 trillion, which corresponds to 49% of the country's GDP in the same period. The banking system is a part of the financial system, composed of independent institutions and financial conglomerates, which must contain at least one institution from a commercial bank, a savings bank or a multiple bank, since it is authorised to receive demand deposits. In March 2012, the banking system's assets totalled BRL4,486 billion, a share of 84% of the whole financial system's total assets. These institutions' evolution of total assets is illustrated by Figure 11.1.

Figure 11.1 Banking-sector asset evolution



The Brazilian banking system's history shows periods of concentration alternating with periods of increase in the number of banks. In the early 1990s, as we have seen, the banking system went through a structural transformation. In that period of banking crisis, privatisations and incentives to the entry of foreign banks, the domestic banking system went through a decrease. In 1994, there were 271 commercial and multiple banks; by 2002, they were 167. In 2012, there were 160 banks.

Figure 11.2 Distribution of the banking sector by capital source (December 2011)

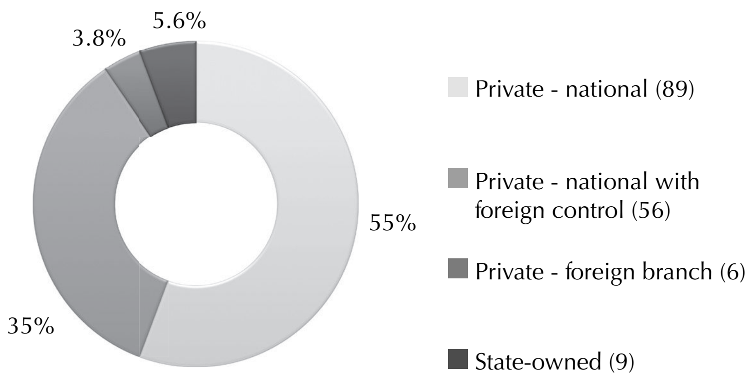


Figure 11.3 Distribution of the banking sector by assets and credit operations

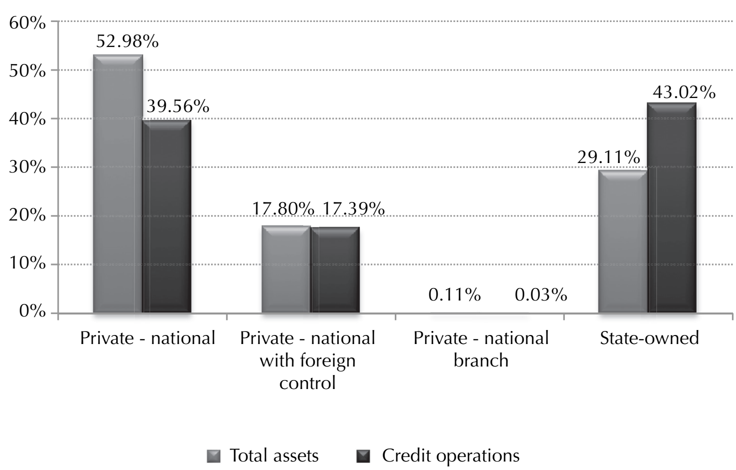


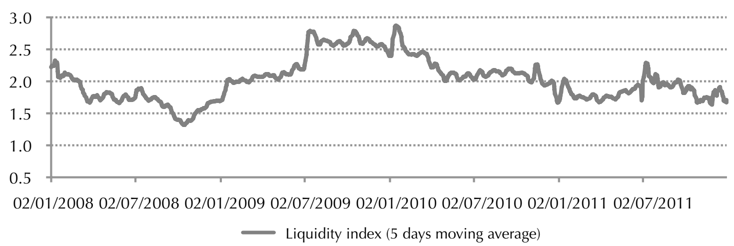
Figure 11.2 shows the division of the Brazilian banking system by type of control (in number of banks and percentages). The participations of each of these categories in the aggregated credit operations and total assets in the same period are shown in Figure 11.3. This figure shows that the state-owned banks increased their participation

in credit operations as a result of government measures to maintain the level of economic activity after the crisis. Total credit operations grew between the second half of 2009 and the same half of 2011, as shown in Figure 11.6. Additional indicators of the financial system's concentration are the HHI and CR4 indexes. HHI is the Herfindahl–Hirschman Index. According to the Horizontal Merger Guidelines, published by the Department of Justice and Federal Trade Commission (EUA), HHI of less than 0.15 means that the market is not concentrated; HHI between 0.15 and 0.25 means that the market is moderately concentrated; and HHI above 0.25 indicates that the market is highly concentrated. CR4 stands for four-firm concentration ratio. It measures the market share of the four largest banks in the system. Values between 50% and 80% indicate medium concentration. The levels of concentration in the Brazilian financial system are monitored by the Central Bank of Brazil. These indexes are calculated for asset totals, credit operations and deposit totals. The HHI values of the system for the second half of 2011 indicate that the Brazilian banking system is non-concentrated to moderately concentrated from the point of view of all these three quantities (respectively 0.13, 0.14 and 0.1509). The CR4 readings for the three quantities in the same period were 67.21%, 69.2% and 72.55%, respectively, which show that the four largest banks, in total assets, hold a slightly higher total deposits ratio, with approximately the same total credit ratio. This means these banks, as a group, do not have a special participation in the system: as credit providers or deposit holders, their participation corresponds to their size.

EFFECTS OF THE SUBPRIME CRISIS ON BRAZILIAN BANKING SYSTEM

Since 2007, important events have been taking place in international banking. The American banking crisis of 2008 spilled over into economies around the world. The collapse of large banks in the US had a domino effect that led to the collapse of even entire economies, as occurred in Greece in the late 2000s. The impact on the Brazilian banking system and economy wasn't as catastrophic. Due stricter regulations and controls imposed in 1995, the Brazilian banking system has remained relatively solid when facing the international crises and has been preserved without much loss. Also, the macroeconomic politics of fiscal austerity and the regime of inflation targeting adopted allowed Brazil to stand out among emergent countries and continue to attract foreign interest. The liquidity situation of Brazilian banks can be shown by the evolution of the system-wide liquidity index in Figure 11.4.

Figure 11.4 System-wide liquidity index



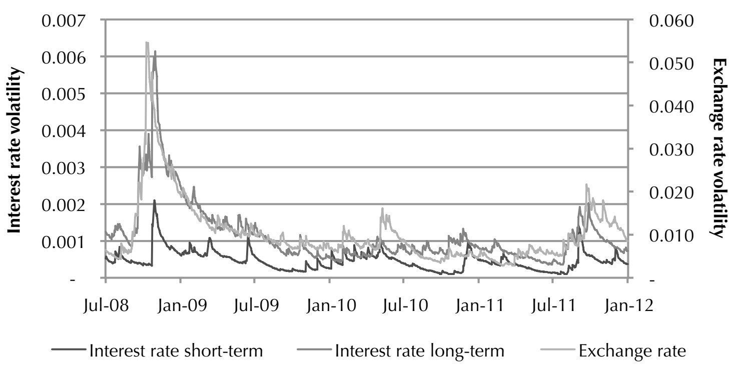
Source: Financial Stability Report - March 2012

The index is calculated by the Central Bank and is the ratio between (a) institutions' total liquid assets available to honour their obligations and (b) the possible losses in liquidity that institutions would be subject to in stress situations. Such situations include unexpected withdrawals and sudden changes in the market scenario. The BCB publishes an aggregated liquidity index for the whole banking sector in the financial-stability report, along with a detailed liquidity analysis of the financial system. More details on calculation of the liquidity index and its use to monitor the financial system liquidity will be presented later.

Volatility in exchange and interest rates usually increases the liquidity required in the case of stress situations (has a negative impact on the index). Figure 11.5 illustrates the behaviour of the volatility of these rates since 2008. The highest volatility occurred, of course, when the crises began. Figure 11.6 shows the finance of credit expansion and liquid assets since 2008.

From the Figures 11.4 and 11.5, it can be observed that the international financial crisis had a greater impact on the Brazilian financial system's liquidity during 2008. During the period, the volatility of the exchange and interest rates was very high and certainly increased the possible losses that the institutions would be subjected to in concrete stress situations. This is related to a decrease in the liquidity index during the period. After 2008, the trajectory of the system's liquidity had a recovery and the trend for the following year was of healthy liquidity conditions. According to the Financial Stability Report (FSR) from the Central Bank in the second half of 2009, the banking system presented an large amount of high-quality liquid assets and had low dependency on foreign resources. These conditions reduced Brazil's vulnerability to liquidity risks and international turbulence. By the first half of 2010, the liquidity of Brazilian financial institutions had returned to the pre-crisis level (BCB 2010).

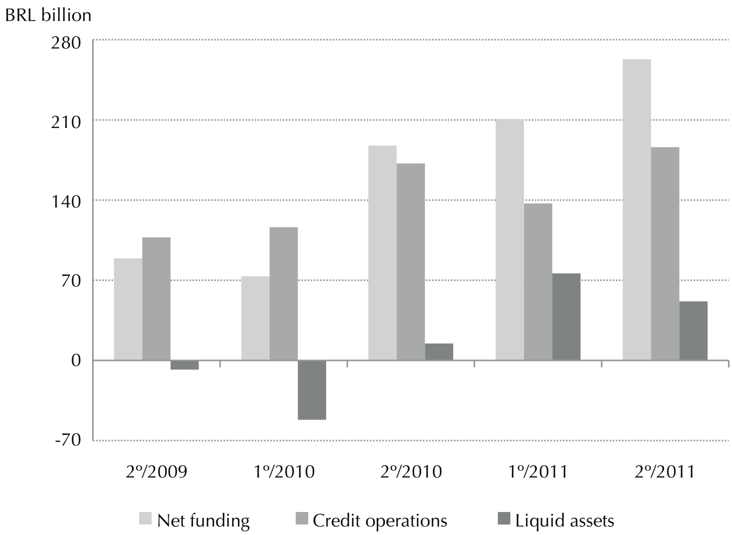
Figure 11.5 Exchange and interest-rate volatility



Source: Financial Stability Report - March 2012

The Financial Stability Report (BCB 2012) concerning the year of 2011 concludes that the banking system's liquidity is in a very favourable situation. The Brazilian banking system had the ability to finance its own operations, mostly with funds raised in the domestic market. In the first half of 2011, the system's funding increased by BRL186.1 billion, representing a 9.1% increase compared with the previous semester. The growth in liquid assets (composed basically of federal government bonds) was remarkable, favoured by the slower growth of the volume of credits (BCB 2011). In the second half of 2011, the system's funding increased by BRL246.9 billion (an 11.2% increase). In this period, the credit expansion was reduced by the available resources from domestic and foreign markets. The liquidity index remained at a good level even after the negative shock caused by the volatility of the interest and exchange rates (BCB 2012).

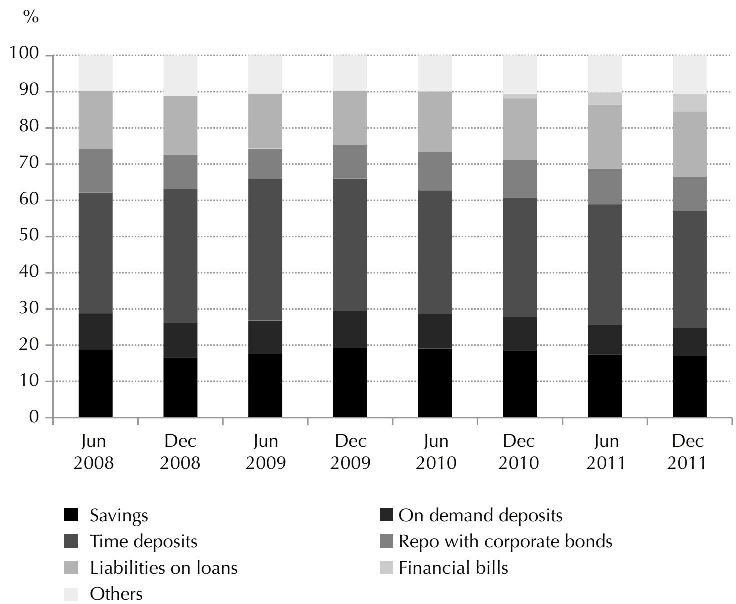
Figure 11.6 Credit operations and liquid assets growth



Source: Financial Stability Report 2012

Deposits (including savings, on-demand and time deposits) have been the major funding source for Brazilian banks. Deposits presented a declining trend in terms of the share of total funding from December 2005 to December 2007. However, in 2008, this trend was reversed due to the crisis's effects on time deposits. Time deposits' interest rate increased to attract funds, which would compensate for the reduction in other sources of liquidity, especially foreign funding. Consequently, the amount of time deposits increased 31.1% in the second half 2008 (BCB 2008 and 2009). Savings deposits have been tracking the funding growth, remaining stable in terms of relative shares. From 2008 to 2011, savings accounted for 17% to about 20% of total funding (see Figure 11.7).[1] Regarding on-demand deposits, we can see in Figure 11.7 that their relative shares declined from 10% in December 2009 to 7.8% in December 2011. On average, these three types of deposits account for more than 60% of total funding between 2008 and 2011. Deposits up to BRL70,000 are guaranteed by the Credit Guarantee Fund (the Fundo Garantidor de Créditos (FGC)). From the total amount of time deposits, the largest holders are households, followed by legal entities (see Figure 11.8).

