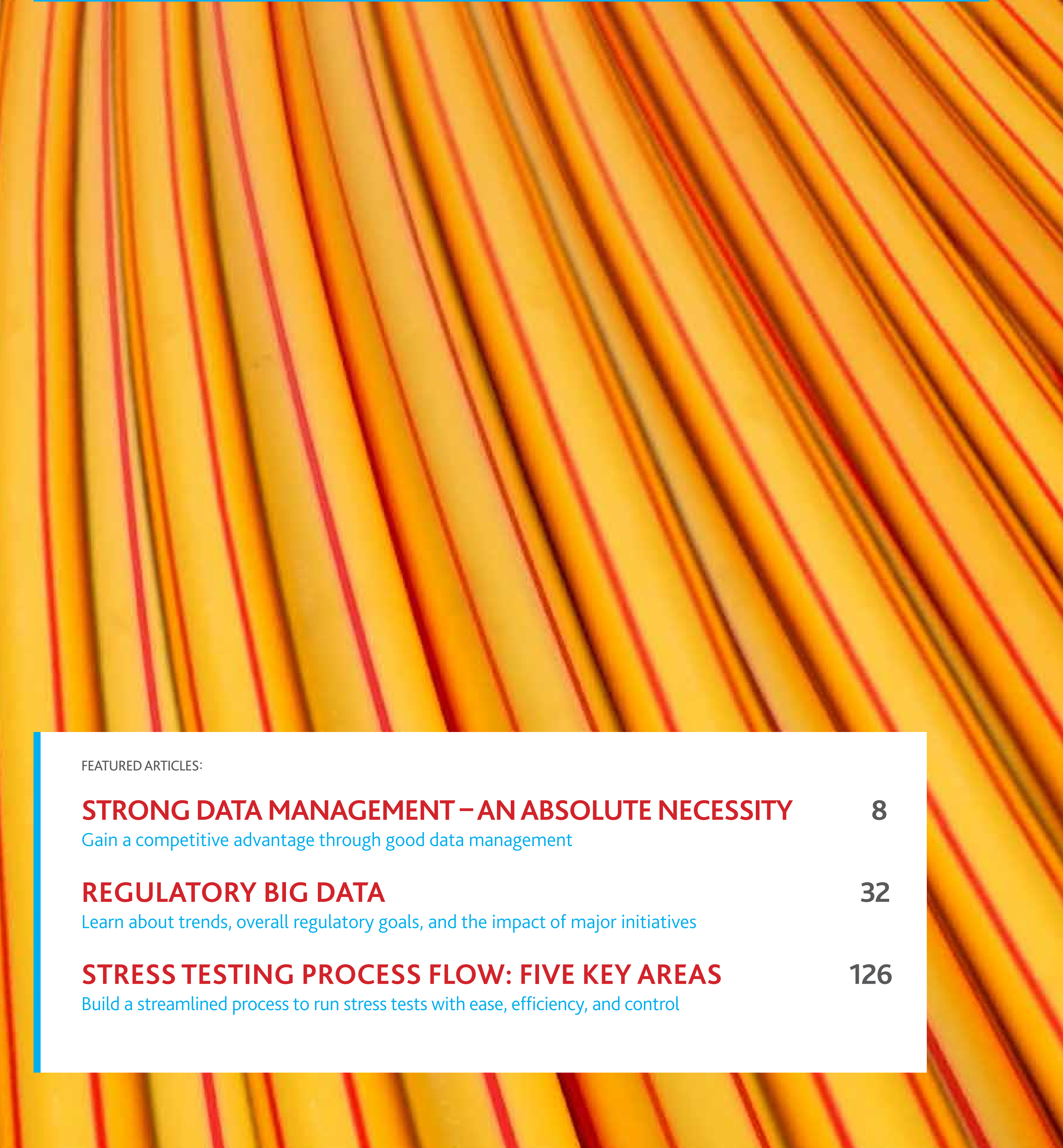
Moody's Analytics

# RISK PERSPECTIVES

## RISK DATA MANAGEMENT

VOL 5 | AUGUST 2015



FEATURED ARTICLES:

Model Risk Management
RWA
PPNR Modeling
LGD
IFRS 9
Macroeconomic Scenarios
LCR
FDSF
Forecasting P&L
Commercial Credit Decisioning
AnaCredit
LGD
Reporting
Systemic Risk
IAS 39
Regulatory Capital
Expected Default Frequency
CCAR
Human Data
Aggregate data
Reporting
ECB
Basel III
PD
DFAST
Data Gaps
Forecasting P&L
BCBS 239
Credit Risk
Finding Alpha
Capital Planning
Data Infrastructure
PD
Analytical Data
The Fed
Data Infrastructure
Risk Appetite

# FROM THE EDITOR

**Welcome to the fifth edition of Risk Perspectives™**, a Moody's Analytics publication created for risk professionals, with the goal of delivering essential insight into the global financial markets.

"Data is the very lifeblood of every bank. It's a shame how little attention is paid to it," a central bank's representative told me recently. As any form of effective risk management requires powerful analytics, a robust infrastructure and – above all – reliable data, this observation sheds light on a problem that has already severely impacted the financial services industry, and stands to impact it further.

For years, supervisors and industry experts have raised concerns about the weak data management practices prevalent in many banks, from poor data quality to fragmented data infrastructure to non-existent data governance. But nothing really changed until the Basel Committee on Banking Supervision published its *Principles for Effective Risk Data Aggregation and Risk Reporting* in January 2013, forcing banks to enhance their data management for good.

Given this development in the market, we decided to dedicate this edition of *Risk Perspectives*™ to data management.

As mentioned above, data management comprises many aspects. With this in mind, we have invited subject matter experts from Moody's Analytics to share their experiences and discuss diverse aspects of data management. As with our first four editions, this issue of *Risk Perspectives*™ offers actionable information to assist risk professionals in their day-to-day efforts to comply with new regulatory guidelines, master data management and infrastructure questions, and create value for their organization through better and more effective risk management.

In the section *Rethinking Risk Management,* we discuss how banks can benefit from stronger data management, an absolute necessity for effective risk management. We also show how banks and insurers can improve their data quality and ultimately gain better insight into the risks to which they are exposed. In *Getting Human Data Right: The Hidden Advantage*, Kevin Hadlock writes about how banks often neglect the human side of their operations, and can better manage risk arising from employee knowledge and skill.

Banking regulations are increasingly quantitative and data-driven. In *Regulatory Spotlight*, we look at key initiatives, such as BCBS 239 and the European Central Bank's analytical credit dataset (AnaCredit), and discuss the regulatory challenges presented by PPNR and CCAR/DFAST.

The *Approaches to Implementation* section discusses how to design a robust data governance process. It also sheds light on data management in Asia-Pacific and in structured finance.

In the final section, *Principles and Practices*, my colleagues describe the impact of better data management on a bank's operations – including how data supports critical business decisions, the impact of data quality on credit risk modeling and stress testing, and the ways in which a loan origination process benefits from better data quality. In *Modeling Techniques and Tools in Scenario-based Risk Appetite Management*, Pierre Gaudin writes how regulatory stress testing requirements are increasingly guiding financial institutions toward scenario based-governance and risk appetite management.

I am sure that our perspectives on the challenges and benefits of robust data management will help you better understand how to address poor data quality, fragmented data infrastructure, and weak data governance in your own organization, and ultimately improve your risk management system to build a more competitive business.

I encourage you to take part in this discussion and help us shape future issues of *Risk Perspectives*™ by sharing your feedback and comments on the articles presented in this fifth edition.

**Dr. Christian Thun**
Senior Director, Strategic Business Development
RiskPerspectives@moodys.com

# CONTENTS



## RETHINKING DATA MANAGEMENT



## REGULATORY SPOTLIGHT

## APPROACHES TO IMPLEMENTATION



## PRINCIPLES AND PRACTICES

# DATA MANAGEMENT BY THE NUMBERS

## 88%

Of all data integration projects either fail completely or significantly overrun their budgets.

Strong Data Management – An Absolute Necessity. Page 8

## $2M

42% of respondents have allocated this budget or higher for IFRS 9 compliance.

IFRS 9 Will Significantly Impact Banks' Provisions and Financial Statements. Page 38

## 100%

Knowledge and skills age so rapidly that the likelihood of employee error approaches 100% by the end of the five-year period.

Getting Human Data Right: The Hidden Advantage. Page 24

## 20

We know of one leading commercial bank that employs 20 full time workers to aggregate and clean data in preparation for the FR Y-14Q quarterly commercial data submission.

The Benefits of Modernizing the Commercial Credit Decisioning Process. Page 100

## 59%

The correct full model is chosen 59% of the time. Overall, the inflation coefficient is statistically significant in around 67% of cases, whereas the unemployment rate coefficient is significant 91% of the time.

Multicollinearity and Stress Testing. Page 104

## 7

Main components of an Insurance Analytics Platform (IAP) architecture.

Using Analytical Data for Business Decision-Making in Insurance. Page 18

## 150

From our analysis of similar initiatives and the preparatory work involved, we expect that the ECB will consider between 24 and 150 – or more – attributes per loan for inclusion in AnaCredit.

Regulatory Big Data: Regulator Goals and Global Initiatives. Page 32

## 43,700

The final portfolio for analysis comprised approximately 43,700 securities, which effectively represent the structured finance universe of non-agency transactions.

Effect of Credit Deterioration on Regulatory Capital Risk Weights for Structured Finance Securities. Page 76

## 30

As a result, the accuracy of liquidity-monitoring models depends on the ability to evaluate realistic credit transitions over a time horizon as short as 30 days.

Modeling Techniques and Tools in Scenario-Based Risk Appetite Management. Page 92

## 47%

Surprisingly, 14 out of 30 G-SIBs revealed that they will not be fully compliant with at least one of the Basel Committee's regulatory principles by the deadline in 2016.

Enhancing Data Management is a Key Competitive Advantage for Japanese Banks. Page 60

## 50%

Between June 1997 and March 1998, GDP contracted by nearly 6% in Korea, 9% in Thailand, and 14% in Indonesia. Equity valuations plummeted by 50% or more in the affected countries.

Measuring Systemic Risk in the Southeast Asian Financial System. Page 66

## 1940s

In the case of commercial loan volume, for instance, the Federal Reserve Board has quarterly data stretching back to the late 1940s.

What if PPNR Research Proves Fruitless? Page 50

# RETHINKING DATA MANAGEMENT

Discusses how to establish better data management to gain a competitive advantage, build a comprehensive FTP framework, use analytical data to improve insurers' business decisions, and manage employee knowledge and skills.

# STRONG DATA MANAGEMENT – AN ABSOLUTE NECESSITY

By Dr. Christian Thun

**Dr. Christian Thun**
*Senior Director, Strategic Business Development*

Christian provides deep expertise on credit risk management, Basel II, and portfolio advisory projects and functions as a main contact for regulators and the senior management of financial institutions.

Banks and businesses have long been plagued by poor data quality, a result of weak technology, lack of management oversight, and simple human error. Inferior data, too long left unchecked, has far-reaching consequences – not the least of which was the 2008 global financial crisis. Banks that establish a strong data management framework will gain a distinct advantage over their competitors and more efficiently achieve regulatory compliance.

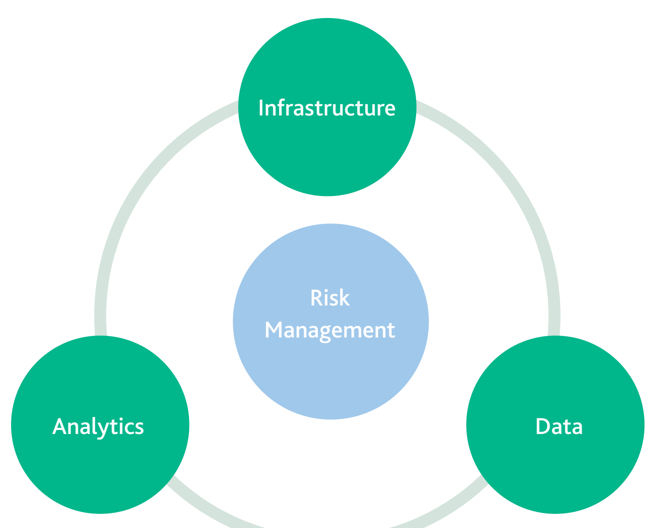
## The data wasn't – and still isn't – good enough

"Five years after the financial crisis, firms' progress toward consistent, timely, and accurate reporting of top counterparty exposures fails to meet both supervisory expectations and industry self-identified best practices. The area of greatest concern remains firms' inability to consistently produce high-quality data."[1]

This quote from the *Progress Report on Counterparty Data* by the Senior Supervisors Group summarizes one of the causes of the financial crisis and the reason that the sizeable investments in improving risk management in the years preceding the crisis seem to have been in vain: There was – and still is – not enough good data about the risk to which a bank is exposed.