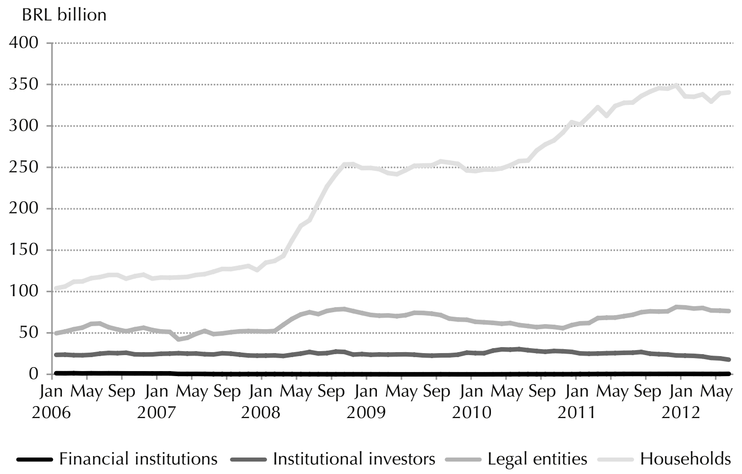
Figure 11.7 Funding sources



Source: Financial Stability Report - March 2012

Financial bills became a more interesting source of funding due to an exemption on reserves requirements for their holders, which became effective in late 2010. Since then, financial bills have presented a growth trend; however, they account for only a small share of the system's total liabilities (BCB 2012). Financial bills are a source of long-term funding and have contributed to the lengthening of the banking system's liabilities profile, as they cannot be redeemed in total or partially before their maturity date (according to the Resolução BCB No. 3.836/2010). This is desirable since the loan's average term has increased due to an increased number of mortgages in the credit portfolios (BCB 2011).

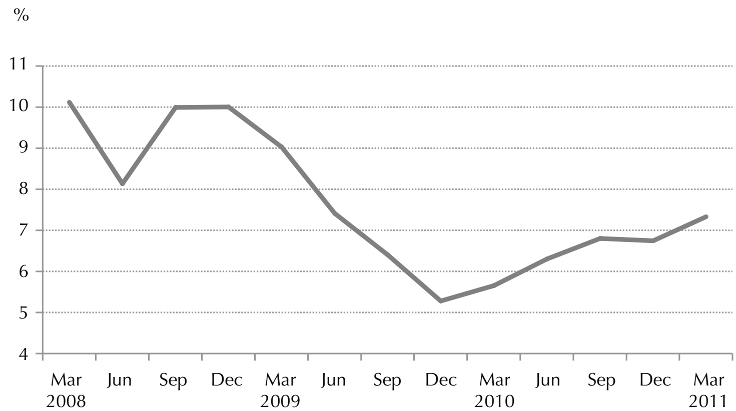
Figure 11.8 Aggregated time deposits



Between 2008 and 2011, liabilities on loans have accounted, on average, for about 16% of total funding. These sources of funding include foreign funding. Most banks that use foreign funding are small foreign banks, whose business model is not related to credit. Nevertheless, only a small part of these banks' funding comes from abroad. The large foreign banks rely mainly on domestic funding. Besides this, liabilities in foreign currency have reduced since the subprime crises (see Figure 11.9). Thus, turbulences in international markets have had a limited impact on the Brazilian banking system (BCB 2012). Liabilities on loans also include loans from the Brazilian Development Bank (BNDES).

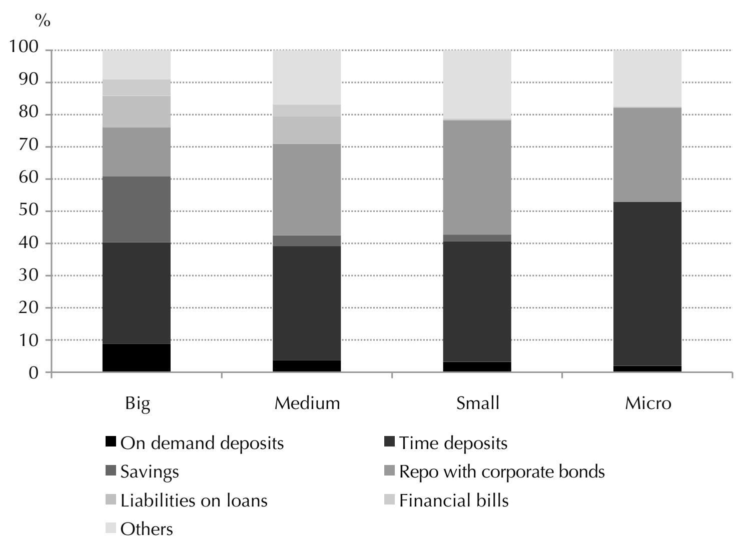
A general look at banks' funding structures highlights the existence of institutional differences. Large banks have more diversified sources of funding, and, due to a wide network of branches, these banks have more access to retail deposits. This source of funding is more stable, reducing the liquidity risk. On the other hand, smaller banks rely mainly on time deposits and have a less diversified funding structure. Financial bills provide a more stable source of funding to their issuers, while being more attractive for their holders, especially if they are large banks, due to a reserve requirement exemption associated with it, which is larger than the one related to time deposits. As smaller banks already have an exemption from reserve requirements due to their low amount of funding, holding financial bills is not as interesting for these banks (see Figure 11.10).

Figure 11.9 External liabilities



Note: Operations with foreign currency or foreign counterpart.
Source: Financial Stability Report - September 2011

Figure 11.10 Funding distribution by bank size



Source: Financial Stability Report - March 2012

Funding-source patterns also differ sharply among the types of control segments. Foreign banks concentrate their funding on time deposits, while public banks tend to emphasise savings. On the other hand, private banks are more focused on repo operations (BCB 2008).

Altogether, the Brazilian banking system relies mainly on domestic sources of funding and is prepared to cope with an occasional liquidity stress. However, liquidity is not equally distributed among banks. Smaller banks that rely on time deposits from large customers are subject to higher liquidity risks during stress periods. These banks can get funding from credit assignment transactions. In August 2011, the Central Bank of Brazil created the Credit Transfer Bureau, in which banks must register credits' assignments (BCB 2011).

Brazilian banks have a more stable funding source, as the reliance on retail deposits is higher than on wholesale funding. Nonetheless, for some banks, institutional investors may represent an important funding source. Therefore, in moments of stress, these banks may incur in liquidity problems. To overcome these problems during the financial crisis the Central Bank of Brazil created a new type of deposit that is guaranteed by the Credit Guarantee Fund (the Fundo Garantidor de Créditos (FGC).

The FGC has an important role in the security of the national financial system. In March 2009, the FGC's Special Guarantee of Time Deposits (DPGE) was implemented. This measure helped the smaller institutions to recover their funding (the amount in the term deposits of small banks grew by about 24% from March to May of the same year). An improvement in the rediscount regulation was also implemented. The deadlines of the rediscount operations were extended and the central bank was authorised to impose restrictive prudential measures to manage the financial institutions (Mesquita and Torós 2010).

The BCB took measures to address the liquidity constraint both in domestic and foreign currencies: bank reserve requirements were lowered; lines of credit in foreign exchange were provided to the private sector; the central bank offered US dollars in spot market auctions and foreign-exchange swap contracts.[2]

Figure 11.11 shows an increase in time deposits, from BRL270 billion in December 2007 to over BRL500 billion in October 2008. The largest growth in deposits was observed in financial institutions and households, followed by companies with a more modest growth. Institutional investors' deposits were maintained at about the same level. That signals a shift towards seemingly less risky investments (that is, time deposits).

Figure 11.11 Time deposits by client type

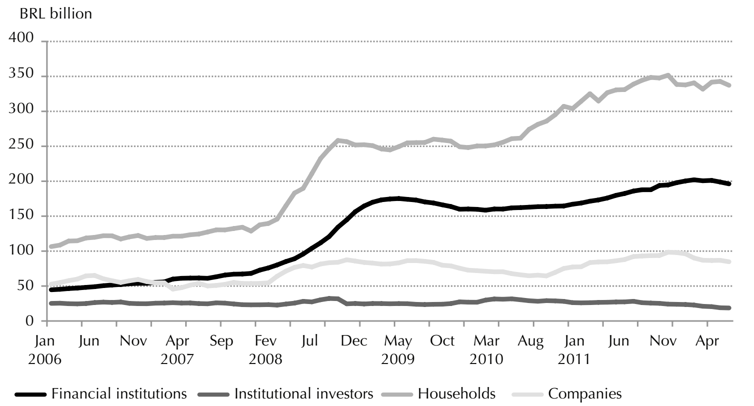
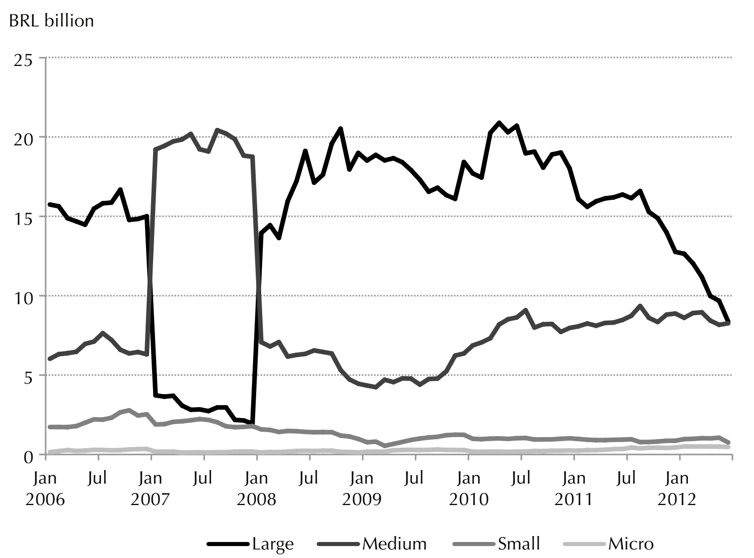
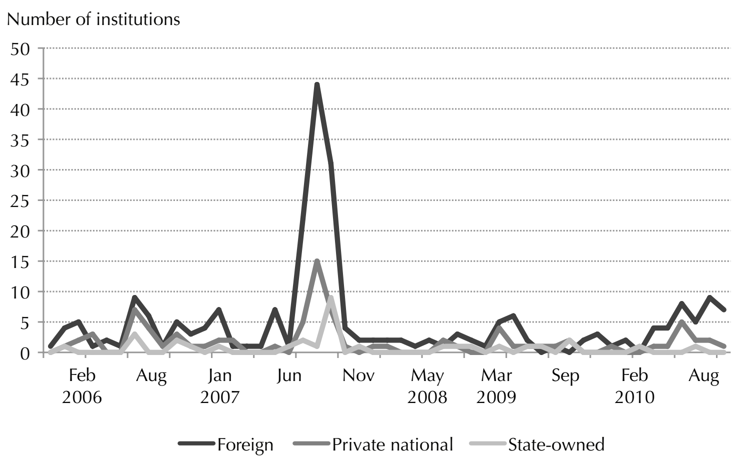


Figure 11.12 Time deposits by institutional investors



Conventional wisdom would expect more informed investors to seek better rates (and therefore riskier investments) in tranquil times, and safer investments in riskier times. That was also evident in time deposits from institutional investors in Brazil. In 2006, large banking institutions and conglomerates had the lion's share of time deposits from institutional investors, about BRL15 billion, whereas the medium-sized banks' share was about BRL6 billion. From January 2007 to December 2007 this was reversed, with about BRL19 billion in time deposits in medium banks and about BRL3 billion in large banks. In January 2008 the situation was once again reversed, as time deposits shifted towards large banks, which are usually regarded as less risky. That movement can be seen quite clearly in Figure 11.12 and signals a flight-to-quality movement in time deposits.

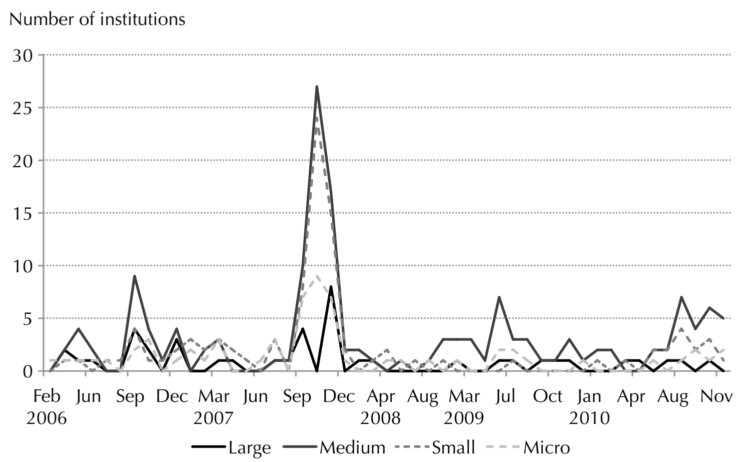
Figure 11.13 Banks and financial conglomerates affected by contagion in time deposits - according to ownership



This flight to quality is also evident in correlation contagion tests. Regarding financial contagion as "a significant increase in correlations after a shock to one institution", a series of correlation-change tests was run based on the Forbes and Rigobon (2002) statistic (FR) devised by Fry, Martin and Tang (2008). In these tests, the log difference of the weekly time deposits' stock was tested for contagion using a vector auto-regressive model and 30-week crisis windows.