Effective risk management that is capable of identifying, assessing, and prioritizing risks is based on a sound infrastructure, powerful analytics, and reliable data. All three ingredients are interconnected and influence each other, as illustrated by Figure 1.

**Figure 1** Three ingredients of effective risk management




Source: Moody's Analytics

- **Infrastructure** comprises not only technical aspects like IT equipment, but also technical organization and processes such as IT governance, roles, responsibilities, and internal policies.
- **Analytics** refers to the wide variety of quantitative modeling techniques that have developed over the past 20 years to better understand the drivers of risk and predict potential losses resulting from credit or market activities.
- **Data** includes not only granular information about risk exposure itself, but also the taxonomies that define and categorize that information and the data governance that maintains the accountability and quality of the data.

As the quote from the Senior Supervisors Group suggests, many banks use seriously flawed data, making meaningful risk management next to impossible. Weak data quality is an impediment not only for risk management, but also for the business of a bank in general. As other risk management experts have pointed out, "If the data quality is poor, the information will be poor and only luck can stop the decisions from being poor."[2]

From important strategic decisions to mundane issues like standard regulatory reports, the story is the same. **A business or business function (like risk management) that has to rely on weak data is ultimately set up for failure**. A bank that uses good quality data has an opportunity to outpace its competitors.

### What is "good data quality"?

There have been numerous attempts in the past two decades to define data quality along a series of dimensions, such as accuracy and consistency.[3] Depending on the individual needs of an organization, that definition can vary.

Table 1 shows the typical criteria used by statistics providers like the Statistics and Regulatory Data Division of the Bank of England and Eurostat.[4] Most of today's banks fall short in at least one of these areas, giving rise to serious concerns for risk managers.

### What are the consequences of poor quality data?

Weak data is a common deficiency in almost all businesses. Still, some companies tolerate a certain level of bad data rather than try to manage or eliminate it, because the sources of poor data quality are myriad and addressing them one by one is a laborious, time-consuming, and expensive exercise.

**Table 1** Typical criteria used by statistics providers

| Dimension | Description |
|---|---|
| Relevance | Relevance is the degree to which data meets current and potential users' needs: whether statistics and concepts (definitions, classifications, etc.) reflect these needs. |
| Accuracy | Accuracy in the data denotes the closeness of computations or estimates to exact or true values: how accurately and reliably the information portrays reality. |
| Timeliness and Punctuality | Timeliness of information reflects the length of time between the availability of data and the event or phenomenon it describes. |
| Accessibility and Clarity | Accessibility refers to the physical conditions in which users can obtain data: where to go, how to order, delivery time, availability of micro or macro data formats, etc.<br><br>Clarity refers to the data's information environment: whether data is accompanied by appropriate metadata, illustrations such as graphs and maps, and information on their quality (including limitations in use). |
| Comparability | Comparability aims at measuring the impact of differences in applied statistical concepts, definitions, and measurement tools/procedures when comparing statistics among geographical areas, non-geographical domains, or over time. |
| Coherence | Coherence refers to the ability to reliably combine the data in different ways and for different uses. |

Source: Moody's Analytics

Sooner or later, however, bad data begins to proliferate across systems, and discrepancies grow rapidly, which results in a number of issues:[5]

» Increased downtime for systems to reconcile data
» Diversion of resources from areas important for the business
» Slower deployment of new systems
» Inability to comply with industry and quality standards
» Frustrated employees whose activities are hampered by poor data
» A cumulative increase in costs

### Quantifying the cost of bad data

There have been several attempts to quantify the cost of bad data quality. The exact cost is difficult to calculate, but research by academics and reports by industry experts provide a number of revealing examples:[6]

» According to a 2010 Forbes survey, data-related problems cost companies more than $5 million annually. One-fifth of the companies surveyed estimated losses in excess of $20 million per year.[7]
» Gartner research shows that 40% of the anticipated value of all business initiatives is never achieved. Poor data quality in both the planning and execution phases of these initiatives is a primary cause.[8]
» Eighty-eight percent of all data integration projects either fail completely or significantly overrun their budgets.[9]
» Seventy-five percent of organizations have identified costs stemming from dirty data.[10]
» Thirty-three percent of organizations have delayed or canceled new IT systems because of poor data.[11]
» Organizations typically overestimate the quality of their data and underestimate the cost of errors.[12]
» One telecommunications firm lost $8 million a month because data entry errors incorrectly coded accounts, preventing bills from being sent out.[13]
» One large bank discovered that 62% of its home equity loans were being calculated incorrectly, with the principal getting larger each month.[14]
» One regional bank could not calculate customer or product profitability because of missing and inaccurate cost data.[15]

These findings provide an idea of the extent to which weak data quality can add to a business's costs. Given that these examples stem from research and industry reports that cover the first decade of the 21st century, one must ask why data quality management has not been addressed more seriously by those responsible.

> Weak data quality is an impediment not only for risk management, but also for the business of a bank in general. As other risk management experts have pointed out, "If the data quality is poor, the information will be poor and only luck can stop the decisions from being poor."

### There are two main reasons for the data quality deficit

Experts have repeatedly identified two main reasons for the weak data quality that plagues many banks – the lack of accountability and commitment by the organization's senior management to address weak data, and the lack of effective technologies to monitor, manage, and correct inaccurate data when needed.

To address the lack of senior management involvement, the Basel Committee on Banking Supervision (BCBS) outlined a number of new responsibilities. Boards must now determine their risk reporting requirements and be aware of the limitations that prevent a comprehensive aggregation of risk data in the reports they receive.[16] Senior management must also ensure that its strategic IT planning process includes both a way to improve risk data aggregation capability and the creation of an infrastructure that remedies any shortcomings against the principles defined by the BCBS.

These obligations will cover the entire value chain of a bank's data, because the BCBS requires that senior management understand the problems that limit the comprehensive aggregation of risk data in terms of:

» **Coverage** – i.e., are all risks included?
» **Technical aspects** – i.e., how advanced is the level of automation, vs. manual processes?
» **Legal aspects** – i.e., are there any the limitations to sharing data?

To comply with these requirements, a bank will need to establish strong data governance covering policies, procedures, organization, and roles and responsibilities as part of its overall corporate governance structure.

By setting up stronger data governance structures, banks will address the first main data quality weakness and define the correct use of and accountability for that data. Data governance should also include the scope of a bank's IT governance by considering data quality aspects and processes.

### Reaching a new data quality standard: A step-by-step process

Because data changes constantly, continuously monitoring it to maintain quality will only become more and more important. Figure 2 outlines the process.[17]

Once data is extracted from source systems, the next step – profiling – applies rules and error checks to assess the overall quality of the data. Profiling involves identifying, modifying or removing incorrect or corrupt data, with the goal of retaining just one unique instance of each datum. This step is also supported by the BCBS, which requests that banks "strive toward a single

> Technology that reliably maintains data quality by automatically applying error checks and business rules and by supporting sound audit trails and lineage can only result in greater confidence in the data.

**Figure 2** Monitoring and maintaining data quality – step-by-step process

| DATA EXTRACTION | DATA PROFILING/ QUALITY | CLEANSING & DE-DUPING | DATA STANDARDIZATION | QUALITY MONITORING | ENRICHMENT |
|---|---|---|---|---|---|
| Extract data from the various source systems. | Make use of data profiling techniques. | This is a dual process – cleansing & de-duping. | Run a series of data quality checks/rules against the data. | Keep track of data quality over time. | Enhance the value of internally held data. |
| » Loans<br>» Customer<br>» Asset<br>» Finance<br>» Forecasts<br>» Modeling<br>» Risk | Use logic algorithms and rules (both general and specific to the business) to produce a picture of overall data quality. | » Identify and modify corrupt or inaccurate data and remove or modify incomplete, incorrect or inaccurate data.<br>» Retain only one unique instance of the data. | Use any of a number of tools, including thousands of pre-built data quality rules (both general and industry specific), enhanced by user-defined rules. | Use software to autocorrect variations based on defined business rules. | Enhance the value of internally held data by appending related attributes from external sources (e.g., consumer demographic attributes or geographic data). |

Source: Moody's Analytics

authoritative source for risk data per each type of risk."[18]

Based on lessons learned, the set of rules and checks will evolve to avoid the repetition of previously identified data errors. Automating these processes will help maintain data quality and even enhance it by making the data more comprehensive.

### Implementing effective technologies

To address the second reason – the lack of effective technologies – banks today have the opportunity to select from a wide range of tools and solutions that support processes to improve and maintain data quality. **Most banks already have some components that could form the foundation of a data quality framework, which they could then enhance with new components as required**.

The requirements for effective technologies hinge on speed, scalability, reliability, and adaptability. Speed and scalability speak to the ever-growing amounts of different types of data stored in multiple, siloed systems based on entities, lines of businesses, risk types, etc. After identifying which system contains the required data, an expert must extract, standardize, and consolidate it to assess its quality.

Despite the fact that many banks employ large numbers of employees to capture, review, and validate data (as well as find gaps), they still struggle with poor data quality in their core systems, as a result of input errors, unchecked changes, and the age of the data (particularly with information stored in legacy systems or compiled manually). Technology that reliably maintains data quality by automatically applying error checks and business rules and by supporting sound audit trails and lineage can only result in greater confidence in the data.

As the requirements for information – as well as the information itself – are constantly evolving, effective technology has to be adaptable. The technology should feature flexible processes to aggregate data in different ways and should be able to include new information or exclude outdated information. It should also reflect new developments within the organization as well as any external factors influencing the bank's risk profile, such as changes in the regulatory framework.

### Summary

Effective risk management relies on three key ingredients: sound infrastructure, powerful analytics, and reliable data. The latter especially has been neglected for too long by too many. Although regulators have repeatedly voiced their concerns, it took a financial crisis to implement much tighter rules. **As a result, banks will have to invest heavily in their data management architecture in the coming years.**

The two main reasons for weak data quality are a lack of senior management commitment and ineffective technology. To benefit from good data management, banks will need to establish strong data governance that sets rules and defines clear roles and responsibilities, while enhancing an existing data quality framework with technologies that offer speed, scalability, reliability, and adaptability.

Good data management will confer a competitive advantage to those banks that have it. The value banks can reap from setting up a better data management framework will be leaner, more efficient and less expensive processes that lead to faster and more reliable business decisions.

1 Senior Supervisors Group, *Progress Report on Counterparty Data*, p. 1, 2014.

2 Mackintoch, J./Mee, P., The Oliver Wyman Risk Journal, Data Quality: *The truth isn't out there*, p.75, 2011.

3 Haug, A./Albjørn, J.S., Journal of Enterprise Information Management, Vol. 24, No. 3, 2011, *Barriers to master data quality*, pp. 292-293.

4 Bank of England, *Data Quality Framework*, p. 7, 2014.

5 Marsh, R., Database Marketing & Customer Strategy Management, Vol. 12 No. 2, *Drowning in dirty data? It's time to sink or swim: A four-stage methodology for total data quality management*, p. 108, 2005.

6 Marsh, R., Database Marketing & Customer Strategy Management, Vol. 12 No. 2, *Drowning in dirty data? It's time to sink or swim: A four-stage methodology for total data quality management*, p. 106, 2005.

7 Forbes, *Managing Information in the Enterprise: Perspectives for Business Leaders*, p.2, 2010.

8 Gartner, *Measuring the Business Value of Data Quality*, p.1, 2011.

9 Marsh, R., Database Marketing & Customer Strategy Management, Vol. 12 No. 2, *Drowning in dirty data? It's time to sink or swim: A four-stage methodology for total data quality management*, p. 106, 2005.

10 Marsh, R., Database Marketing & Customer Strategy Management, Vol. 12 No. 2, *Drowning in dirty data? It's time to sink or swim: A four-stage methodology for total data quality management*, p. 106, 2005.

11 Marsh, R., Database Marketing & Customer Strategy Management, Vol. 12 No. 2, *Drowning in dirty data? It's time to sink or swim: A four-stage methodology for total data quality management*, p. 106, 2005.

12 Marsh, R., Database Marketing & Customer Strategy Management, Vol. 12 No. 2, *Drowning in dirty data? It's time to sink or swim: A four-stage methodology for total data quality management*, p. 106, 2005.

13 Eckerson, W. W., The Data Warehouse Institute Report Series, *Data Quality and the Bottom Line*, p. 9, 2002.

14 Eckerson, W. W., The Data Warehouse Institute Report Series, *Data Quality and the Bottom Line*, p. 9, 2002.

15 Eckerson, W. W., The Data Warehouse Institute Report Series, *Data Quality and the Bottom Line*, p. 9, 2002.

16 BCBS, *Principles for effective risk data aggregation and risk reporting*, p. 7, 2013.

17 Heale, B., Risk Perspectives, Vol. 4, ***Data:** The Foundation of Risk Management*, p. 53, 2014.

18 BCBS, *Principles for effective risk data aggregation and risk reporting*, p. 8, 2013.

# BUILDING A COMPREHENSIVE FTP FRAMEWORK FOR STRESS TESTING, RISK APPETITE, AND FORECASTING P&L

By Nicolas Kunghehian


**Nicolas Kunghehian**
*Director, Business Development*

Nicolas provides insight on ALM, liquidity, and market risks to help financial institutions define a sound risk management framework.



Funds transfer pricing (FTP) is of growing concern to banks and regulators. But what does FTP have to do with stress testing? A comprehensive FTP framework can help organizations use the results of stress tests to forecast their P&L across departments and lines of business, ensuring that each unit's strategy aligns with that of the greater organization.


### Current FTP systems are incomplete

Virtually all banks use funds transfer pricing, and yet there are no practices common to all. Consequently, regulators are asking them to improve their FTP systems. Banks are developing comprehensive frameworks to meet these demands, but stress testing has been left out of that framework.

Even though banks do not believe that stressed scenarios should be part of an FTP transaction, integrating stress testing into an FTP framework is more important now than ever.

While each bank has its own organizational structure, some FTP components can be valued using market prices – hence, the methodology is the same for all banks. But costs or risks connected with some types of transactions are generally not monitored until a critical loss occurs. This is what recently happened, for example, with higher liquidity funding costs and low interest rates.

### Moving to an FTP framework: goals and challenges

The liquidity crisis severely impacted FTP systems. Once banks took liquidity funding costs into account, they realized that some of their transactions were barely profitable.

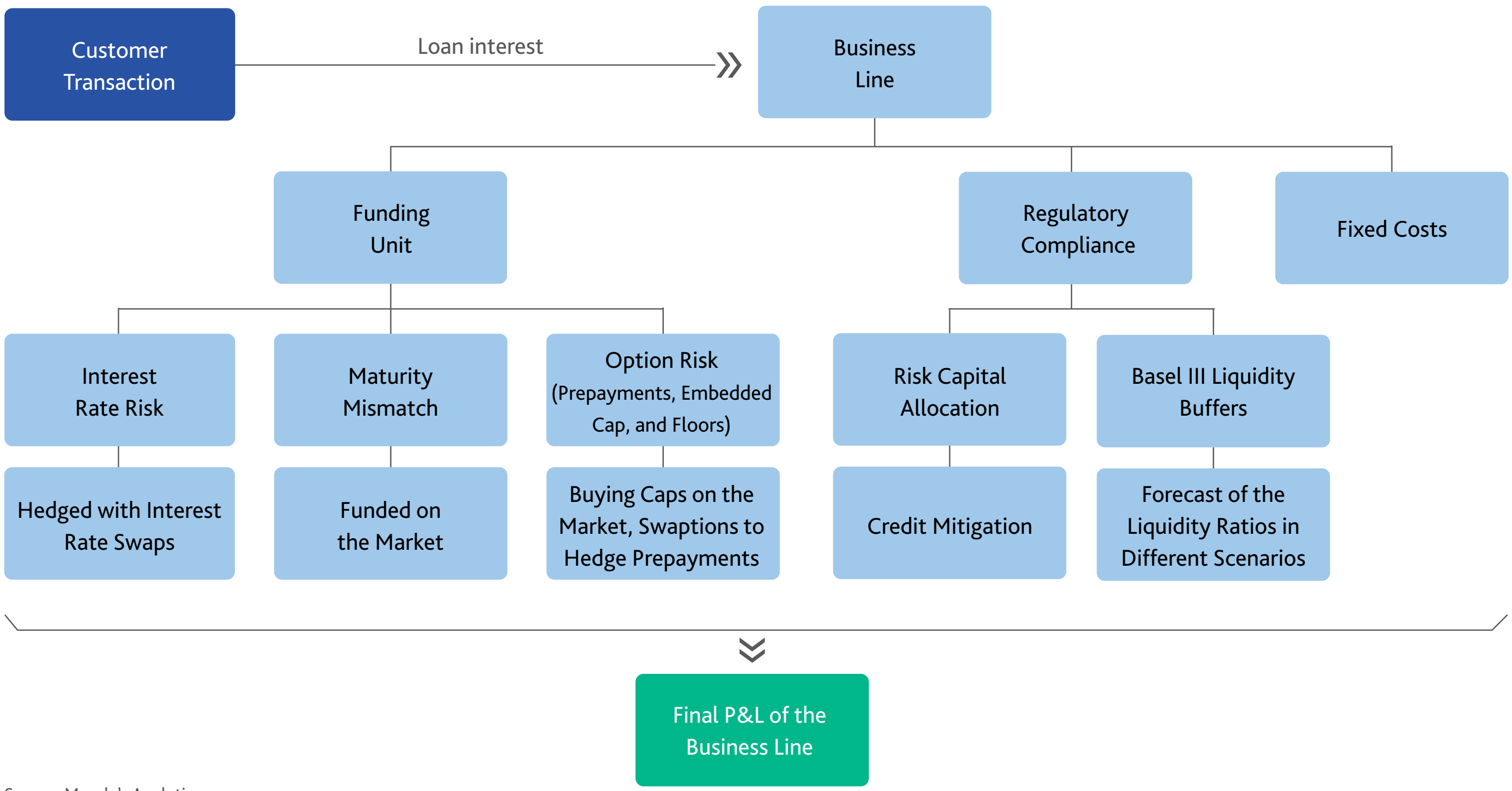
In 2009, the European Banking Authority (EBA) published guidelines on liquidity cost allocation,[1] emphasizing that banks should have "robust strategies, policies, processes, and systems" for liquidity risk management that should "include adequate allocation mechanisms of liquidity costs, benefits, and risks."

But the liquidity components of the FTP – also called liquidity transfer pricing – are not the only components that need to be carefully monitored. Due to tough economic conditions and the cost of regulatory compliance for both capital and liquidity ratios, the overall P&L of some business units has dropped dangerously close to zero.

The main goals of a robust and consistent FTP system are to correctly allocate the P&L to each line of business and to forecast different costs in different scenarios. The general framework will generate P&L for different departments and, depending on the way this framework is built, guide each department to a specific P&L strategy. **It is therefore critical that this framework be aligned with a bank's overall strategy to help incentivize its teams to make profitable business decisions and better manage its overall P&L**.

Unfortunately, moving to a comprehensive framework will increase the costs allocated to each line of business, as it will reveal new

**Figure 1** FTP system process




Source: Moody's Analytics

FTP components that were either previously hidden or not monitored. Internal costs will be higher for all transactions. This is why some transactions may appear to have a negative P&L, a change banks will need to explain to all business units. The framework will then become more than a technical tool – it will indicate the need for a strong change management plan.

## Main framework characteristics

Banks should take several factors into account when designing a comprehensive FTP framework.

### Granularity

If a bank wants to learn which transactions are profitable, it must calculate FTP at the transaction level. (Aggregation is usually not possible or advisable; funds should be aggregated prudently, if at all.) For example, a global FTP given to a line of business without taking into account the way the principal is amortized would lead to a higher maturity mismatch.

### Consistency

Another pitfall of an FTP calculation is the use of inconsistent methodologies across a bank. Most of the time, banks use different methodologies for each line of business. This can result in incentives and behaviors that are not necessarily aligned with the firm's overall strategy. **At any time, the sum of the P&L across all lines of business must equal the P&L of the overall firm**.

### Responsiveness

Finally, the framework should be updated as frequently as possible. A system that is not updated regularly runs the risk of lagging behind the rate of transactions, especially as markets tend to move very quickly.

## Forecasting P&L

Once this framework has been put into place, P&L can be calculated at the line-of-business level. The total P&L of the bank can be divided along lines of business, if the "transfer" units in charge of managing the different types of costs/risks are taken into account.

**There are now different departments or profit centers, none of which is only a cost center**. They will each be charged for what they cost, making it easier to calculate their P&L. The ability to concretely measure risk is very important from an analysis point of view.

To better drive business, it is also critical to run simulations to forecast P&L under different scenarios, including stress test scenarios.

### Integrating stress testing into an FTP framework

The 2008 financial crisis prompted risk managers to focus on assessing risks under stressed scenarios. Regulators, as well as the top management within organizations, are now asking for P&L metrics as a standard output of any stress testing exercise.

If organizations want to analyze the results of their stress test reports for their impact on P&L, they need to build a comprehensive framework like the one previously described. However, they are likely to run into two stumbling blocks.

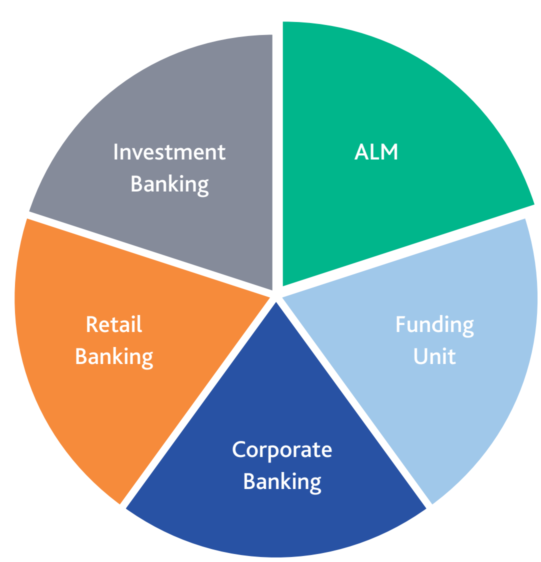
First, FTP is not ordinarily calculated using a stress testing scenario. Banks that use this methodology will likely be less competitive than banks that do not because their FTP costs are higher, leading to higher client rates. In other words, banks that calculate FTP with this framework are accounting for an additional cost that other banks might not consider.

However, this cost is real and should be measured. Take, for example, the likelihood of a customer using a line of credit that is higher than in a stressed scenario. The cost of liquidity would be higher, ending in a loss for the treasury. If this scenario is not part of a bank's FTP framework, it should – at a minimum – be part of its risk appetite framework to make the bank aware of the real risks presented by that scenario.

Second, it is very important to be able to measure and forecast the P&L of each business unit for various scenarios. For example, low interest rates tend to result in a lowering of the commercial margin. If, on the asset side of the business, a client asks for lower rates, the bank is more or less forced to comply to keep the customer happy and stay competitive. But on the liability side, there is a barrier that cannot be breached: 0%. No customer would accept negative rates for a checking account.

Because of this tightened margin – the difference between the rate received on the asset side and the rate paid on the liability side – it is important

**Figure 2** Lines of business, with ALM generally in charge of the FTP process and allocation




Source: Moody's Analytics

to measure FTP rates and forecast them with a high degree of accuracy.

### FTP for risk appetite

A bank's senior management and operational teams tend to view stress testing as only a regulatory compliance or reporting obligation, not as a benefit to their day-to-day work. But they must acknowledge that stress testing scenarios are important for measuring extreme events and their consequences, particularly FTP components, which have historically been neglected (e.g., liquidity risk before the subprime crisis).