The test results indicate how many institutions were affected by contagion within each crisis window, and are summarised in Figures 11.13 and 11.14. The contagion results indicate that most banks affected by contagion were small and medium-sized banks. Regarding ownership, foreign institutions were the most affected by contagion, followed by Brazilian private domestic banks. The peak of contagion was in the windows starting in September to November 2007 and ending in March to May 2008. These time-deposit movements and time-deposit contagions seem to indicate that, during the financial crisis, there was an investor movement towards assets such as guaranteed time deposits or time deposits at large national institutions that were deemed safer at the time. During the crisis, the market perception was that the resilience of small and medium-sized banks reduced, which was translated into the transfer of time deposits from these institutions to large ones, corresponding to a liquidity transfer between them.

Figure 11.14 Banks and financial conglomerates affected by contagion in time deposits – according to size



LIQUIDITY STRESS TESTS IN BRAZIL

Central bank's approach

In Brazil, liquidity risk monitoring is part of the banking supervisory process and includes a continuous follow-up of the systemically important financial institutions and a liquidity stress test. The liquidity stress test combines the bottom-up and top-down approaches. It considers, for each individual financial institution, the different classes of assets and raised funds, but does not take into account the linkages among institutions, resulting in a liquidity index for each institution. This index is a short-term liquidity index similar to Basel III's LCR (see Figure 11.4).

The liquidity index is the ratio between the total liquidity and the estimated liquidity needs. The total liquidity is the amount of liquid assets each institution can dispose of to meet its obligations. It is calculated as the sum of active market operations with maturity on the next day (eg, involving federal securities, active interbank deposits and bank deposit certificates maturing the next day), with active interbank deposits and bank deposit certificates maturing after the next day, weighted by coefficients associated with a possible early redemption of these instruments. The calculation of the total liquidity also considers the balance of other accounting assets: cash, shares, foreign currencies and investments in mutual funds, gold and foreign federal securities.

The estimated liquidity needs is the liquidity level an institution needs to keep to withstand funding volatility and losses under market stress. It is calculated from:

- deposits' volatility under stress on a two-week horizon;
- deposits' concentration index (excluding interbank deposits), taking into account value ranges and client profiles (individuals, firms, financial institutions and institutional investors);
- Interbank deposits raised maturing after the next working day, considering, for short-term Interbank deposits, that they will not be renewed, and a possible early redemption for the remaining Interbank deposits;
- remaining liabilities on the balance sheet; and
- stressed market net positions.

Liquidity stress tests are very useful to assess whether specific banks have liquidity vulnerabilities. In this case, bank supervision can follow up a bank's risks and make accurate interventions. Furthermore, it is useful to design proper public policies to reduce shocks that stem from systemic liquidity problems. The Central Bank of Brazil has performed macroeconomic stress tests and monitored the liquidity of financial institutions to identify possible sources of liquidity stress. Additionally, it has sought to enhance the efficiency and stability of the Brazilian financial system by improvements to the accounting procedures for registering credit assignment operations, by the reduction of the issuance limits of DPGEs by the FGC, by changes on the balance-sheet items subject to reserve requirements and by the gradual introduction of Basel III's recommendations (BCB 2012).

An important measure in the case of Brazil has been the DPGE, which has helped create a liquidity cushion for medium-sized banks, which were suffering from a liquidity shortage immediately after the crisis. These measures have proven to be very successful at relatively low cost, and have increased confidence in the financial system, which is crucial in the middle of a crisis.

The main lesson to be drawn from the financial crisis is that liquidity is crucial. Evaluating it on a continual basis is important and the results from liquidity stress tests can be a very useful monitoring tool and suggest whether liquidity problems are local, specific to certain banks or systemic, in which case public policies can be triggered to help circumvent these problems.

Individual banks' approaches

This section presents some results from the liquidity stress-testing survey carried out by the Central Bank of Brazil on June 2012. The survey aimed to better understand the methods and scenarios that banks used in their liquidity stress tests. It is similar to the survey applied to European banks (ECB 2008).

To mitigate liquidity risks, banks need effective risk management. Fundamental to this task, liquidity stress tests allow banks to assess the possible impact of exceptional but plausible stress scenarios on their liquidity position and can help them to determine the size of liquidity buffers.

The respondent banks say liquidity risk is considered the second most important type of risk in their risk management; the most important is credit risk. Although some banks have been performing liquidity stress tests since about 2002, the majority of them began to perform these tests after 2008.

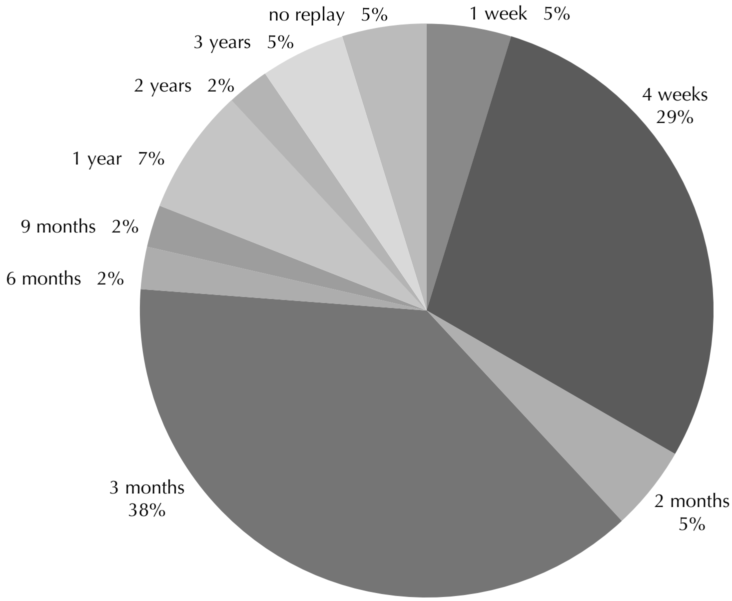
A total of 46 large banks received the survey and 27 banks provided information about their liquidity stress tests, including the largest Brazilian banks. From these banks, 23 perform internal liquidity stress tests while 4 of them use vendors' models.

All banks but one in the survey quantify liquidity risk tolerance. In the sample, 17 banks affirm they quantify risk tolerance by a system of limit settings. These limits are usually defined based on expert judgement. In eight banks, the quantification of liquidity risk tolerance is based on stress tests. Other forms, less frequently used, to quantify liquidity risk tolerance are: cashflow forecast (6 banks), concentration of the liquidity sources (2) and survival horizon (1). The ECB (2008) affirms that banks focus on risk containment – systems of limits interrelated with liquidity risk tolerance – rather than the quantification of liquidity risk tolerance *per se*. The explanation for this is that the quantification of liquidity risk tolerance is a difficult task. The major problem in the area of liquidity risk management is that liquidity risk events are of low probability but high impact, which implies that is not feasible to assign probabilities to all (reasonably well-defined) possible liquidity shocks. It seems that Brazilian banks have the same focus.

Time horizon

The time horizon of liquidity stress tests indicates the horizon the bank considers necessary to take corrective measures to mitigate liquidity risks occasionally detected. The majority of banks (17) perform liquidity stress tests monthly and some banks (8) perform them daily. Time horizons for stress-test scenarios mainly vary between four weeks and three months, although longer time horizons are also cited (see Figure 11.15). Almost every bank uses short or medium time horizons to perform their stress tests. However, the period considered as short, medium or long is not uniform among banks. A short period may comprise from one to twelve weeks, while a medium period comprises from two to twelve months. The most commonly time horizons considered are four weeks for a short period and three months, for a medium period.

Figure 11.15 Time horizon

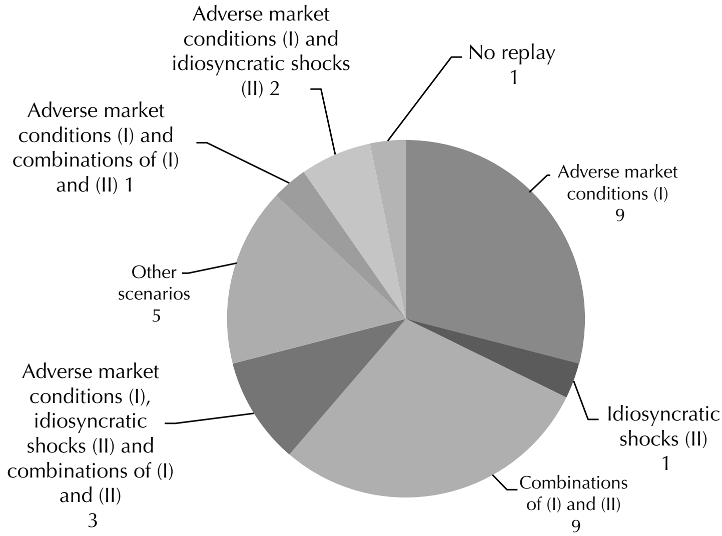


Source: BCB survey

Scenarios

The scenarios banks use consider the risk sources and magnitudes they relate to their business. Most banks (15) perform tests under market-wide stress scenarios, but only six banks use idiosyncratic scenarios. A considerable number of the surveyed banks (13) use a combination of adverse market conditions and idiosyncratic shocks to their institutions. Of these banks, only 9 run the combined scenario, while 3 also run both market and idiosyncratic scenarios separately and one bank also runs the market scenario. Of those banks that do not run tests with combined scenarios, the majority (15) rely exclusively on either tests with market stress scenarios (9) or tests with a firm-specific stress scenario (1). Five banks declared that they considered other types of stress test scenarios and one did not respond to the question (Figure 11.16).

Figure 11.16 Types of stress-test scenario



Source: BCB survey

The surveyed banks described a multiplicity of scenarios with different sets of assumptions concerning the effect that these scenarios were expected to have on both the assets and liabilities sides of their balance sheets. However, there are some sources of stress that are common in most scenarios:

- reduction in asset prices;
- increased collateral and margin calls;
- increased delinquency;
- reduced access to funding markets;
- increased deposits withdrawals;
- non-rollover of term deposits; and
- utilisation of credit lines previously approved.

Although most banks claim they perform a combination of adverse market conditions and idiosyncratic-scenarios tests, it is not defined which shocks they consider as coming from market conditions or from bank-specific situations. Only a few banks consider bank-specific sources of stress, such as downgrade and liquidity problems in the group.

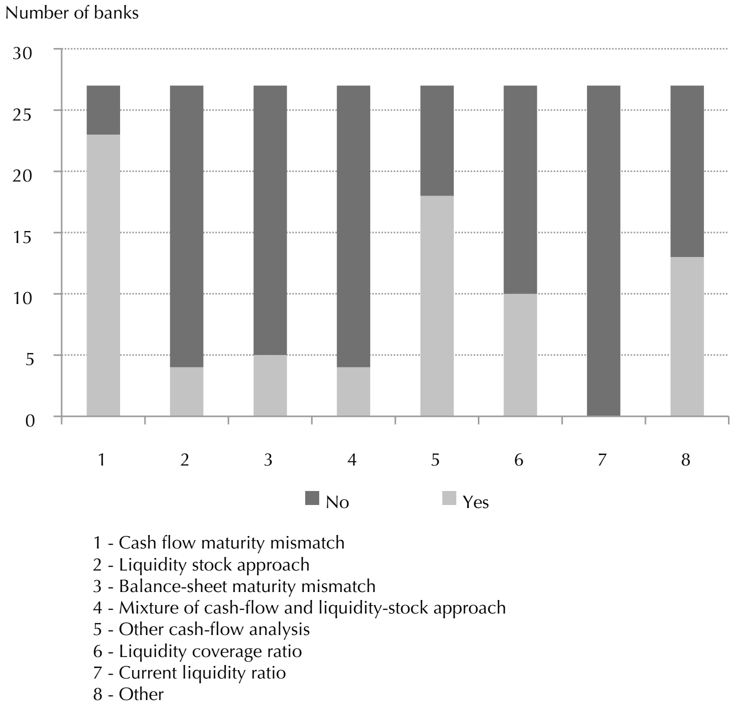
Most banks make assumptions about deposits in their stress scenarios. These assumptions are consistent with the structure of the BBS and the economic outlook. In the BBS, banks rely on domestic funds provided mainly by deposits. Another source of stress, usual for more than one-third of the banks, is an increase in delinquency. Brazil has experienced a fast credit growth, so banks seem to be aware of the effects of credit risk on liquidity.

According to the IMF (2012), the Brazilian financial sector is exposed to international commodities and capital markets' volatility effects, but the risks related to them are significantly mitigated by a flexible exchange rate; strong macro- and microprudential policy frameworks; and financial institutions' sound balance sheets, high capital, profitability and abundant liquid assets. However, banks consider this source of stress by means of assumptions about collateral or margin calls.

The vast majority of banks consider prospective approaches. Most banks forecast their cashflows by means of assumptions about the impact on inflows and outflows. However, it is not clear how these assumptions are made. It seems to be based on expert judgement.