**Ignoring certain risks is dangerous for a bank's risk management operations, even if those risks are unlikely to be realized**. Neglecting to price these risks at the P&L of the bank will lead to incorrect incentives for operational teams and, ultimately, affect the organization's profitability. Risks can also be managed or monitored using a risk appetite framework, but for consistency the risk appetite should be reflected in the FTP price so that all units can see the direct financial impact of the risk on their P&L.

Ignoring certain risks is dangerous for a bank's risk management operations, even if those risks are unlikely to be realized. Neglecting to price these risks at the P&L of the bank will lead to incorrect incentives for operational teams and, ultimately, affect the organization's profitability.

In conclusion, banks will find that investing in a comprehensive framework will prove to be more effective in the long run, as there will be less important losses. If losses do occur, they will already be measured and priced for all business units. FTP is one of the most efficient tools for spreading risk appetite to all teams of the bank.

1 EBA, *Guidelines on liquidity cost benefit allocation*, October 2010.

# USING ANALYTICAL DATA FOR BUSINESS DECISION-MAKING IN INSURANCE

By Brian Heale

**Brian Heale**
*Senior Director, Business Development Officer, Global Insurance*

Brian is an insurance and Solvency II specialist who has significant experience in technology solutions for the global insurance industry. He has an in-depth knowledge of the life and pensions business, coupled with a comprehensive understanding of enterprise technology.

Regulatory compliance is mandatory, but it doesn't have to just be a burden. Insurers can leverage their regulatory investment to greatly benefit their business, specifically by creating data-driven executive dashboards. This article details the organizational and data challenges that insurers face when harnessing the historical and forward-thinking information needed to create interactive dashboards. It explains how these challenges can be effectively managed using an Insurance Analytics Platform (IAP), leading to better decision-making at all levels of the business.

### Insurers have more work to do despite progress

There is, among many insurers, a feeling of regulatory "burnout" and disillusionment. For the last few years, insurers around the globe have been heavily focused on implementing regulatory initiatives, in particular Solvency II (and equivalent regimes), while also responding to the implications of International Financial Reporting Standard 4 (IFRS 4) and regulatory stress testing.

Hundreds of millions of pounds and euros have been spent on Solvency II projects that are now nearing completion, but insurers need to do more work to realize the potential business benefits of these investments.

This continued regulatory burden, combined with a low interest rate/low inflation environment, is making generating value increasingly challenging for insurance companies. Margins are under pressure and firms have to work much harder to remain competitive and deliver returns to shareholders and/or policyholders. Firms must look for new opportunities to support growth, including designing products that are aligned with this new world and adopting alternative investment strategies to generate higher returns and manage costs.

### Managing more effectively with better risk-based performance metrics

Our discussions with a number of insurance CROs, CFOs, and CEOs over the last six months or so indicate that they have the immediate regulatory situation under some degree of control. Therefore, their focus is turning to running their businesses more effectively and making informed risk-based decisions.

Business decision-making fundamentally revolves around three high-level measures: **profitability, capital, and growth**. These three factors need to account for the entire risk profile of the business.

There are two aspects to assessing the interaction of these high-level measures: understanding the historical (e.g., year-to-date) performance of the firm tracked against their strategic business plan, and modeling the interaction of these measures over future time horizons under differing stressed scenarios.

Figure 1 illustrates the type of information to which we believe C-suite executives need to have access. **Both historical and forward-looking perspectives are critical for effective risk-based decision-making**.

Equally important is having the available information much more quickly – ideally in real time – and in a format that is readily understandable. **This in essence translates to a series of interactive executive dashboards with drill-down and "what-if" capabilities that display the requisite analytical information**.

### Four challenges of creating interactive dashboards

On the face of things, creating these interactive dashboards seems relatively straightforward. In reality, however, insurers must anticipate multiple challenges, both in terms of data and organization.

#### 1. Vision for risk-based performance metrics

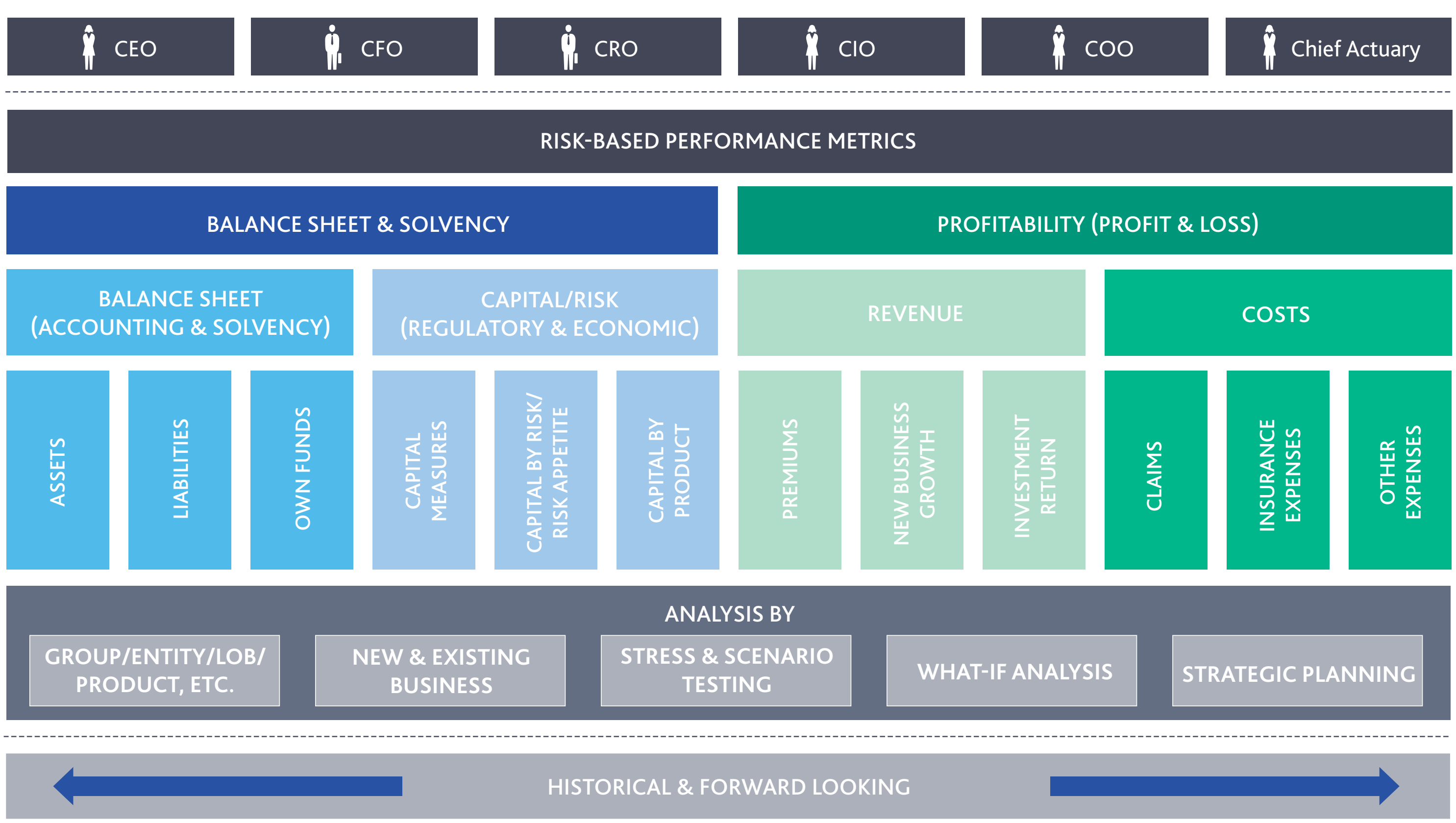
Although insurers have a good understanding of the type of historical information they need, the requirements tend to be siloed within functional areas (e.g., finance or risk). Creating a common vision across the entire business is not difficult at the highest level, but it becomes more challenging when trying to define the exact requirements across numerous stakeholders. Even when the requirements are well understood, the right solution is needed to deliver the business benefits in a cost-effective manner.

Invariably, it will be ownership and implementation of this vision that is the most difficult part. Adopting a top-down pragmatic approach helps firms focus on what is most important and avoid a "boil the ocean" scenario in which considerable time and effort are spent trying to resolve all the granular issues without much visible business benefit.

#### 2. Multiple data sources and inconsistent data

While much of the historic analytical information (financial, risk, capital, or investment information) required for decision-making may already exist within an organization, it is usually fragmented across multiple systems and a plethora of spreadsheets. This

**Figure 1** Information needed by the C-suite




Source: Moody's Analytics

information has to be collated – often using manual processes and even more spreadsheets – a procedure that has to be repeated each time information is required, whether for regulatory or business purposes such as board meetings. This makes producing the necessary information and metrics a difficult and time-consuming job.

Consequently, the first challenge is extracting, transforming, aggregating, and storing all of the information required in a logical and structured manner and making it easily available to the enterprise. Many insurers have existing operational datamarts or warehouses, but these are typically based on legacy systems and are not necessarily suitable for storing the type of analytical data needed at the required levels of granularity.

A second problem relates to consistency across different data sources. If data sources for a particular use (e.g., assets, profitability, etc.) are inconsistent, there may be questions about the underlying data quality, which can undermine senior management's confidence in the provided Management Information.

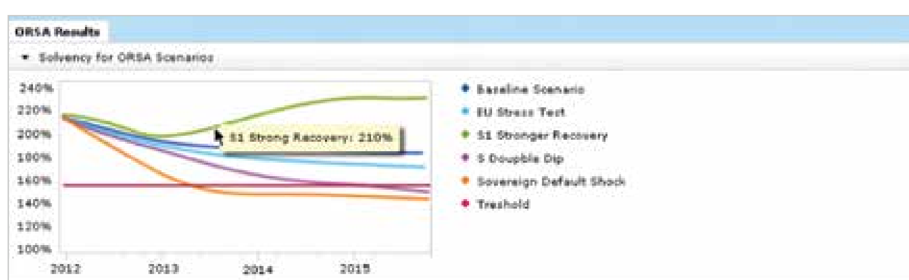
### 3. Forward-looking projections

Historical information is the most readily available to any organization. While it is important for monitoring the progress against business metrics and targets (or for regulatory purposes), historical information is limited in terms of its strategic planning and decision-making capabilities.

> Running what-if analyses can be a time-consuming process, especially if actuarial models are involved. Having to wait days or weeks for this information does not support the decision-making process. The lack of accurate and timely information often means that decisions are driven by gut feeling rather than sound analysis.

Forward-looking projections by scenario and their corresponding "what-if" analyses are an important part of the C-suite toolkit. Regulators, under the guise of processes such as ORSA, are also increasingly using them. Figure 2 illustrates an insurer's solvency ratio projected over a five-year time horizon based on a baseline scenario (most likely) and four alternative scenarios. However, forward-

**Figure 2** ORSA results




Solvency Ratio

| Solvency Ratio | 2012 | 2013 | 2014 | 2015 | 2016 |
|---|---|---|---|---|---|
| Baseline Scenario: | 211,0% | 193,0% | 184,1% | 178,6% | 175,0% |
| EU Stress Test: | 211,0% | 188,0% | 171,2% | 167,9% | 161,0% |
| S1 Stronger Recovery: | 211,0% | 199,6% | 209,4% | 213,8% | 218,1% |
| S2 Mild Double Dip: | 211,0% | 182,3% | 176,9% | 171,6% | 157,8% |
| S3 Double Dip: | 211,0% | 180,5% | 173,3% | 156,1% | 140,5% |
| S4 Severe Double Dip: | 211,0% | 176,9% | 161,2% | 145,2% | 126,4% |
| Sovereign Default Shock: | 211,0% | 176,7% | 150,7% | 144,4% | 136,9% |
| Sovereign Default Shock & Deflation: | 211,0% | 167,9% | 143,1% | 137,2% | 130,0% |

Highly Above Treshold
Above Treshold
Below Treshold
Highly Below Treshold
Treshold: 150,0%

Source: Moody's Analytics

looking projections also present a considerable challenge.

First, projecting an insurer's balance sheet is not always as straightforward as it sounds, particularly for complex organizations or those with complex assets and/or liabilities (e.g., path-dependent liabilities, as is common for life insurers).

Second, a key part of risk-based decision-making is the ability to measure return on capital. This means that firms need to be able to make projections across multiple regimes, such as solvency regimes for capital and accounting regimes (e.g., IFRS) for profitability.

### 4. It takes too long!

A final challenge is the length of time it takes to generate the relevant metrics, particularly for risk-based decision-making. Running what-if analyses can be a time-consuming process, especially if actuarial models are involved. Having to wait days or weeks for this information does not support a dynamic decision-making process. **The lack of accurate and timely information often means that decisions are driven by gut feeling rather than sound analysis**.

## Building an Insurance Analytics Platform (IAP)

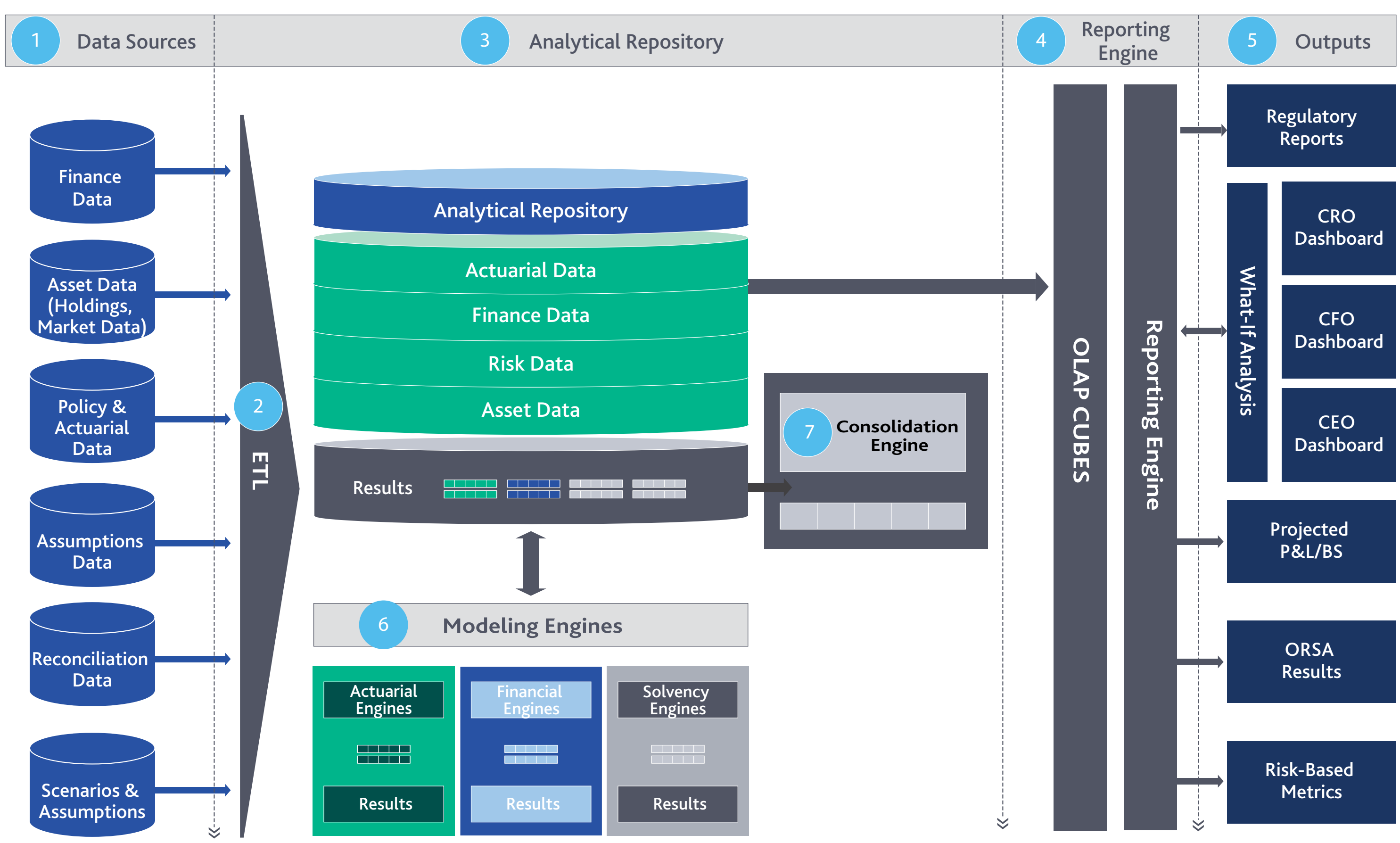
We believe that an Insurance Analytics Platform can be used to solve many of these challenges and provide the foundation for the management of risk-based performance metrics to support better decision-making.

Figure 3 illustrates the conceptual architecture of what an IAP might look like for an insurer.

### 1. Insurance analytical repository

The central core to the IAP is a dedicated insurance analytical data repository that stores the relevant asset, actuarial, finance, and risk

**Figure 3** IAP conceptual architecture




Source: Moody's Analytics

data (analytical data) and model run results, enabling the generation of a range of executive reports and interactive dashboards.

The repository acts as the common "clearing house" for the analytical data across the enterprise. The underlying data model can be designed to support the storage of both historical and forward-looking analytical data for the purpose of providing drill-down analysis of risk-based performance metrics. **The "clearing house" concept ensures that there is consistency of data for the analytics, while also ensuring complete transparency/audit trails from the source data**.

The "raw" data then has to be extracted, transformed, and loaded from multiple data sources (1 and 6 in Figure 3) before quality and validation checks can be undertaken in the repository. Most insurers have an existing extract, transform, and load tool (2) for this purpose. Importantly, the repository varies from a typical insurance database in a number of ways primarily in terms of the level of granularity and ability to store complex results such a cash flows.

### 2. Reporting engine

Generating the physical reports and dashboards requires a reporting engine (4) capable of querying the repository, organizing the data logically, and rendering the output in the selected format. This is typically facilitated by what are termed On Line Analytical Programming cubes, which are multi-dimensional views of data held in the repository. They enable high levels of granularity and provide drill-through paths.

### 3. Senior management dashboards

Outputs can be generated in a variety of formats, typically reports, spreadsheets, and dashboards. **From the perspective of decision-makers, interactive dashboards are particularly valuable**. Such dashboards should focus on the analytical information/metrics that are used to manage the business and make decisions.

» Provide drill-down analyses from the high-level business metrics, offering different levels of aggregation, drill-through, and granularity.
» Generate tailored views of the analytical management information dependent on the stakeholder (CEO, CFO, CRO, etc.) or functional area needs.
» Provide a "what-if" interface to enable comparison of the different (pre-run) scenarios against each other or the base scenario (e.g., compare the impact of an extra 5% new business growth on profitability and solvency).
» Present both point-in-time and forward-looking analytical management information.

### 4. Consolidation engine

Insurance companies are complex entities, necessitating a way to easily consolidate all the data from various sources. Thus, a key component of the IAP is a consolidation engine. In essence, a consolidation engine provides a mechanism for mapping the underlying analytical data onto the organizational structure of the business. The engine consolidates the granular results to present an enterprise view. This aligns the data model to the business and supports effective drill-down analysis.

### 5. Forward-looking capability

As we have already alluded to, one of the most difficult challenges is projecting forward key metrics and analytical information for strategic purposes. Most firms have some forward-looking capability, especially to meet the needs of ORSA under Solvency II. **The main problem is that most insurers have not invested in the end-to-end infrastructure to support the efficient production of multi-year results across a range of scenarios**.

Given what we have seen in the banking sector with multi-year stress testing, we expect this will be an area that insurance companies will increasingly look at in the coming years, which would naturally integrate with the IAP. Even where there is still a heavy reliance on existing capabilities with use of spreadsheets and manual processes, these capabilities can be integrated into the IAP and also used to help support better data management.

We believe that it should be possible to run a pre-defined set of scenarios and store the results in an analytical repository. This means that within defined parameters the CRO/CFO/CEOs would have "real-time" access to a range of results via interactive dashboards. If the information required were to be beyond the scope of the pre-defined scenarios, the models would have to be re-run.

More generally, we believe that insurers will use proxy techniques to enable scenarios to be run more quickly without relying on individual business units to produce results. The benefits gained through speed, accessibility, and centralization can easily offset a reduction in accuracy, provided the results are "good enough." Creating a forward-looking projection is a complex process and a detailed analysis is beyond the scope of this article.

## Conclusion

There is little doubt that insurers exist in an increasingly competitive and attritive environment. The ability to quickly make informed business decisions based on accurate historic and forward-looking information is crucial, but that information is difficult to collate as it is spread across a plethora of systems.

To meet the information challenge, firms need to have a clear vision of the enterprise metrics required to support their business, and adopt a top-down approach to ensure appropriate focus on the delivery of business benefits.

An IAP can help firms implement their vision. The end capability should be a flexible dashboard that focuses on key business metrics, can be tailored to address the needs of different stakeholders within the organization, and provides drill-down analysis. The analytical data repository can leverage the important source data via a robust data model designed to support the dashboard's capabilities.

Projecting balance sheets, capital, and profits by scenario in a timely manner to support the forward-looking metrics requires significant investment. However, the IAP can produce outputs from the manual processes that are currently in place at most organizations. As these processes become more streamlined, the platform must be flexible enough to cope with the changes.

# GETTING HUMAN DATA RIGHT: THE HIDDEN ADVANTAGE

By Kevin Hadlock

**Kevin Hadlock**
*Senior Director*

Kevin is a Global eLearning Solution Specialist. He has designed numerous distance-learning and web-based training programs, developed and taught many seminars, webinars, and full, blended training programs, and has authored content used globally by thousands of credit trainees.

With their focus on profit margins, data and risk management, and compliance with an increasing number of regulations, financial institutions often pay insufficient attention to the human side of their operations. This article addresses that deficiency and explains the sea change taking place in how risk professionals acquire "human data" – the quantifiable ability of employees to do their jobs well.

Risk professionals are prone to mismanaging the risks and rewards associated with employee knowledge and skill levels. Improving, capturing, and driving this critical – but frequently forgotten – data can help institutions gain a competitive advantage.

## Knowledge and skill: The data risk professionals forget

After years spent working with many banks around the world in the credit and financial sector, I have observed that few institutions engage in persistent human data quantification and management. They may conduct the occasional gap analysis, sometimes followed by a burst of training activity, but the discipline of continuously gauging employee knowledge and skills and then optimally providing training and access to self-directed and socially-driven learning is almost nonexistent.

This lack of an effective ongoing process leads inevitably to negative outcomes, such as costly one-time training ventures (where the training ages quickly and is too expensive to refresh on the fly), employees left to grasp at every informal learning source they can find (frequently Wikipedia or Google), and C-level executives who cannot see the value in spending on training because they do not believe investing in their employees will reap rewards in kind.

So when profits decline and budgets tighten, training gets whacked – and human data suffers. As a result, performance deteriorates and risk increases. Right when the need is greatest to minimize risk and maximize reward, the needle usually gets pushed in precisely the wrong direction!

## Human beings: Great risk, great reward

Employees are a financial institution's double-edged sword: They represent its single greatest source of risk and its most profound opportunity for reward. In spite of all an organization may do to comply with regulations, establish and monitor sound policies and procedures, and enhance its image in the marketplace, a wrong or fraudulent decision by just one employee can "undo" the millions of dollars and countless hours invested in optimizing business prospects.

For example, a loan officer who fails to notice key credit risks may grant a loan that quickly goes into default, costing the bank several million dollars in lost principal and interest and causing serious reputational damage. The profitability of dozens or even hundreds of performing loans can essentially be nullified in the process.

Conversely, an astute credit analyst may determine that a borrower has upside that isn't readily apparent and so advises decision-makers.

The result could be the granting of a loan that leads to a highly profitable and expanding long-term relationship that touches many areas of the bank in a positive way.

I have experienced both situations and have seen the positive and negative effects on whole communities. Credit professionals in each instance had vast amounts of data and transparency at their fingertips. Knowing and applying sound credit and risk principles, or failing to do so, were the deciding factors.