Concerning scenario revisions, all respondents reported that liquidity stress scenarios are revised, with 19 banking conducting revisions regularly. From these banks, eight review their scenarios annually and six do it monthly. The events that trigger adjustments in the stress scenarios include, in no particular order of importance, changes in the macroeconomic scenario; changes in policies, guidelines and practices at the group level; changes in regulations; changes in monetary policy; business developments; changes in the levels of delinquency; changes in markets. From the 27 banks, 23 need either approval from an asset-and-liability committee, a risk committee or a board of directors for significant adjustments to the liquidity stress test scenarios. Regarding the stress-test level, eleven banks perform them at the entity level, while eight perform stress tests at the group level. However, only six banks perform stress tests at both levels. Five banks perform liquidity stress tests at other levels, such as the currency level.

Figure 11.17 Measurement approach to liquidity stress tests



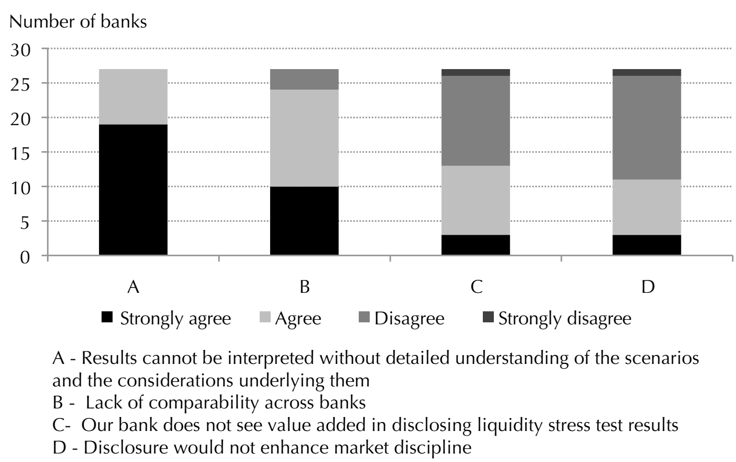
Source: BCB survey

Banks use more than one approach to quantify their liquidity risk exposure (see Figure 11.17). According to the survey, the most common type of measurement approach (23 banks) is the cashflow maturity mismatch, followed by other cashflows analyses (18). The main advantages of the cashflow maturity mismatch seem to be that it is transparent, flexible and simple and gives a general overview of risk (ECB 2008). Matz and Neu (2007) argue that measures built on maturity mismatch and cashflow modelling help to reflect the dynamic nature of liquidity. The main disadvantage is that it is considered to be a short-term tool that does not reveal long-term liquidity problems (ECB 2008).

In summary, the respondent banks consider liquidity risk an important source of risk. The importance attributed to it increased after 2008, which can be related to the start of performing liquidity stress tests by the majority of institutions. The time horizon and sources of stress considered reflect the threats against which the individual institutions want to be protected, which depend on the particularities of their business.

Banks are reluctant to disclose the results of their stress tests, doing so, on demand, mainly to rating agencies and supervisors. Only a few banks frequently disclose their stress-test results to auditing firms, committees and boards. What possible reasons do banks give for this reluctance? Although most banks agree that disclosure would enhance market discipline in liquidity risk management and see value added in disclosing the results of liquidity stress tests, all banks agree strongly (19) or agree (8) that the results of liquidity stress tests cannot be interpreted without a detailed understanding of the scenarios and the considerations underlying them (Figure 11.18).

Figure 11.18 Disclosure policy of stress testing



Source: BCB survey

CONCLUSIONS

This chapter discusses the effects of the financial crisis on the Brazilian banking system. The financial crisis has had major impacts worldwide, and liquidity risks have risen accordingly. There was an urgent need for macroprudential measures to help banking systems regain confidence and increase their liquidity to cope with additional risks.

We have presented the liquidity stress-testing approach in use in the Central Bank of Brazil and the results of a survey on liquidity stress testing that has been applied to banks that operate in the Brazilian banking system.

Overall, the Brazilian Banking system has experienced a small impact from the financial crisis due to several macroprudential measures and strong bank supervision and regulation. This impact affects banks differently. Medium-sized banks experienced a strong liquidity constraint due to a fly-to-quality movement in time deposits. Regarding ownership, foreign banks were the most affected by contagion. To avoid a confidence crisis, the BCB took measures both in domestic and foreign currencies that helped banks to overcome liquidity problems.

The survey applied to the largest Brazilian banks showed that liquidity risk is the second most important risk in their risk management. It seems that the crisis led to an improvement in the banks' risk management, since most of them started to perform liquidity stress tests after the period of turbulences starting in 2007. There is a considerable diversity in liquidity stress-test scenarios. However, most banks use a combination of adverse market conditions and tests of idiosyncratic-shock scenarios. The findings show that banks do not rely on any single measure of liquidity but they have a preference for measurements related to cashflows.

Benjamin M. Tabak gratefully acknowledges financial support from CNPQ Foundation. The opinions expressed in this chapter are those of the authors and do not necessarily reflect those of the Central Bank of Brazil.

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1 An analysis of the distribution of these deposits among its holders shows that, in 2006, 54.1% of the total amount was concentrated at the level of up to BRL100 per account, with 41,565,238 depositors (BCB 2007).

2 For more details about the measures taken by Brazilian authorities, see Mesquita and Torós (2010) and Silva and Harris (2012).

3 Adapted from "a significant increase in cross-market linkages after a shock to one country (or group of countries)", by Forbes and Rigobon (2002).

12

Determining the Severity of Macroeconomic Stress Scenarios

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Federal Reserve Bank of New York

In the midst of the 2008 financial panic caused by the collapse of the subprime housing market, the US government responded with unprecedented measures, including liquidity provision through various funding programmes, debt and deposit guarantees and large-scale asset purchases. In February 2009, the US banking supervisors conducted the first-ever system-wide stress test on 19 of the largest US bank holding companies (BHCs), known as the Supervisory Capital Assessment Program (SCAP) (Federal Reserve 2009a). The stress test required these 19 BHCs to undergo simultaneous, forward-looking exercises designed to determine whether they would have adequate capital to sustain lending to the economy in the event of an unexpectedly adverse scenario. By conducting this SCAP exercise, the supervisors hoped that it would reduce uncertainty and restore confidence in the US financial institutions. In their 2010 staff reports, Peristian, Morgan and Savino (2010), of the Federal Reserve Bank of New York, concluded that the SCAP might have helped to quell the financial panic by releasing vital information about the BHCs. They claimed, "While investors did not need supervisors to tell them which banks had capital deficiencies, they were surprised by the size of the capital gaps and they used that information to revalue banks."

Since conducting the SCAP in 2009, the Federal Reserve System has conducted annual stress tests on the US banking system, called the Comprehensive Capital Analysis and Review (CCAR).

Additionally, the Dodd–Frank Wall Street Reform and Consumer Protection Act requires the Federal Reserve Board to conduct annual stress tests of bank holding companies with total consolidated assets of US$50 billion or more. In each CCAR, the Federal Reserve Board generates an adverse macroeconomic scenario (two adverse scenarios in 2013) and requires BHCs to submit at least one adverse scenario that is related to their own specific portfolios and risk profiles. While the 2013 instructions for CCAR indicate that the adverse scenario developed by the BHC must reflect "a severely adverse economic and financial market environment", it does not specify what should be the "appropriate severity" of an adverse scenario used for the capital planning. This chapter will discuss the severity of the supervisory adverse scenarios and provide a simple methodology to compare the severity of different adverse macroeconomic scenarios. In particular, the key questions we aim to answer are:

- how to measure the severity of a firm's BHC macro stress scenario;
- how severe the BHC stress scenario is when compared with the supervisory stress scenarios; and
- what implications can be drawn about the credibility of the BHC's stress scenario.

THE US SUPERVISORY STRESS SCENARIOS

As part of the Federal Reserve System's Comprehensive Capital Analysis and Review (CCAR), US domiciled top-tier bank holding companies (BHCs) are required to submit comprehensive capital plans, including *pro forma* capital analyses, based on at least one BHC defined adverse scenario. The adverse scenario is described by quarterly trajectories for key macroeconomic variables (MVs) over the next nine quarters (or longer, as in 2013). In addition, the Federal Reserve generates its own supervisory stress scenarios so that firms are expected to apply both BHC and supervisory stress scenarios to all exposures to estimate potential losses under stressed operating conditions. Separately, firms with significant trading activity are asked to estimate a one-time potential trading-related market and counterparty credit losses under their own BHC scenarios and market stress scenarios provided by the supervisors.[1]

For the supervisory stress scenarios, the Federal Reserve provides firms with global market shock components that are one-time, hypothetical shocks to a large set of risk factors. For the last two CCAR exercises, these shocks involved large and sudden changes in asset prices, rates and CDS spreads that mirrored the severe market condition in the second half of 2008.

Since CCAR is a comprehensive assessment of a firm's capital plan, the BHCs are asked to conduct an assessment of the expected uses and sources of capital over a planning horizon. In the 2009 SCAP, firms were asked to submit stress losses over the next two years, on a yearly basis. Since then, the planning horizon has changed to nine quarters. For the last three CCAR exercises, a BHC is asked to submit its pro forma, post-stress capital projections in its capital plan beginning with data as of September 30, and spans the nine-quarter planning horizon. The projections begin in the fourth quarter of the current year and conclude at the end of the fourth quarter two years forward. Hence, for defining BHC stress scenarios, firms are asked to project the movements of key macroeconomic variables over the planning horizon of nine quarters. Our analysis on determining the severity of macro stress scenarios is based on the movements of the macroeconomic variables in these nine quarters. As for determining the severity of the global market shock components for trading and counterparty credit losses, it will not be discussed in this chapter because it is a one-time shock and the evaluation will be on the movements of the market risk factors rather the macroeconomic variables. This is examined in Chapter 3.

In the 2011 CCAR, the Federal Reserve defined the stress supervisory scenario using nine macroeconomic variables: Real GDP, Consumer Price Index (CPI), Real Disposable Personal Income, Unemployment Rate, Three-Month Treasury Bill Rate, 10-Year Treasury Bond Rate, BBB Corporate Rate, Dow Jones Index and National House Price Index (Federal Reserve 2011a). In CCAR 2012, the number of macroeconomic variables that defined the supervisory stress scenario increased to 14. Besides the original nine variables, the added variables were Nominal GDP Growth, Nominal Disposable Income Growth, Mortgage Rate, Market Volatility Index and Commercial Real Estate Price Index (Federal

Reserve 2011b) Additionally, there is another set of 12 international macroeconomic variables, three macroeconomic variables and four countries/country blocks, included in the supervisory stress scenario. As for CCAR 2013, the Federal Reserve System uses the same set of variables to define the supervisory adverse scenario (Federal Reserve 2012) as in 2012. Since the BHCs are required to define their own adverse scenarios of "a severely adverse economic environment", one way to determine the "appropriate severity" of the BHCs' stress scenarios is to compare them with the supervisory adverse scenarios. Although it is stated that the BHC stress scenarios should reflect the BHC's unique vulnerabilities to factors that affect its exposures, activities and risks, by comparing the severity of the BHC's and supervisory stress scenarios we can determine whether the estimates of the losses are consistent with the relative severity of the stress scenarios. For example, if the BHC's own stress scenario is determined to be more severe than the supervisory scenario, but the estimated losses from the supervisory scenario are larger, then we would need to examine the details of the stress loss estimation methodology to determine the causes of this inconsistency.

ALIGNING THE US SUPERVISORY STRESS SCENARIOS

Let us consider the two CCAR supervisory stress scenarios in 2011 and 2012 and the supervisory severely adverse scenario in 2013. By comparing the forecast of the macroeconomic variables over the next nine quarters, we will try to determine which scenarios are the most and least severe.

In general, comparing severity of stress scenarios is relative. That is, we can usually deduce with relative confidence that Scenario A is more severe than Scenario B, but it is much more challenging to quantify how much more severe is Scenario A over Scenario B. In other words, it is much more difficult to define a metric to measure the severity of a stress scenario. Later in this chapter, we will attempt to use a historical event as a reference to give some sights on the measurement of severity.