### Knowledge and skill: Human data that matters

So, how do credit-granting organizations minimize the downside of employee risk, while maximizing the upside? Is it enough to focus solely on optimizing systems or fine-tuning policies? Does compliance with all the regulations and risk management regimes put forth by all the governments and supremely qualified boards in the world eliminate risk once and for all? Does best practice data management solve all ills? As much as these practices might help, the answer to each of these questions, is "no" – as long as people are involved.

All banks train their employees to one degree or another. What too often gets left out, however, is a refined, dynamic focus on knowledge and skill that are core to what I call "human data." **Organizations tend to focus on performance, which is obviously appropriate. But it is the rare institution that appreciates the speed of change taking place in its employees' areas of expertise**.

Performance consultant and learning expert Jane Hart notes that, "the half-life of a given stock or skill is constantly shrinking – and is now around five years."[1] In practical terms, this means that by the time an employee is seasoned and comfortable, the definitions of seasoning and comfort have changed, often dramatically.

### An example of outdated human data

So how could this scenario play out? The poor loan officer from my earlier example has an accounting degree and, upon joining the bank, is trained in the classic way: months of classroom and workbook training, followed by placement in a division loan center under a manager who is a 25-year veteran. The training focuses largely on EBITDA as a primary determinant of borrower creditworthiness, a view reinforced by the employee's manager. On the job, the new officer is required to use a recently licensed spreadsheet application to capture borrower financial information and generate analysis-enabling reports. He notices that one such piece of output is a Uniform Credit Analysis (UCA) cash flow report and asks his manager if it has merit. The manager responds that she is not familiar with the report and that it appears to have little value in any case, so he disregards it.

Shortly thereafter, a large existing borrower requests a renewal on a long-term line of credit, and the new officer is tasked with conducting a credit analysis and making a recommendation.

> The probability of errors creeping into an employee's work output rises at an increasing rate the farther he or she gets from fresh, relevant human data. Knowledge and skills age so rapidly that the likelihood of employee error approaches 100% by the end of the five-year period.

Using all his training and his manager's guidance, he focuses squarely on EBITDA, failing to notice that the company's performance varies significantly from year to year. He doesn't realize that, while useful in assessing risk for generally stable companies, EBITDA often fails to capture the critical nuances of enterprises in flux. So, seeing profits still in the black, he grants the large renewal request (with his manager's approval), not noticing that true cash flow has become increasingly negative for the past three years, although he has projected it to remain positive for the foreseeable future. Within a year, the loan goes bad. The loan officer is now at a loss, wondering why it happened and how he might have predicted the failure.

The problem in this example is not that the bank didn't invest in the new loan officer's human data, but that there was no means in place to keep that data fresh and up to date. Both his formal training and his manager's guidance were grounded in established analytical principals, but failed to take into account what for them was an emerging analytical technique – cash flow analysis – that would have been greatly facilitated by the introduction of the automated spreadsheet tool. Upon an exhaustive debrief, key decision makers realized that staff had bypassed information that had been at their fingertips. They modified the policy to require an analysis of cash flow for all commercial loans in the future.

This is a true story that illustrates that human data must be updated constantly. Furthermore, systems or processes must be put in place to ensure that knowledge and skills are readily updateable. In other words, professional currency cannot be an accident. **If the elevation or adjustment of human data is left to chance, risk will outweigh reward and the likelihood of costly mistakes will increase**.

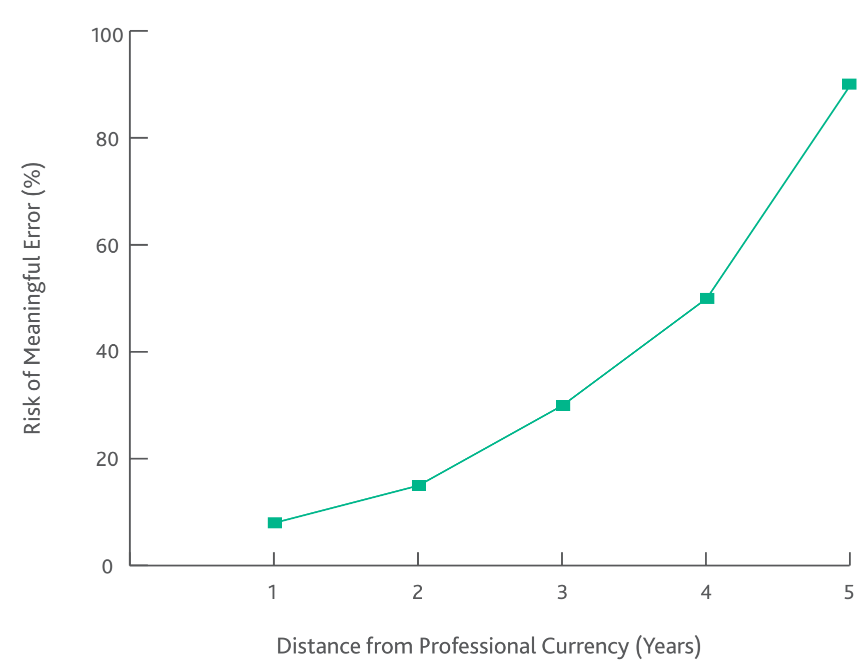
Figure 1 illustrates that the farther away an employee is from having current human data, the higher the likelihood he or she will make meaningful errors.

Figure 1 isn't defensible on a purely empirical basis, but rather is meant to be illustrative. I could have used any time frame for the "Distance from Professional Currency" axis; I chose to use Hart's five-year skills half-life figure, as it has researched relevance. Using a straight percent scale for the "Risk of Meaningful Error" axis and then assigning specific percentages at one-year intervals is likewise unscientific. I have drawn the progression simply to emphasize that the probability of errors creeping into an employee's work output rises at an increasing rate the farther he or she gets from fresh, relevant human data. Knowledge and skills age so rapidly that the likelihood of employee error approaches 100% by the end of the five-year period.

### How today's risk professionals can elevate their own human data

Interestingly, employees themselves often best recognize both the need for professional currency and the implications of not having it. They sense the urgency of having up-to-date knowledge and skill more than their organizations do because they are the ones who

**Figure 1** The relationship of "professional currency" to risk




Source: Moody's Analytics

have to keep their jobs and advance their careers. For them, the stakes are both high and personal.

On a related note, recent surveys and workplace studies show that, although formal training provided by the institution is useful, it provides only a fraction of the ongoing learning that employees need and is thus at the low end of the scale in terms of human data value-added.[2] Additional insight provided by Hart is again useful.[3] Her research into how employees learn what they need to do their jobs – in other words, to maintain their professional currency – is summarized in Table 1. The findings are listed in order of descending usefulness.

Although still important, formal training is at the bottom of the list for the approximately 700 survey respondents. **Other means of acquiring current human data score higher, and most of them are either employee-directed or socially sourced**. This is a multi-year trend that reflects the current and ongoing reality of business. The advent of technology-enabled access to knowledge on virtually every topic, as well as to other people via social networks and forums, has put the means of human data enhancement squarely in the hands of the employees themselves.

### Learning and performance ecosystems enhance performance

This article is not arguing against formal training provided by the institution. Quite the contrary, it remains a primary and foundational way for an organization to communicate its way of doing business to its staff and will always have a role in workplace learning and performance. But the trends and facts identified in Table 1 actually make a great deal of sense from the business side. Organizations simply do not have the budgets or dexterity to keep pace with every change and nuance in an increasingly dynamic business world – and then to nimbly and fully communicate them to every staff member. This would require expense and administrative overhead that virtually no company could efficiently take on.

What financial institutions can do, however, is a much better job of creating structured but open environments that combine formal training with self-guided and social learning, so that professional currency is optimized rather than achieved coincidentally or, worse, accidentally.

Perhaps the most promising approach to installing such environments is a construct

**Table 1** 2013 "Learning in the Workplace" survey results

| | Not Important | Quite Important | Very Important | Essential | V. Imp. & Essential |
|---|---|---|---|---|---|
| Knowledge sharing within your team | 3% | 12% | 30% | 55% | 85% |
| Web search for resources (e.g., Google) | 2% | 17% | 32% | 49% | 81% |
| Conversations and meetings with people | 2% | 19% | 40% | 39% | 79% |
| Personal and professional networks and communities | 3% | 22% | 35% | 40% | 75% |
| External blog and news feeds | 8% | 22% | 40% | 30% | 70% |
| Content curated from external sources | 9% | 29% | 39% | 23% | 62% |
| Self-directed study of external courses | 14% | 33% | 35% | 18% | 53% |
| Internal job aids | 20% | 37% | 26% | 17% | 43% |
| Internal company documents | 13% | 44% | 29% | 14% | 43% |
| Company training/e-learning | 25% | 42% | 20% | 13% | 33% |

Source: Jane Hart Blog

known as a "learning and performance ecosystem." In their white paper on this subject, Marc J. Rosenberg and Steve Foreman make the case that "we must move away from individual, siloed, 'one-off' [learning] solutions to an ecosystem comprised of multi-faceted learning and performance options that enhance the environments in which we work and learn."[4]

integrated and all-encompassing approach to employee training is paramount if business enterprises are to compete well and survive. In other words, six weeks, or even six months, of new hire training alone doesn't cut it anymore – if it ever did.

Although they don't say it in as many words, what Rosenberg and Foreman suggest is that optimized human data is so critical, and its insufficiency so pervasive, that a new, more integrated and all-encompassing approach to employee training is paramount if business enterprises are to compete well and survive. In other words, six weeks, or even six months, of new hire training alone doesn't cut it anymore – if it ever did.

They define learning and performance ecosystems as structures that strengthen "individual and organizational effectiveness by connecting people, and supporting them with a broad range of content, processes, and technologies to drive performance." They address six primary components of these ecosystems and depict them in an interrelated way:

1. Talent management
2. Performance support
3. Knowledge management
4. Access to experts
5. Social networking and collaboration
6. Structured learning

There is more to a learning and performance ecosystem than training. At the heart of it all is human data – the knowledge and skills employees need to do their jobs effectively. That data comes from structured learning, social networking and collaboration, access to experts, and effective performance support systems. It is managed, optimized, and applied most effectively and broadly over time through sound talent and knowledge management schemes.

Although they don't say it in as many words, what Rosenberg and Foreman suggest is that optimized human data is so critical, and its insufficiency so pervasive, that a new, more integrated and all-encompassing approach to employee training is paramount if business enterprises are to compete well and survive. In other words, six weeks, or even six months, of new hire training alone doesn't cut it anymore – if it ever did.

**Once employees are turned loose in the workplace, having a more thoughtful, dynamic approach in place will be critical to maintaining their knowledge and skills**. Organizations that fail to do so fall behind, sometimes quickly. The results then show up in falling bottom lines – and, in the case of credit-granting organizations, in decreasing credit quality and loan losses.

## Quantifying human data as a step in managing risk

If you work in credit and risk long enough, you begin to see everything in numbers. You start to believe that life must be quantified to be understood. Thankfully, there are ways to quantify, if imperfectly, human data.

In his report on tracking the knowledge and skills of credit professionals, "People Risk: Improving Decision Making in Commercial Lending,"[5] Ari Lehavi of Moody's Analytics explains an exam-based methodology for collecting metrics on human data in the area of fundamental credit risk assessment. He shares critical empirical details and broad results, all of which shed light on the strengths and weaknesses exhibited by lenders, analysts and relationship managers at banks around the globe. He further breaks this information down geographically and by subject matter (i.e., financial risk, marketplace/industry risk, management risk, and risk mitigation).

The most salient feature of all of these details about human data is that it is clearly actionable.

In other words, evaluating it accurately can lead to direct remediation that shores up weak areas and demonstrably elevates the quality of that human data. Among the report's key findings are the following:

- The average test score across subjects included in the assessment exceeded the minimum subjective pass threshold by a mere 2%.
- Financial risk had the weakest relative score. Approximately 42% of people answered fewer than 70% of the questions correctly in this critical subject area.
- Major banks around the world showed a wide disparity in test performance across all areas of risk.
- An institution's aggregate skill and knowledge test performance correlated highly with its relative default risk. Although there may be other contributing factors, the lower the bank's average score, the higher its relative default risk, as measured by Moody's Baseline Credit Assessment rating.