Table 12.1 The Federal Reserve supervisory adverse scenarios with nine quarters of projections

CCAR 2011 Common Variables	**Q3 2010**	**Q4 2010**	**Q1 2011**	**Q2 2011**	**Q3 2011**	**Q4 2011**	**Q1 2012**	**Q2 2012**	**Q3 2012**	**Q4 2012**
Real GDP	13,261	13,332	13,393	13,255	13,206	13,138	13,178	13,229	13,343	13,453
Real Disposable Personal Income	10,237	10,271	10,299	10,318	10,236	10,179	10,081	10,054	10,047	10,066
Unemployment Rate	9.6	9.6	9.6	10.1	10.6	11.0	11.1	11.0	10.9	10.6
CPI	218.0	219.0	219.9	220.9	221.7	222.3	222.9	223.4	224.0	224.7
3-Month Treasury Yield	0.16	0.16	0.19	0.07	0.13	0.13	0.13	0.13	0.13	0.13
10-Year Treasury Yield	2.90	2.57	2.64	2.66	2.79	2.77	2.71	2.98	3.12	3.35
BBB corporate yield	5.07	4.69	4.86	5.88	6.26	6.46	6.16	6.27	6.22	6.25
Dow Jones Total Stock Market Index	11,947	12,069	11,822	9,116	8,809	8,716	10,682	11,083	11,498	11,930
National House Price Index	142	140	139	137	134	132	130	128	127	126

CCAR 2012 Common Variables	**Q3 2011**	**Q4 2011**	**Q1 2012**	**Q2 2012**	**Q3 2012**	**Q4 2012**	**Q1 2013**	**Q2 2013**	**Q3 2013**	**Q4 2013**
Real GDP growth	2.46	-4.84	-7.98	-4.23	-3.51	0.00	0.72	2.21	2.32	3.45
Real Disposable Personal Income growth	-1.73	-6.02	-6.81	-4.29	-3.16	-0.57	0.74	1.66	2.69	2.27
Unemployment Rate	9.09	9.68	10.58	11.40	12.16	12.76	13.00	13.05	12.96	12.76
CPI inflation rate	3.09	2.21	1.78	1.02	0.89	0.35	0.23	0.21	0.30	0.32
3-Month Treasury Yield	0.02	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10

Table 12.1 *(continued)*

10-Year Treasury Yield	2.48	2.07	1.94	1.76	1.67	1.76	1.74	1.84	1.98	1.98
BBB corporate yield	4.87	5.65	6.83	6.81	6.75	6.45	6.07	5.83	5.74	5.51
Dow Jones Total Stock Market Index	11,771.86	9,501.48	7,576.38	7,089.87	5,705.55	5,668.34	6,082.47	6,384.32	7,084.65	7,618.89
National House Price Index	136.86	135.13	131.61	127.50	123.12	119.08	115.15	111.92	109.77	108.48

CCAR 2013 Common Variables	**Q3 2012**	**Q4 2012**	**Q1 2013**	**Q2 2013**	**Q3 2013**	**Q4 2013**	**Q1 2014**	**Q2 2014**	**Q3 2014**	**Q4 2014**
Real GDP growth	2.0	-3.5	-6.1	-4.4	-4.2	-1.2	0.0	2.2	2.6	3.8
Real Disposable Personal Income growth	0.8	-3.8	-6.7	-4.6	-3.2	-1.5	0.8	0.9	2.5	2.8
Unemployment Rate	8.1	8.9	10.0	10.7	11.5	11.9	12.0	12.1	12.0	11.9
CPI inflation rate	2.3	1.8	1.4	1.1	1.0	0.3	1.0	0.9	0.7	0.6
3-Month Treasury Yield	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
10-Year Treasury Yield	1.6	1.4	1.2	1.2	1.2	1.2	1.2	1.5	1.7	1.9
BBB corporate yield	4.2	5.6	6.4	6.7	6.8	6.5	6.2	6.2	6.0	5.9
Dow Jones Total Stock Market Index	14997.8	12105.2	9652.6	9032.8	7269.1	7221.7	7749.3	8133.9	9026.1	9706.7
National House Price Index	143.4	141.6	137.9	133.6	129.0	124.7	120.6	117.2	115.0	113.6

Before we begin to examine the three supervisory scenarios, we have to make the following key assumptions.

- All scenarios start on the same quarter, Q3 2010, and the projections are over the nine quarters from Q4 2010 to Q4 2012. Hence the scenarios are compared by measuring the change over the nine quarters on the macroeconomic variables.
- The scenarios are compared on the set of common macroeconomic variables. For example, in 2012 and 2013, the Market Volatility Index is included in the supervisory stress scenario, but not in 2011, thus this variable is excluded. Therefore, the set of common macroeconomic variables for comparison are all the variables that are defined in the supervisory scenario of 2011 CCAR.

Of the nine macroeconomic variables, Real GDP, CPI, and Real Disposable Personal Income are expressed as growth rates in 2012 and 2013 (see Table 12.1). To convert them back to Real GDP, CPI and Real Disposable Personal Income, we use Equation 12.1 to convert growth rates into actual values, and align all the starting values using the Q3 2010 actual values. For variables such as Unemployment Rate (UR), we first align all the starting values to be Q3 2010, then we use the percentage change over the period (Equation 12.2) to convert the 2012 and 2013 projections to the projections with the same starting values. For example, the Real GDP Growth Rate (Real_GDPGR) is converted to Real GDP (Real_GDP) by the following equation:

$$Real\_GDP_{i+1} = Real\_GDP_i * \left\{\left(1 + \frac{Real\_GDPGR_{i+1}}{100}\right)^{0.25}\right\} \tag{12.1}$$

For other variables, the alignment is just the percentage change over the period,

$$UR\_2011_{i+1} = UR\_2011_i \left(1 + \frac{(UR_{2012\ i+1} - UR_{2012\ i})}{UR_{2012\ i}}\right) \tag{12.2}$$

Table 12.2 The macroeconomic variables with nine quarters of projections on the four scenarios

Scenario	CCAR Common Variables	Q3 2010	Q4 2010	Q1 2011	Q2 2011	Q3 2011	Q4 2011	Q1 2012	Q2 2012	Q3 2012	Q4 2012
2011	Real GDP	13,261	13,332	13,393	13,255	13,206	13,138	13,178	13,229	13,343	13,453
2012	Real GDP	13,261	13,097	12,828	12,690	12,577	12,577	12,599	12,668	12,741	12,849
2013	Real GDP	13,261	13,143	12,938	12,793	12,657	12,619	12,619	12,687	12,769	12,889
Hypothetical	Real GDP	13,261	12,690	12,690	12,690	12,690	12,690	12,690	12,690	12,690	12,690
2011	Real Disposable Personal Income	10,237	10,271	10,299	10,318	10,236	10,179	10,081	10,054	10,047	10,066
2012	Real Disposable Personal Income	10,237	10,079	9,903	9,795	9,717	9,703	9,721	9,761	9,826	9,881
2013	Real Disposable Personal Income	10,237	10,138	9,964	9,847	9,768	9,731	9,750	9,772	9,832	9,901
Hypothetical	Real Disposable Personal Income	10,237	9,700	9,700	9,700	9,700	9,700	9,700	9,700	9,700	9,700
2011	Unemployment Rate	9.58	9.61	9.62	10.11	10.56	11.02	11.12	11.04	10.87	10.64
2012	Unemployment Rate	9.58	10.20	11.15	12.02	12.82	13.45	13.70	13.75	13.66	13.45
2013	Unemployment Rate	9.58	10.53	11.83	12.66	13.60	14.07	14.19	14.31	14.19	14.07
Hypothetical	Unemployment Rate	9.58	12.66	12.66	12.66	12.66	12.66	12.66	12.66	12.66	12.66
2011	10-Year Treasury Yield	2.90	2.57	2.64	2.66	2.79	2.77	2.71	2.98	3.12	3.35
2012	10-Year Treasury Yield	2.90	2.42	2.27	2.05	1.95	2.05	2.04	2.15	2.31	2.32

Table 12.2 (*continued*)

2013	10-Year Treasury Yield	2.90	2.54	2.18	2.18	2.18	2.18	2.18	2.72	3.08	3.44
Hypothetical	10-Year Treasury Yield	2.90	2.80	2.80	2.80	2.80	2.80	2.80	2.80	2.80	2.80
2011	3-Month Treasury Yield	0.16	0.16	0.19	0.07	0.13	0.13	0.13	0.13	0.13	0.13
2012	3-Month Treasury Yield	0.16	0.69	0.69	0.69	0.69	0.69	0.69	0.69	0.69	0.69
2013	3-Month Treasury Yield	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16
Hypothetical	3-month Treasury yield	0.16	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50
2011	BBB corporate yield	5.07	4.69	4.86	5.88	6.26	6.46	6.16	6.27	6.22	6.25
2012	BBB corporate yield	5.07	5.87	7.11	7.09	7.03	6.71	6.31	6.07	5.97	5.73
2013	BBB corporate yield	5.07	6.76	7.73	8.09	8.21	7.85	7.48	7.48	7.24	7.12
Hypothetical	BBB corporate yield	5.07	8.09	8.09	8.09	8.09	8.09	8.09	8.09	8.09	8.09
2011	CPI	218.0	219.0	219.9	220.9	221.7	222.3	222.9	223.4	224.0	224.7
2012	CPI	218.0	219.2	220.2	220.8	221.3	221.4	221.6	221.7	221.9	222.0
2013	CPI	218.0	219.0	219.8	220.4	220.9	221.1	221.6	222.1	222.5	222.9
Hypothetical	CPI	218.0	222.0	222.0	222.0	222.0	222.0	222.0	222.0	222.0	222.0
2011	Dow Jones Total Stock Market Index	11,947	12,069	11,822	9,116	8,809	8,716	10,682	11,083	11,498	11,930
2012	Dow Jones Total Stock Market Index	11,947	9,643	7,689	7,195	5,791	5,753	6,173	6,479	7,190	7,732
2013	Dow Jones Total Stock Market Index	11,947	9,643	7,689	7,195	5,791	5,753	6,173	6,479	7,190	7,732

Table 12.2 (*continued*)

Hypothetical	Dow Jones Total Stock Market Index	11,947	7,200	7,200	7,200	7,200	7,200	7,200	7,200	7,200	7,200
2011	National House Price Index	142.4	140.4	139.1	136.8	134.3	131.8	129.6	127.8	126.8	126.4
2012	National House Price Index	142.4	140.6	136.9	132.6	128.1	123.9	119.8	116.4	114.2	112.8
2013	National House Price Index	142.4	140.6	136.9	132.6	128.1	123.8	119.7	116.3	114.2	112.8
Hypothetical	National House Price Index	142.4	120.0	120.0	120.0	120.0	120.0	120.0	120.0	120.0	120.0

After aligning the supervisory stress scenarios from CCAR 2011, 2012 and 2013, we also create an additional hypothetical stress scenario to illustrate how the severity of stress scenarios can be compared between the supervisory scenarios and a "BHC-developed" stress scenario, as part of the BHC's requirements under CCAR. Table 12.2 shows the three supervisory and the hypothetical scenarios as they are all aligned at Q3 2010. All the scenarios have the same set of macroeconomic variables and they are all aligned to the same value as of Q3 2010. Hence, by comparing the changes of the macroeconomic variables over the next nine quarters, we can examine the severity of each scenario relative the others.

HISTORICAL TREND OF THE MACROECONOMIC VARIABLES

In generating the supervisory adverse scenarios, the Federal Reserve emphasises that the scenarios are not economic forecasts, but rather hypothetical scenarios that show significant contraction in economic activities. A contraction in economic activities means macroeconomic indicators such as GDP, employment, stock indexes, investment spending, capacity utilisation, household income, housing prices and inflation fall, while the unemployment rate and personal and corporate bankruptcies rise. Of the nine common macroeconomic variables, the one that is most related to stress economic conditions is a drop in Real GDP. As for the rest of the common variables, most economists would agree that a stress economic condition will associate with a decrease in Real Disposable Personal Income, Dow Jones Index and House Price Index, and an increase in Unemployment Rate. However, for CPI, BBB Corporate Bond Rate, Three-Month Treasury Yield and the 10-Year Treasury Yield, it is not so clear that an increase or decrease in any one of these variables will indicate a stress economic condition.

We will use historical data to examine each of the common variables to understand its relationship with historical recessions. All the historical values are obtained from the Board of Governors' document on Supervisory Scenarios[2].

In the US, from 1980 to 2013, there have been nine periods of negative economic growth over one fiscal quarter or more (see Figure 12.1). According to the National Bureau of Economic Research (NBER), there have been five periods considered recessions:[3]

- ❏ January 1980–July 1980: 6 months;
- ❏ July 1981–November 1982: 16 months;
- ❏ July 1990–March 1991: 8 months;
- ❏ March 2001–November 2001: 8 months; and
- ❏ December 2007–June 2009: 18 months.

Figure 12.1 US Real GDP growth, 1980–2012

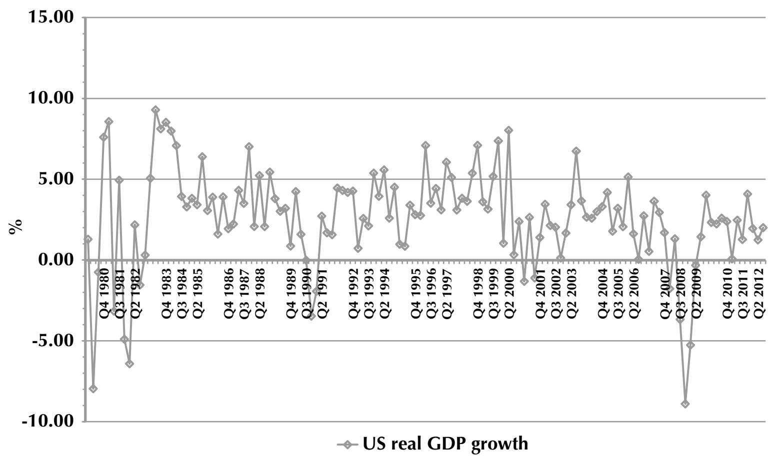
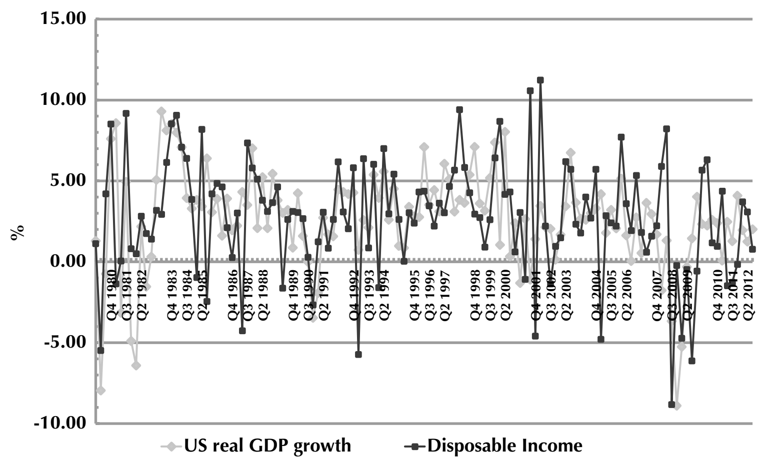


Figure 12.2 US Real GDP growth and income, 1980–2012



From Figure 12.2, we can see that a drop in GDP Growth Rate is usually associated with a drop in the Real Disposable Personal Income Growth Rate. Thus, we can state, in general, a stress economic condition is associated with a drop in Real Disposable Personal Income Growth.

Figure 12.3 US Real GDP growth and Dow Jones Index

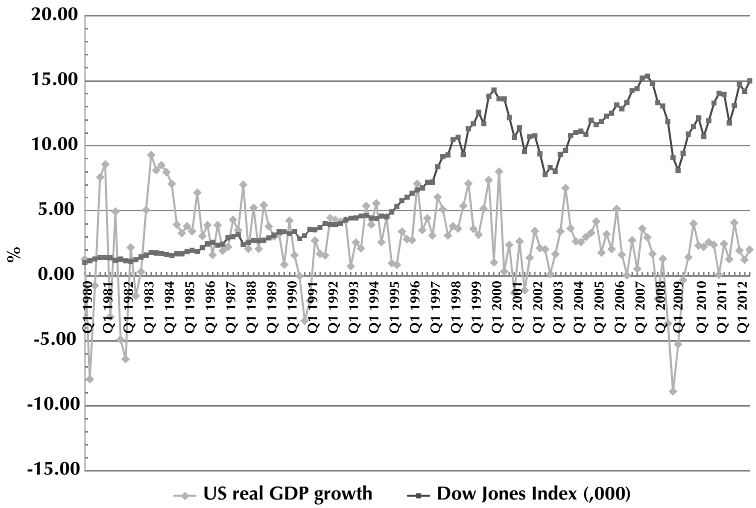
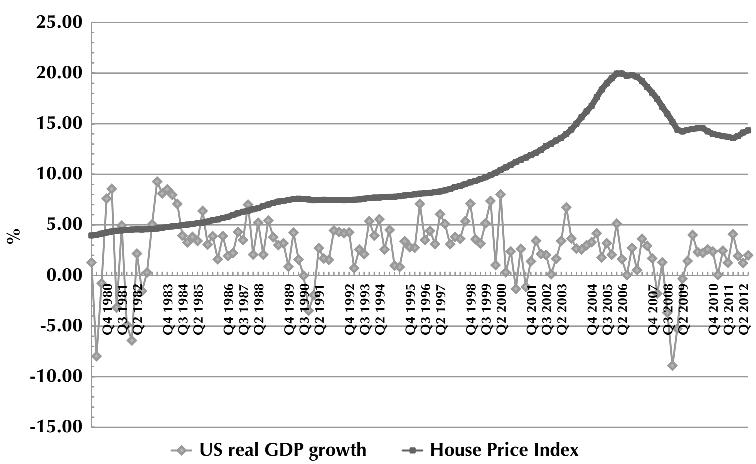


Figure 12.4 US Real GDP growth and House Price Index



From Figure 12.3, we can see that the last two recessions are associated with significant drops in the Dow Jones Index, and from Figure 12.4 we see that the most severe recession followed a huge drop in the House Price Index. Hence, we can also confidently claim that a stress economic condition is associated with a drop in Dow Jones Index or House Price Index.

Figure 12.5 US Real GDP growth and unemployment rate

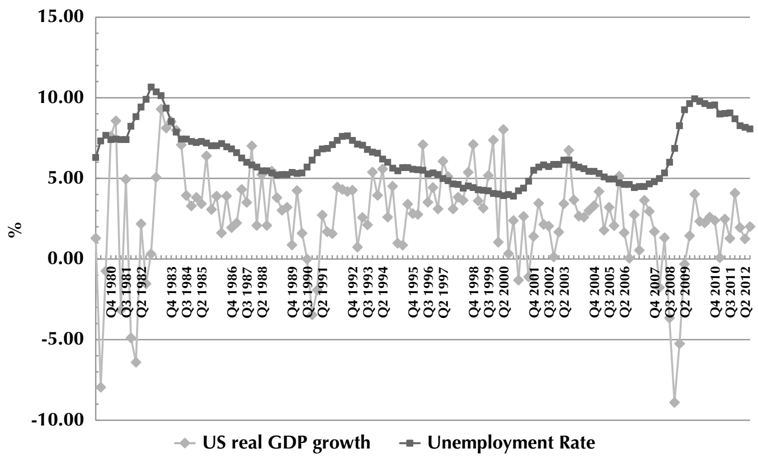


Figure 12.6 US Real GDP growth and BBB bond rate

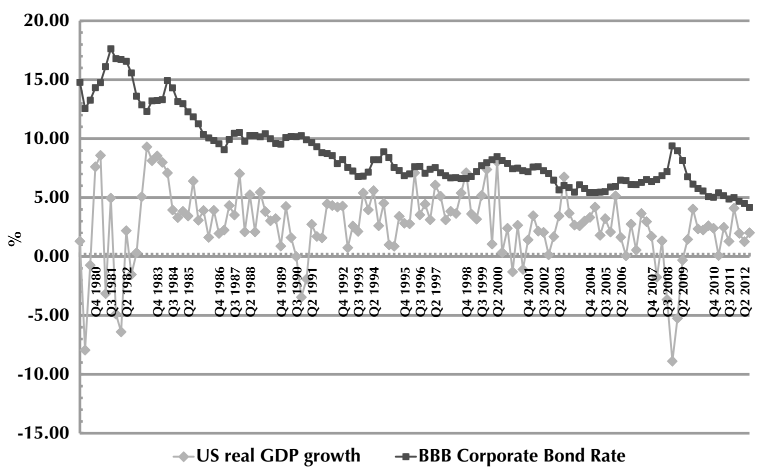


Figure 12.5 clearly shows that each recession was associated with a rise in the unemployment rate. However, for BBB Corporate Bond Rate – although for the recessions in 1981 and 2008 we see a high increase in the BBB Rate – the rest of the data does not show a high association between GDP Growth Rate and BBB Bond Rate (Figure 12.6).

Figure 12.7 US Real GDP growth and CPI percentage change

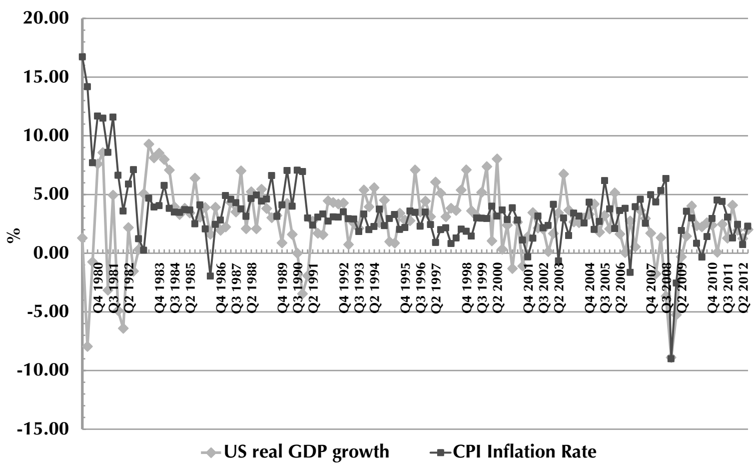
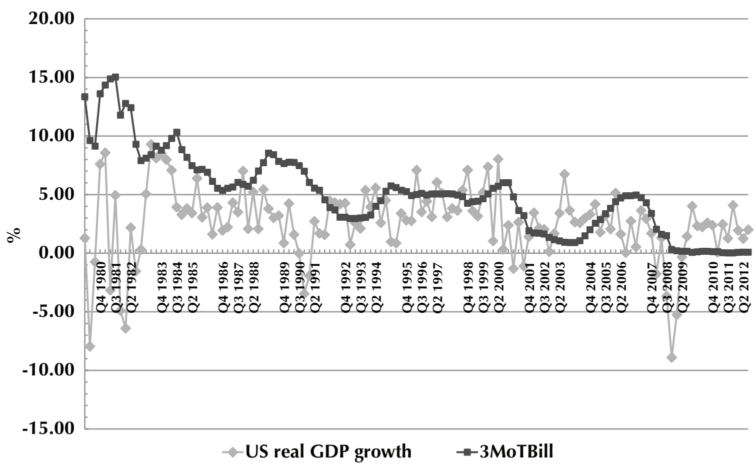


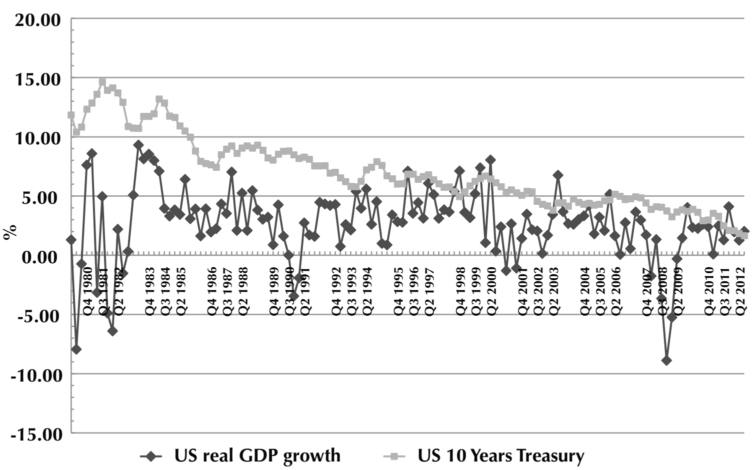
Figure 12.8 US Real GDP Growth and 3 months T bill



From Figure 12.7, we see only that a sharp drop in CPI is associated with the last recession, but, for the rest of the historical data, there is no obvious association between change in CPI and GDP Growth Rate.

As for the Three-Month Treasury Yield and the US 10-Year Treasury Yield, from Figures 12.8 and 12.9, there is no clear association between Real GDP Growth Rate and Treasury Yields. From examining the historical data, of the nine common macroeconomic variables defined in the stress scenarios we have seen that four of them – CPI, Three-Month Treasury Yield, 10-Year Treasury Yield and BBB Corporate Bond Rate – do not show any "directional" indication that either an increase or decrease in value is necessarily associated with a stress economic condition ("directional" means that, if a macroeconomic variable increases in value, then, historically, the economic condition always reacts the same way, either less or more severe in the same direction). Thus, these four variables will not be further considered in our discussion for measuring the severity of a stress scenario.

Figure 12.9 US Real GDP Growth and US 10-Year Treasury Yield



NINE-QUARTERS PROJECTIONS OF THE MACROECONOMIC VARIABLES

We will now examine the projections of the remaining five macroeconomic variables in each of the four stress scenarios. From Figures 12.10 and 12.11, we can clearly see that the 2011 supervisory scenario is the least severe in terms of GDP and Real Disposable Personal Income. The 2013 scenario follows the same pattern as the 2012 scenario, but the drop at every quarter is only slightly less than that of 2012. As for the Hypothetical portfolio, it has the biggest drop in disposable income. However, the severity in Real GDP is not conclusive because the projected GDP in the Hypothetical are higher than scenarios 2012 and 2013 in some quarters, but lower in other quarters.