This last finding is particularly enlightening and reinforces the first proposition in this article – that subpar human data contributes to higher risk in a credit-granting organization. However, perhaps our key takeaway from Lehavi's report is that human data can be quantified and improved. And institutions that engage in this type of process, effectively and consistently, gain a current and highly useful sense of the level of human data in the organization, both individually and collectively.

## Investing in individuals rewards the organization

Institutions that have the foresight and will to implement integrated learning and performance ecosystems – or critical components thereof – in the near term will have the advantage over both the medium and long terms. **There is no "one size fits all" answer to this, but an abiding appreciation for the essential nature and inherent worth of human data, and the criticality of continuously optimizing it, is the foundation on which to build**.

Organizations that grasp this, and then make well-considered efforts to go beyond providing formal training to creating a permanent learning-is-performing environment – subscribed to and supported by all levels of the organization – will swing the risk/reward pendulum inexorably toward the reward side. This, in turn, will unlock human potential and corporate profits at an increasing rate. Thus is the power of human data and the reason for giving it its due.

1 Jane Hart, *Social Learning Handbook 2014*, page 20, 2014.

2 Don Taylor, *What will be big in workplace learning in 2015?*, January 7, 2015.
Allison Rosset, *Trending in Workplace Learning 2015*, January 13, 2015.

3 Jane Hart Blog, April 22, 2013, *http://www.c4lpt.co.uk/blog/2013/04/22/company-training-of-little-value*.

4 Marc J. Rosenberg and Steve Foreman, The eLearning Guild, *Learning and Performance Ecosystems, December 2014*.

5 Ari Lehavi, Moody's Analytics, *People Risk: Improving Decision Making in Commercial Lending*, November 18, 2014.

# REGULATORY SPOTLIGHT

Looks at how risk data management will impact financial institutions' preparation for regulations, including regulatory big data initiatives, PPNR stress testing, and IFRS 9.

# REGULATORY BIG DATA: REGULATOR GOALS AND GLOBAL INITIATIVES

By Michael van Steen

**Michael van Steen**
*Senior Director, Enterprise Risk Solutions*

Michael helps deliver advanced portfolio credit risk, stress testing, correlation, and valuations solutions to global banks, asset managers, hedge funds, insurance companies, and regulatory organizations.

Big data isn't just for Silicon Valley. This article discusses the trend of large data set capture and analysis by regulators, referred to here as "regulatory big data," by detailing the motivations and goals of regulators and examining three significant regulatory big data initiatives: AnaCredit in the European Union (EU), FDSF in the UK, and FR Y-14M in the United States. It then analyzes how these efforts complement other significant, and concurrent, regulatory reporting and IT efforts.

## A new big data paradigm emerges

Financial institutions worldwide are facing an increased level of regulatory scrutiny in the aftermath of the Great Recession. Regulatory efforts entail new and expanded reports, templates, and calculations from financial institutions that are often little more than detailed presentations of information summarized in existing regulatory disclosures such as call reports and loan loss summaries. Many institutions view them as just another mile on the seemingly endless "produce another report" treadmill – one that significantly increases their compliance costs.

However, a new paradigm – "regulatory big data" – is emerging worldwide in which an institution provides its bulk underlying granular data to regulators for their regulatory, risk assessment, and stress testing efforts.

## What is regulatory big data?

In the technology world, big data generally refers to an amount of data (both structured and unstructured) so vast that analysis of it requires new processing techniques. Examples of big data include a major search engine's index of all the web pages it has crawled, the monthly cash register transaction receipts at a national supermarket chain, and a hospital's analysis of patient treatment plans to determine ways to lower readmission rates.

This data generally lacks the well-defined structure that would allow it to fit neatly into standard relationship database tables. Additionally, the often multi-terabyte to petabyte size of this data is quite challenging for a typical relational database management system. As a result, technology companies have developed a wide variety of new software frameworks – MapReduce, Apache Hadoop, and NoSQL, to name a few – to analyze and process these big data repositories, often in parallel with traditional database tools.

Regulatory big data is a catch-all term (like big data) to describe the capture and processing of larger sets of regulatory data via the use of both traditional and newly developed data processing tools. Although this data isn't of the same magnitude as, for example, a record of clicks on a popular website, its volume is much greater than the summary regulatory reports submitted today. Big data tools and techniques can help regulators process the large amounts of data produced by financial institutions for oversight and compliance purposes.

### Regulatory big data: Regulator goals and uses

Regulators aim to use big data sets to complement traditional banking supervision, help maintain financial stability, and establish monetary policy regulation procedures. Proposals and rules from regulatory bodies such as the Basel Committee on Banking Supervision (BCBS), the Bank of England, and the Federal Reserve (Fed), as well as speeches and articles on the topic by regulators, have elucidated a variety of goals for regulatory big data, among them:[1]

- **Producing a rich regulatory dataset** with finer granularity than current reports provide
- **Eliminating real or perceived data gaps** in existing reporting by requiring more frequent and less aggregated data submissions
- **Reaping the benefits of advanced big data technology *without* the need to use proprietary technology** from big data firms
- **Aggregating an obligor's total indebtedness** across multiple institutions
- **Establishing a tools and data submissions framework** to provide a comprehensive overview of banks and their obligors at the push of a button

To start the process of working toward these goals, various regulatory big data initiatives have been advocating, if not mandating, that firms provide a much finer level of data granularity than ever before, oftentimes down to individual loans. They are also pushing for consistent identification and organizing of counterparties through initiatives like the Legal Entity Identification (LEI) effort and more frequent (e.g., monthly instead of quarterly or annually) data submissions.

This new data would provide regulators with the ability to:

- Build a foundation for more comprehensive and frequent institutional stress testing
- Measure institutional and obligor interconnectedness and contagion risk, by looking at obligors common to multiple institutions
- Conduct micro- and macro-prudential risk analysis, enhanced by the ability to assess the risk of obligors across firms and the movement of risk factors over time

In summary, the increased quantity, and the likely more frequent submission, of data for regulatory big data initiatives presents an opportunity for regulators to enhance their understanding of both the institutions they regulate and the credit exposures of individual obligors across institutions.

In the following sections, we provide information on three current regulatory big data initiatives:

**Figure 1** Regulatory big data


Source: Moody's Analytics

Analytic Credit Dataset (AnaCredit) in the European Union (EU); Firm Data Submission Framework (FDSF) in the UK; and Capital Assessments and Stress Testing (FR Y-14M) in the US. We discuss the features of these initiatives, as well as the regulatory motivation and, critically, the effect on firms subject to these rules.

### Regulatory big data: AnaCredit (EU)

AnaCredit is an EU-proposed Central Credit Register (CCR) of, initially, loans to non-financial corporations. AnaCredit's aim is to build up and link existing national CCRs to a Europe-wide credit data repository accessible by the European Central Bank (ECB) and other European nations' central banks. Essentially, AnaCredit mandates the collection of granular data from financial institutions.

Only countries subject to the ECB (i.e., euro-denominated countries) are considering this initiative, so non-euro zone countries such as the UK are not taking part. AnaCredit's rollout will initially apply to an estimated 3,500 banks in the EU. Other lenders, including non-EU institutions operating in the EU, do not fall under the initial scope.

> The increased quantity, and the likely more frequent submission, of data for regulatory big data initiatives presents an opportunity for regulators to enhance their understanding of both the institutions they regulate and the credit exposures of individual obligors across institutions.

Implementation timelines have shifted since AnaCredit was formally introduced through the ECB decision (ECB/2014/6) on February 24, 2014;[2] the latest estimate is for a phased implementation starting in January 2018.

The objectives of ECB/2014/6 are to define:

*"…preparatory measures necessary to establish in a stepwise manner a long-term framework for the collection of granular credit data based on harmonized ECB statistical reporting requirements. This long- term framework shall include by the end of 2016: (a) national granular credit databases operated by all Eurosystem NCBs, and (b) a common granular credit database shared between the Eurosystem members and comprising granular credit data for all Member States whose currency is the euro."*

The ECB intends to leverage existing national CCRs as a foundation for AnaCredit, but a large amount of work still needs to be done. For example, the ECB must roll out specific AnaCredit regulations, which are not expected until the second quarter of 2015 at the earliest.

Though they are not the final rules for AnaCredit, the ECB/2014/6's "prepare for AnaCredit" regulations shed some light on both the work needed and the likely capabilities of this system. The preparatory work mandated by ECB/2014/6 includes:

- Identifying relevant end-user needs
- Defining the granular credit data sets that will be collected and linked
- Developing a way to transmit granular credit data securely
- Developing detailed operational arrangements, given the sensitivity of the data
- Establishing a timetable for specific steps and deliverables and for monitoring progress
- Addressing confidentiality, use of data, and governance

Looking at existing European credit registers and the overall goals of these regulatory big data initiatives, we think it likely that, ultimately, the AnaCredit system will include:

- Data on obligors, including unique identifiers – in particular, the identifiers being developed as part of LEI – enabling the linking of obligors across institutions
- Amount of assets, financial derivatives, and certain off-balance sheet items
- Loan IDs, inception and maturity dates, interest rates, and any financial guarantees

tied to loans

- Analytic measurements such as loan performance data, borrower probability of default (PD), and exposure Loss Given Default (LGD) estimates

From our analysis of similar initiatives and the preparatory work involved, we expect the ECB will consider between 24 and 150 – or more – attributes per loan for inclusion in this initiative, although the exact number and composition have not yet been determined. There are several other unknowns, including:

- The lower reporting threshold – specifically, the euro level of individual loans that do not need to be reported
- The schedule of assets that need to be reported
- The reporting schedule for institutions, particularly foreign institutions operating in the EU and non-bank financial companies

The resulting analytic dataset – although the exact composition, rollout schedule, and asset mix are still undecided – will provide the ECB and national central banks with a comprehensive view of loan exposures in an institution and of obligors across institutions. Once assembled, AnaCredit's large granular dataset will allow regulators a view into the institutions they regulate that is not currently available with summary-level reports.

### Regulatory big data: Firm Data Submission Framework (UK)

The Firm Data Submission Framework (FDSF), another example of a regulatory big data project, is a quarterly granular reporting requirement from the Bank of England's Prudential Regulation Authority (PRA). FDSF applies to the UK's eight Systematically Important Financial Institutions (SIFIs) and was developed to provide quantitative, forward-looking assessments of the capital adequacy of the UK banking system and the individual institutions in it.

Like the Fed's Comprehensive Capital Analysis and Review (CCAR), on which it is loosely based, FDSF requires that institutions collect data from all of their significant operating units and use this data, based on PRA guidance and stress scenarios, in a wide variety of stress calculations.

The FDSF requires a level of granular data and analysis far in excess of the typical reports submitted to UK regulators. The intense scrutiny and significance of this exercise (which, in the event of unsatisfactory results, could prompt the regulator to prohibit capital payouts) means that each institution requires extensive audit trails, detailed documentation of assumptions, full traceability of calculations, and the analysis of many scenarios.

As with other regulatory big data initiatives, the data required for FDSF would be sourced from a variety of internal areas (e.g., individual business units, each likely having multiple products and associated accounting systems and assumptions) in myriad formats. Assembling this data is not as simple as appending rows to an existing table, however; reporting date time gaps and missing data are likely, as is the need to try out various assumptions on key parameters such as expected losses and probabilities of default. Moreover, the calculated stress results are also likely to vary significantly by product line and geography – a downturn in UK property prices, for example, will likely have a significantly different impact on a Scottish residential mortgage portfolio than on a Greek shipping loan book.

An additional layer of complexity arises from the potential need to map internal data structures to those defined by the PRA. Although a bank's systems may have just a few occurrences of key attributes as "exposure," an institution has to reconcile all of them with the PRA's precise definition. An extensive audit trail is also necessary so an institution can drill down and aggregate the data as needed or requested by the PRA.

As with AnaCredit, the FDSF rules define regulatory big data according to the following parameters:

- An extensive amount of data
- Data that typically needs extensive mapping, aggregating, and cleaning prior to submission for use in stress testing calculations

The use of the data is quite complicated, as multiple, iterative stress tests are typically required of the banks subject to this regulation. In practice, however, the ability of big data tools to handle large datasets of partially structured data (i.e., not fully contained in clean relational database tables) facilitates the FDSF initiatives. Banks can use flat files of raw data from differing systems, scripting languages, and statistical packages to manage this large load of data and complicated analytic requirements, while maintaining a strict data quality regime.