Figure 12.10 Projections of the four scenarios – Real GDP

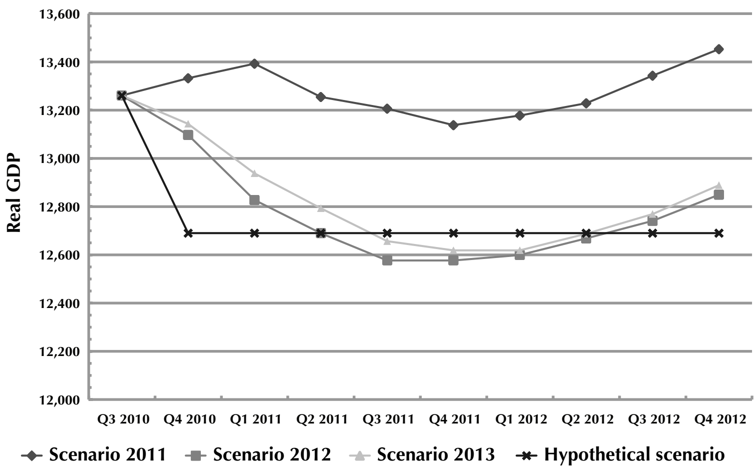


Figure 12.11 Projections – Real Disposable Personal Income

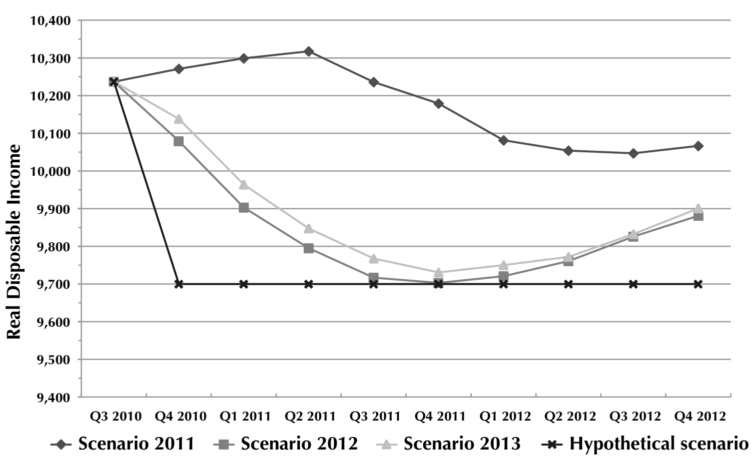


Figure 12.12 Projections – Dow Jones Index

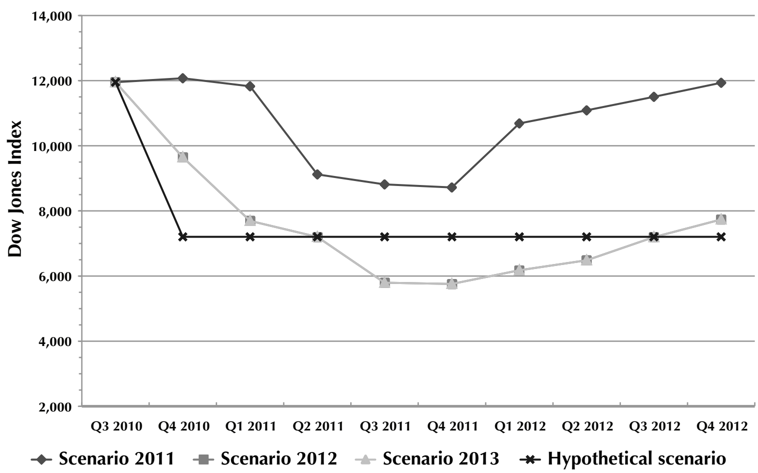
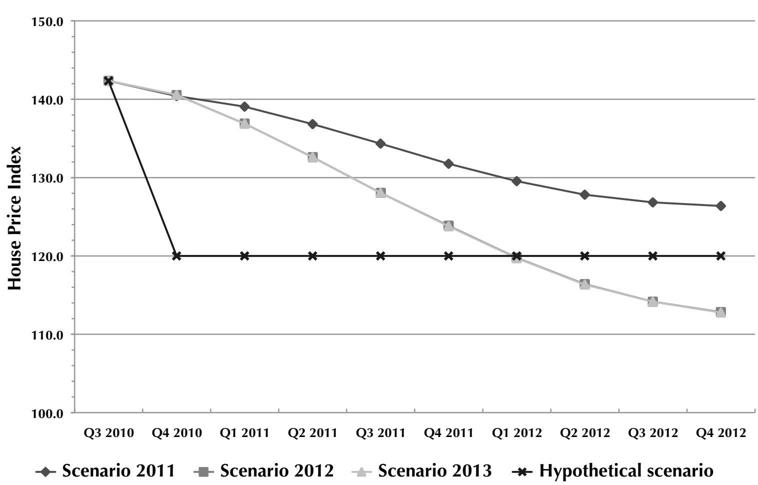


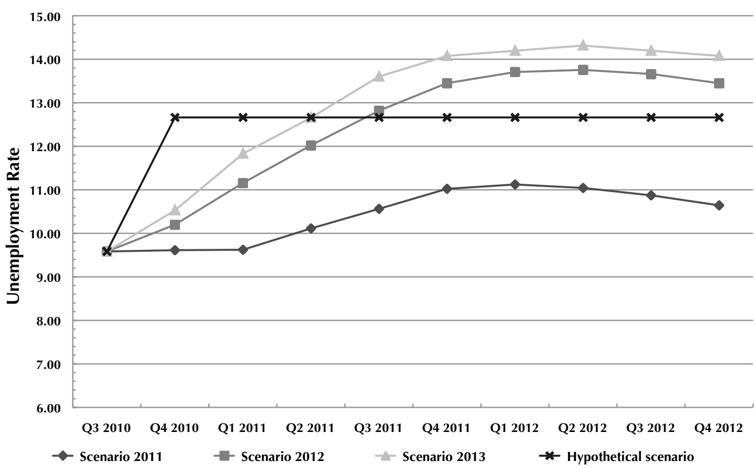
Figure 12.13 Projections – House Price Index



We now focus on the next two "directional" macroeconomic variables: Dow Jones Index and House Price Index. From Figures 12.12 and 12.13, we can see that scenarios 2012 and 2013 are exactly the same. The three supervisory scenarios follow similar patterns. On the Dow Jones Index, there is a sharp drop in the beginning, followed by an increase after the fourth quarter, and scenario 2011 shows that the drop is the mildest. As for the House Price Index, the projections are all declining quarter after quarter, and the decline in scenario 2011 is also the mildest. Since the Hypothetical cut across the curve of scenarios 2012 and 2013, by examining the charts, apart from scenario 2011, it is not conclusive which one is the most severe scenario.

Finally, on examining the Unemployment Rate (Figure 12.14), we see that the three supervisory scenarios all project that the unemployment rate will go up over the next six quarters, then plateau, and finally drop slightly at the end. It is also obvious that scenario 2011 is the mildest, and it is inconclusive between the Hypothetical scenario and scenarios 2012 and 2013. By now, we have established that for the three supervisory scenarios – since each of the variables we have seen follows the same pattern, on the whole – scenario 2011 is the mildest, and scenario 2012 and 2013 are almost the same except that scenario 2012 is slightly more severe.

Figure 12.14 Projections – Unemployment Rate



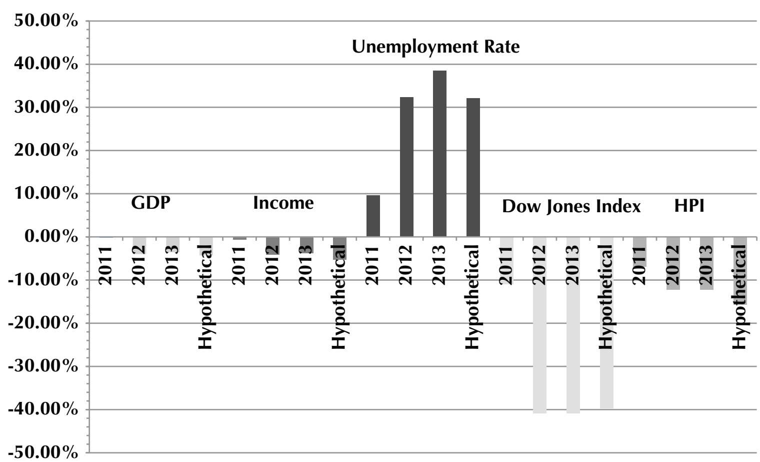
When comparing the Hypothetical scenario with the 2012 and 2013 scenarios in Unemployment Rate, there are some quarters in which the hypothetical scenario has the higher Unemployment Rate, and some quarters in which the 2012 and 2013 scenarios have the higher Unemployment Rate. Therefore, in order to make an overall comparison, it is necessary to develop a statistic to summarise, measure and standardise the severity of each variable over the nine quarters.

Since we have aligned all the scenarios to the same starting point, the severity of each quarter is determined by the percentage change with respect to the starting quarter (Q3 2010). Thus, a probable summary statistic is the average of the percentage change with respect to the starting quarter. Another choice is the maximum change over the nine quarters, but the maximum value ignores the projections with recovery at the end of the nine quarters. The average of the percentage change is computed by Equation 12.3 below, where i is the index for the four scenarios, and j is the index for each of the projections.

$$Ave\ \%\ Change\ UR_i = \sum_{j=1}^{9} \frac{100}{9}\left(\frac{(UR_{i,j} - UR_{i,3Q2010})}{UR_{i,3Q2010}}\right) \tag{12.3}$$

This summary statistic can be computed for the five "directional" macroeconomic variables in each scenario. We now have a measure to compare the severity of the scenarios on each of the variables independently of the other variables. From Figure 12.15, we can see that the longer the vertical bar is away from zero, the more severity it indicates. Thus, for Unemployment Rate, the longest bar is in 2013, which means the most severe scenario is 2013. For GDP, Disposable Income, and HPI, the Hypothetical scenario is the most severe. For Dow Jones Index, the 2012, 2013 and Hypothetical scenarios are more or less the same. Viewing across the chart, we see that the 2011 scenario is the least severe in each of the five variables.

Figure 12.15 Average change in macroeconomic variables from Q3 2010



In terms of the magnitude of severity, we see that Unemployment Rate and Dow Jones Index have 30% to 40% average deterioration in scenarios 2012, 2013 and the Hypothetical, whereas the other variables are much less severe. Hence, we have a measurement of severity for each macroeconomic variable. In the next section, we will suggest some ways to combine all these measurement to give an overall view of the severity of a stress scenario.

AN OVERALL ASSESSMENT OF THE SEVERITY

At the start of our discussion, we mentioned that measuring severity is, in general, relative. However, some economists (Edge 2012) have tried to use historical recessions as anchors, and relate the stress scenarios to historical recessions to get some sense of magnitude as compared with past recessions. We will discuss other methodologies in more detail in the next section. For now, we will propose a simple methodology to summarise the severity of each scenario with reference to a historical recession.

For each macroeconomic variable, we have four scenarios. We will use an ordinal ranking to assign a rank to each of the scenario by using the Average % Change, giving rankings of 1–4 to indicate least to most severity. When the Average % Change shows that two scenarios are very similar (within 1% of each other), we assign the average of the two ranks to both scenarios. Since severity in Unemployment Rate is associated with increasing value, the lowest rank is given to the lowest Average % Change. Table 12.3 gives the ranking of each variable and the total ranking. By summing across the rank of each variable, we arrive at a statistic that gives an overall ranking (Total Rank) of the scenarios. With this simple methodology, we have determined the severity of the four macro stress scenarios. In order of severity, the most severe scenario is Hypothetical, followed by 2013, 2012 and 2011. However, on further examination, the differences in Total Rank between the Hypothetical, 2013 and 2012 scenarios are not that significant (<20%), hence these three scenarios are comparable in terms of severity.

Table 12.3 Ranking of each macroeconomic variable and the total rank of the scenario

	Real GDP		Disposable Income		Unemployment Rate		Dow Jones		HPI		
Scenario	**Ave % Change**	**RANK**	**Ave % Change**	**RANK**	**Ave % Change**	**RANK**	**Ave % Change**	**RANK**	**Ave % Change**	**RANK**	**Total Rank**
2011	0.2	1	-0.6	1	9.7	1	-11.0	1	-6.88	1	5.0
2012	-4.0	3	-4.1	2.5	32.4	2.5	-40.8	3	-12.2	2.5	13.5
2013	-3.5	3	-3.7	2.5	38.5	4	-40.8	3	-12.2	2.5	15.0
Hypothetical	-4.3	3	-5.2	4	32.2	2.5	-39.7	3	-15.7	4	16.5

Table 12.4 Nine-quarters values of changes for 2008 Recession[4]

Common Variables	**Q3 2010**	**Q1 2008**	**Q2 2008**	**Q3 2008**	**Q4 2008**	**Q1 2009**	**Q2 2009**	**Q3 2009**	**Q4 2009**	**Q1 2010**
Real GDP	13,261	13,202	13,245	13,122	12,820	12,649	12,639	12,684	12,810	12,884
Real Disposable Personal Income	10,237	10,385	10,592	10,350	10,344	10,220	10,208	10,048	10,033	10,172
Unemployment Rate	9.58	9.98	10.64	11.98	13.70	16.50	18.49	19.23	19.83	19.49
Dow Jones Index	11,947	10,748	10,540	9,574	7,326	6,541	7,598	8,797	9,269	9,804
House Price Index	142	137	131	126	120	114	112	113	114	115

Since all these four scenarios are hypothetical forward-looking scenarios, and we now have some understanding of the severity among them, the next logical question should be how they are related to our historical experience. Looking back at the past postwar recessions, we see that the most severe recession is the 2008 recession (December 2007 to June 2009), which lasted 18 months. In order to align with the nine projected quarters of our scenarios, we will use the NBER data and choose the consecutive nine quarters of Real GDP Growth Rate when the recession began in the first quarter of 2008. After aligning for Q3 2010 as the starting quarter and the conversion of the values as described in the last section on the remaining nine quarters, we have the similar values on the macroeconomic variables for comparison in Table 12.4. The first column has the actual values as in Q3 2010. This is used as the anchor to align all the scenarios that have the same starting values. The rest of the nine columns are from Q1 2008 to Q1 2010 (projections of nine quarters as in all supervisory scenarios). The values in these nine columns are scaled to the starting values of the first column, and so the 2008 Recession values start from the second column.

After we calculate the average percentage change of the five variables over the nine quarters, we find that the Average % Change on Real Disposable Personal Income is slightly positive (0.2%). Thus, during the 2008 Recession, the Real Disposable Personal Income is not "directional", as we once thought. We have come to realise that it is not necessarily true that Real Disposable Personal Income will decrease in a severe stress economic condition, especially when we are looking at the overall change in nine quarters. Therefore, including the Real Disposable Personal Income will taint our measurement of severity. Hence we will drop the Real Disposable Personal Income from our ranking on the overall severity. We can now put the Average % Change of the rest of the variables back into the ranking methodology and observe the ranking of the recession with other scenarios.

From Table 12.5, we observe that 2008 Recession is ranked as the most severe, followed by Hypothetical, 2013, 2012 and 2011. However, apart from the unemployment rate in 2008 Recession, the differences among the four most stressful scenarios are not so significant that they can be easily separated. In fact, for the Dow Jones Index, 2008 Recession is the second least severe of the five scenarios. Hence we conclude that the Hypothetical, 2013 and 2013 scenarios have similar severity to 2008 Recession.

Table 12.5 Ranking of each macroeconomic variable and the total rank of the scenario and recession

	Real GDP		Unemployment Rate		Dow Jones		HPI		
Scenario	**Ave % Change**	**RANK**	**Ave % Change**	**RANK**	**Ave % Change**	**RANK**	**Ave % Change**	**RANK**	**Total Rank**
2011	0.2	1	9.7	1	-11.0	1	-6.88	1	4.0
2012	-4.0	3.5	32.4	2.5	-40.8	4	-12.2	2.5	12.5
2013	-3.5	3.5	38.5	4	-40.8	4	-12.2	2.5	14.0
Hypothetical	-4.3	3.5	32.2	2.5	-39.7	4	-15.7	4.5	14.5
08 Recession	-2.8	3.5	62.2	5	-25.4	2	-15.5	4.5	15.0

In all our discussion so far, we have assumed that all the directional variables are of the same importance, hence we have not assigned different weights when aggregating the ranks of each variable. However, we know different macroeconomic variables will affect different banking institutions. For example, banks with large credit-card portfolios are more sensitive to the unemployment rate; banks with large mortgage portfolios are more sensitive to house prices; and banks with large corporate portfolios are more sensitive to real GDP and equity indexes. In addition, the severity of the loss is related to the credit quality of the portfolio. Thus, the severity of the stress scenario also depends on the risk profile and the businesses of a bank. Based on the bank's experience, different weights can be assigned to different variables to emphasise the importance of certain variables.

PANEL 12.1 CASE STUDY: BANCO DE ESPAÑA STRESS SCENARIO

In this chapter, we have demonstrated the use of a simple method to assess the relative severity of a stress macroeconomic scenario. To illustrate how simple that methodology is, let us try to assess the severity of the stress-test exercise (Wyman 2012) that was conducted by Oliver Wyman in 2012 on behalf of the Banco de España. Page 83 of the report describes the adverse scenario with eight macroeconomic variables, and four of them, Real GDP, Unemployment Rate, Housing Prices and Madrid Stock Exchange Index, are similar to the variables we have studied. After aligning the starting values, the average percentage change over the two-year periods for the four variables are, Real GDP −5.1%, Unemployment Rate 19.9%, Madrid Stock Exchange Index −52.5% and Housing Prices −21.7%. Compared with the scenarios in Table 12.5, except for the Unemployment Rate, the other three variables are the most extreme among all the scenarios examined. If we use the ranking assignment as above, this adverse scenario is the most severe among all the six scenarios.

However, comparing the severity of these scenarios this way is not without problems. First, there is no reason to assume that the macroeconomic variables will affect the economies of Spain and the US in the same way. In addition, Spain's unemployment rate is already at 21.6% to begin with, and 21.6% is double what we saw in the 2008 recession. We can say Spain is already under an economic stress that we have not seen in the US since the Great Depression. Thus, we face additional challenges when comparing scenarios across different countries with different starting values on the macroeconomic variables.

OTHER METHODOLOGIES OF MEASURING SEVERITY

Our approach to assessing severity is entirely ordinal and so the relative ranks do not reflect anything about the magnitudes of the average percentage change, or the degree of severities. Ranking the scenarios will necessarily give some scenarios high rankings even if all the scenarios are quite mild, and some scenarios low rankings even if all the scenarios are quite severe. As we saw earlier, our approach is to give relative ranking to the scenarios under consideration. By comparing the scenarios with 2008 Recession, we have attempted to give the four scenarios a reference point besides comparing them with each other.

There have been other attempts to quantify the severity of stress scenarios. One of them is to determine the probability of occurrence of a stress (or worst) scenario. The general belief is that the less likelihood there is of an occurrence of a stress scenario, the more severe the stress scenario will be. In the 2009 SCAP exercise, in Footnotes 3 and 4 of Federal Reserve (2009b), the supervisors attempted to assign a probability of occurrence to the adverse scenario by claiming that "the likelihood that the average unemployment rate in 2010 could be at least as high as in the alternative more adverse scenario is roughly 10 percent. In addition, the subjective probability assessments... imply a roughly 15 percent chance that real GDP growth could be at least as low, and unemployment at least as high... [and] there is roughly a 10 percent probability that house prices will be 10 percent lower than in the baseline by 2010". Another example appears in an article on Economy.com in which Ed Friedman (2012) assigned probabilities to the Fed's 2013 CCAR scenarios. He first put the probability for each baseline scenario at around 50%. Then he claimed, "The Fed's Severely Adverse scenario is comparable to one that Moody's Analytics terms S4. We currently see a 4% chance that this scenario will occur. The Fed's Adverse scenario is more puzzling... we believe [it] has about a 10% chance of occurring." It seems to us that most of this assigning of probabilities is based on judgement rather than any empirical derivation.

Table 12.6 Score of each macroeconomic variable and the average score of the scenario and recession

	Real GDP		Unemployment Rate		Dow Jones		HPI		
Scenario	**Ave % Change**	**SCORE**	**Ave % Change**	**SCORE**	**Ave % Change**	**SCORE**	**Ave % Change**	**SCORE**	**Average SCORE**
2011	0.2	0	9.7	16	-11.0	43	-6.88	44	26
2012	-4.0	100	32.4	52	-40.8	100	-12.2	78	83
2013	-3.5	100	38.5	62	-40.8	100	-12.2	78	85
Hypothetical	-4.3	100	32.2	52	-39.7	100	-15.7	100	88
08 Recession	-2.8	100	62.2	100	-25.4	100	-15.5	100	100

One of the more interesting approaches to quantifying severity is proposed by two Federal Reserve Board economists, Rochelle Edge and Sam Rosen. Their simple approach (2012) is for each scenario, they will score the Average % Change of the common variables by assigning a value of 100 to the variable if the deterioration in the variable equals what occurred in 2008 Recession (most severe), and by assigning a value of 0 to the variable if the deterioration equals what occurred on the average in the two recessions (mild recessions) before 2008 Recession. Below, we use a modified version of their approach to illustrate how severity can be quantified.

For each common variable in 2008 Recession, we assign a score of 100 for the Average % Change, and 0 if the Average % Change is 0. In addition, we cap the score of each variable at 100 and assign a floor of 0. We then use a simple linear interpolation to convert each variable of a scenario into a score. For example, the Average % Change in UR in 2008 Recession is 62.3%, and in Scenario 2013 is 38.5%. Thus the score for 2008 Recession in UR is 100, and for Scenario 2013 is given by the following equation:

$$Score\_2013_{UR} = 100\left(1 + \frac{(38.5-62.2)}{62.2}\right) = 62 \tag{12.4}$$

Table 12.6 gives the results of the scoring approach. Using 2008 Recession as a reference point, Scenario Hypothetical, 2013 and 2012 are very similar to and a bit less severe than the 2008 recession. The 2011 scenario is the mildest and its average score is quite different from the rest. Although our choices in this approach are sometimes arbitrary, nonetheless the approach is intuitive and informative, and gives a good sense of how the scenarios are compared.

So far, the approaches we have discussed do not assume any correlations among the four common macroeconomic variables. The overall assessment is made by summing each variable independently. A statistical approach proposed by Debashish Sarkar (2012) attempted to solve the major problems of the aggregating of information across different variables and across time. He suggested using the Mahalanobis distance to solve these problems with a set of weights. The distance, D, is defined by the following equation:

$$D = \sqrt{(x-\mu)' W^{-1} (x-\mu)} \tag{12.5}$$

In the formula, X is a vector that stacks different variables in a scenario through time. The vector μ stacks the same variables for a reference scenario. The matrix W collects the weights. This approach is to construct W based on the variance–covariance matrix of the out-of-sample forecast errors. While the main challenge of this approach is that the distance measure is not directional, it is also very sensitive to the choice of W and the reference scenario. Sarkar's results showed that this approach is best used in conjunction with some other methods and is more efficient for identifying outlier/problem scenarios. Similarly, in a somewhat related paper, Breuer *et al* (2009) also suggested using the Mahalanobis distance to quantify the plausibility of a severe stress scenario.

Lastly, we mention another approach that aggregates the information in different macroeconomic variables through a simple forecasting framework. In their 2012 paper, Guerrieri and Welch (2012) derived several forecasting models to predict some key metrics that measure the "health" of a bank holding company. The key metrics that they wanted to forecast were: net charge-offs on loans and leases, pre-provision net revenue (PPNR), net interest margin (NIM) and the Tier 1 regulatory capital ratio. The forecast is based on a set of macroeconomic variables: Real GDP Growth, Unemployment Rate, the growth rate of the national house price index, the term spread, the growth rate of the S&P 500 index, the implied volatility of the S&P 500 index options, and the real interest rate. For each macroeconomic variable V_i and for each key banking metric, C, they used a simple (lag) regression that takes the form:

$$C_t = \alpha + \beta C_{t-1} + \gamma_1 V_{t-1}^i + \gamma_2 V_{t-2}^i + \gamma_3 V_{t-3}^i + \gamma_4 V_{t-4}^i + u_t \tag{12.6}$$

They used the Consolidated Reports of Condition and Income (Call Report) of the Federal Deposit Insurance Corporation to develop their forecasting models. By applying the historical information from the Call Report data and the changes in the macroeconomic variables in the stress scenarios to the forecasting models, we can obtain the forecast estimates of the key metrics. Consequently, we can then use the results, eg, average forecast charge-offs, to quantify the severity of the scenarios. The usefulness of this approach depends highly on the accuracy of the forecasting models, especially on the later forecasting quarters. However, Guerrieri and Welch found large root-mean-square errors for the forecasts of all the metrics, and their best-performing model did not beat a random walk at all horizons for forecasting pre-provision net income.

CONCLUSION

Our approach is based on examining the extremities of each of the directional variables, and adding up the extremities without considering the correlation and the timing of the macroeconomic variables. We have avoided trying to quantify the severity and used ordinal ranking to smooth out the "noises" of the variations. There is no error estimate in our assessment, nor do we give any confidence levels on our assessment: there is a danger of pseudo-accuracy when we try to find precision, and precision is difficult to define. It is exceptionally difficult to validate a model to assess the severity of a stress scenario. In the previous section, we mention that economy.com states that the 2013 Fed Severely Adverse scenario has a 4% chance that it will occur. The interesting question is why it is 4% and not 10%? The figure seems arbitrary. No one will dispute that the 2008 recession is the most stressful economic period since the Great Depression. Using the 2008 recession as a severe stress scenario, someone might say it is a 1-in-80-year event because it is the most severe recession for 80 years. However, if another recession as severe as or more severe than the 2008 recession happens in the next 10 years after 2008, then it reduces the occurrence of such a severe event to a 1-in-45-year event. Thus, it is quite difficult to quantify such a rare event with certainty because any occurrence of a similar event in the future will render the estimate to be inaccurate.

One of the principles of stress testing listed in the 2009 BIS (BIS BCBS 2009) paper is, "Stress tests should feature a range of severities, including events capable of generating the most damage whether through size of loss or through loss of reputation." The challenge is how to define an event that will generate the most damage to a bank. In their paper, Borio, Drehmann and Tsatsaronis (2012) concluded that "stress tests failed spectacularly when they were needed most: none of them helped to detect the vulnerabilities in the financial system ahead of the recent financial crisis". To improve the performance of macro stress tests, they suggested increasing the severity of the scenarios. The financial crisis of 2008 can be used as a starting point to gauge the severity of a bank's stress scenario. According to the above 2009 BIS paper, "prior to the (2008) crisis, however, banks generally applied only moderate scenarios, either in terms of severity or the degree of interaction across portfolios or risk types... Scenarios that were considered extreme or innovative were often regarded as implausible by the board and senior management."

Have the banks learned their lessons? Are they designing severe stress scenarios that will result in estimates of losses that show their vulnerabilities? In this chapter, we have suggested a simple way to answer these questions, and discussed alternate methodologies to answer the same questions. In many countries, banking regulators are requiring banks to perform stress testing on an annual basis. As more data is gathered from these exercises, it will enhance further research on this topic, and hopefully the macro stress tests will become a valuable tool in the banks' risk-management arsenal.

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1. In 2013, six US BHCs were subject to estimate trading losses: Bank of America Corp, Citigroup, Goldman Sachs, JPMorgan Chase, Morgan Stanley and Wells Fargo & Co.
2. Historical Data: 1976 through Second Quarter 2012--October 9, 2012 (Excel) - available for download at http://www.federalreserve.gov/bankinforeg/ccar.htm
3. See http://www.nber.org/cycles.html
4. The nine quarters from Q1 2008 to Q1 2010 are converted to Q3 2010 as the starting values.

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