### Regulatory big data: FRY Y-14M Reporting (US)

The FR Y-14M reporting program is a regulatory big data initiative by the Fed in the United States. Under FR Y-14M, bank holding companies with consolidated assets of $50 billion or more must submit detailed home equity and credit card loan data, along with portfolio and address data, to the Fed on the last business day of each month.

In contrast to the existing – and predominantly – summary and aggregated reporting required of banks and bank holding companies, FR Y-14M is a true regulatory big data program, as it requires reporting of all portfolio and service loans and lines in several broad portfolio categories every month. The FR Y-14M initiative, like the AnaCredit and FDSF regulations, aims to furnish regulators with the tools and data necessary to monitor very granular risk in a timely, near-continuous fashion.

Institutions subject to these requirements must contend with several complex technical challenges, given the significant amounts of sensitive data they have to prepare and submit every month. The Fed requires that bank holding companies subject to these rules report all of the following active and serviced lines and loans in its portfolio:

- Revolving, open-end loans secured by one to four family residential properties and extended lines of credit
- Junior-lien closed-end loans secured by one to four family residential properties
- Domestic credit cards

Additionally, banks have to report detailed information on previously reported loans that migrate out of the portfolio (e.g., are paid off or have defaulted), as well as information to facilitate address-matching across loans and portfolio-level information.

An extensive amount of information is required for each loan. For example, domestic first liens require 137 lines of data per loan that includes a wide range of data elements, such as origination credit score, current credit score, probability of default, mortgage insurer, valuation at origination and at current time, foreclosure status, and both actual (if any) loss given default and expected loss given default.

The Fed uses the data collected under FR Y-14M for a wide range of regulatory purposes, including assessing a bank's capital adequacy, supporting periodic supervisory stress tests, and even enforcing Dodd-Frank consumer production measures.

The sheer volume of information banks must provide every month, the detailed and sensitive nature of data collected, and the disparate uses of this data – everything from consumer protection to stress testing – all present new technical challenges for banks and regulators. Because the Fed's analysis of a bank's FR Y-14M data could result in regulatory actions with a material impact (e.g., restricting dividend payouts), banks must take extreme care to ensure that this data is accurate, timely, and auditable.

### Complementary efforts

**Moody's Analytics research reveals that to meet these challenges, institutions are building complementary processes outside their traditional credit-relational database management systems and using new big data analysis and formatting tools**. They seek to separate their large-scale data processing efforts from other reporting and analysis of the database, all while maintaining a clear and auditable record of data submissions.

As an illustration of the tools and technology available today, one institution implemented a single, large monthly data extraction script to move masses of raw data (i.e., in a non-submission format and missing several calculations) from its database to a large set of flat files, then relied on an open source statistical package to clean up and append the data to a large statistical data file. The institution then used another set of procedures in the statistical program to extract and format the data for its monthly submissions and to build a detailed log of the preparation of the data submitted. In addition, the regulators themselves are also launching several complementary efforts that are transforming banks' data handling and reporting techniques.

- **The Global Financial Markets Association (GFMA),** among others, is coordinating the LEI initiative, wherein each single legal entity is assigned a unique ID. LEIs will facilitate aggregation of an obligor's exposures across institutions and easy analysis of an entity's exposures within an organization, as well as the use of external data on an obligor to supplement the data an institution might have.
- **The Bank for International Settlements (BIS)** has produced "Principles for effective risk data aggregation and risk reporting" (BCBS 239 publication) that comments on, among other areas, the risk infrastructure and risk aggregation methods of larger banks. As the publication shows, regulators recognize how critical risk infrastructure and technology are at large financial institutions.
- **The G20's Data Gaps Initiative (DGI)** is a set of 20 recommendations for enhancing economic and financial statistics, covering broad topic areas such as "Monitoring Risk in the Financial Sector" and "Financial Datasets." Although aimed primarily at regulatory bodies, the DGI will have a profound effect on individual firms, given that it calls for standardized reporting templates for large international exposures and an overall higher level of reporting data granularity from most financial firms.

The common theme of these initiatives is that financial institutions have to produce much larger volumes of data in a more consistent and controlled way. **Organizations must have the infrastructure and the skills in place to consistently produce and submit large data sets of critical information to their regulators**.

> Because the Fed's analysis of a bank's FR Y-14M data could result in regulatory actions with a material impact (e.g., restricting dividend payouts), banks must take extreme care to ensure that this data is accurate, timely, and auditable.

### The age of regulatory big data is here

AnaCredit, FDSF, and FR Y-14M are the first of what look to be numerous efforts by regulators to capture more granular data much more frequently, from the firms they regulate.

This emphasis on raw data places considerable technical and operational burdens on institutions. Regulatory reporting will no longer comprise an Excel file or two emailed every quarter but, rather, an extensive process of assembling highly sensitive data, which regulators can then use for critical tasks like approving a bank's dividend policy.

Institutions need to take a fresh look at their data handling, reporting, technology, and security architecture to ensure that they meet these significant new challenges. The emergence of big data tools and technologies, many of which are open source, can help institutions achieve compliance.

1 Michael Ritter, Deutsche Bundesbank, Chair of the ESCB Working Group on Credit Registers, *Central Credit Registers (CCRs) as a Multi Purpose Tool to close Data Gaps*, May 2014.

Anne Le Lorier, Deputy Governor – Banque de France, Seventh ECB Statistics Conference, *Towards the banking Union: Opportunities and challenges for statistics*, October 2014

2 "Decision of the European Central Bank of 24 February 2014 on the organisation of preparatory measures for the collection of granular credit data by the European System of Central Banks (ECB/2014/6)"

# IFRS 9 WILL SIGNIFICANTLY IMPACT BANKS' PROVISIONS AND FINANCIAL STATEMENTS

By Cayetano Gea-Carrasco

**Cayetano Gea-Carrasco**
*Head of Stress Testing Services and Advisory*

Cayetano works with financial institutions on credit portfolio management across asset classes, derivatives pricing, CVA / Counterparty Credit Risk analytics, stress testing, and liquidity management.

International Financial Reporting Standard 9 (IFRS 9) will soon replace International Accounting Standard 39 (IAS 39). The change will materially influence banks' financial statements, with impairment calculations affected most. IFRS 9 will cover financial institutions across Europe, the Middle East, Asia, Africa, and Oceania.

IFRS 9 will align measurement of financial assets with the bank's business model, contractual cash flow of instruments, and future economic scenarios. In addition, the IFRS 9 provision framework will make banks evaluate how economic and credit changes will alter their business models, portfolios, capital, and the provision levels under various scenarios.

Given the IFRS 9 requirements in terms of classification, measurement, and impairment calculation and reporting, banks should expect to be required to make some changes to the way they do business, allocate capital, and manage the quality of loans and provisions at origination. Banks will face modeling, data, reporting, and infrastructure challenges in terms of both:

1. Reassessing the granularity (e.g., facility-level provisioning analysis) and/or credit loss impairment modeling approach (e.g., consistency regarding the definition of default between Basel and IFRS 9 models).
2. Enhancing coordination across their finance, risk, and business units.

Effectively addressing these challenges will enable bank boards and senior management to make better-informed decisions, proactively manage provisions and effects on capital plans, make forward-looking strategic decisions for risk mitigation in the event of actual stressed conditions, and help in understanding the evolving nature of risk in the banking business. In the end, a thoughtful, repeatable, consistent capital planning and impairment analysis should lead to a more sound, lower-risk banking system with more efficient banks and better allocation of capital.

To help minimize the challenges faced by financial institutions when transitioning to IFRS 9, we conducted the *Moody's Analytics 2015 IFRS 9 Survey* to give practitioners a snapshot of the "current state" of the industry. Moody's Analytics has also included a series of comments on best practices and industry trends.

## Survey Findings: Implications for Financial Institutions

IFRS 9 will affect the business models, processes, analytics, data, and systems across several dimensions.

### Capital, lending, underwriting, and origination

» Provision levels are expected to substantially increase under IFRS 9 versus IAS.

» Further equity issuances may be needed, with the potential for greater pro-cyclicality on lending and provisioning owing to IFRS 9. Capital levels and deal pricing will be affected by the expected provisions, but must be evaluated under different economic cycles and scenarios.

» Banks will have to estimate and book an upfront, forward-looking expected loss over the life of the financial facility and monitor for ongoing credit-quality deterioration.

- Rating and scoring systems may have to be updated, especially for those banks without Internal Ratings-Based (IRB) models.

### Asset reclassification, reconciliation, and measurement

- Banks will need to reclassify assets and reconcile them with IAS. They will also need to map products that can be categorized before the calculation (contractual cash flow test) or create a workflow to capture the purpose (business model test). An additional effort could be required to identify those products that can be considered out of scope (e.g., short-term cash facilities and/or covenant-like facilities).
- Institutions will have to align, compare, and reconcile metrics consistently (e.g., Basel vs. IFRS 9).

### Cross-coordination across risk, finance, and business units

- Financial institutions will have to coordinate finance, credit, and risk resources for which current accounting systems are not equipped.

### Credit impairment calculation and valuation

- The IFRS 9 provision model will make banks evaluate, at origination, how economic changes will affect their business models, capital plans, and provisioning levels.
- A methodology to calculate a forward-looking measurement will have to be developed and/or updated (e.g., transformation from TTC to PiT), while the cash flow valuation analysis must be scenario-driven.
- IFRS 9 will affect the existing documentation and hedge accounting frameworks.

### Data, systems, processes, reporting, and automation

- Systems will need to change significantly to calculate and record changes requested by IFRS 9 in a cost-effective, scalable way.
- Data requirements will increase to meet IFRS 9-related calculations and ongoing monitoring.
- Retrieval of old portfolio data will also be needed, especially for the transactions originated before the A-IRB models have been introduced.
- IFRS 9 impairment calculation requires higher volumes of data than IAS, which may substantially increase the performance and computational requirements of a credit-loss impairment calculation engine.
- Financial reporting and reconciliation will be needed to align with other regulatory requirements.

### Documentation and governance

- IFRS 9 makes the provisioning exercise a cross-functional activity, with coordination needed across the risk, finance, accounting, and business functions.

## IFRS 9 is a Game Changer

IFRS 9 is the International Accounting Standards Board's (IASB) response to the financial crisis, aimed at improving the accounting and reporting of financial assets and liabilities. IFRS 9 replaces IAS 39 with a unified standard. In July 2014, IASB finalized the impairment methodology for financial assets and commitments. The mandatory effective date for implementation is January 1, 2018; however, the standard is available for early adoption (e.g., via local endorsement procedures).

IFRS 9 introduces changes across three areas with profound implications for financial institutions:

1. The classification and measurement of financial assets
2. The introduction of a new expected-loss impairment framework
3. The overhaul of hedge accounting models to better align the accounting treatment with risk management activities

Replacing IAS 39 with IFRS 9 will significantly impact banks' financial statements, the greatest impact being the calculation of impairments:

| Parallel Run | 71% | Capital Plan | $2M |
|---|---|---|---|
| More than 82% of respondents plan to conduct a parallel run ahead of the implementation | Of the respondents have an IFRS 9 roadmap in place for the implementation | 32% of respondents consider IFRS 9 a business benefit for capital planning activities and timely provision planning | 42% of respondents have allocated this budget or higher for IFRS 9 compliance |

Source: Moody's Analytics

- IAS 39 – A provision is made only when there is a realized impairment. This results in "too little, too late" provisions and does not reflect the underlying economics of the transaction.
- IFRS 9 – Aligns the measurement of financial assets with the bank's business model, contractual cash flow characteristics of instruments, and future economic scenarios. Banks may have to take a "forward-looking provision" for the portion of the loan that is likely to default, as soon as it is originated.

IFRS 9 has also several common characteristics with the Financial Accounting Standards Board's (FASB) Current Expected Credit Loss (CECL) model provisioning framework to be implemented in the US.

### Who Will Be Subject to IFRS 9?

IFRS 9 will be required for financial institutions in Europe, the Middle East, Asia, Africa, and Oceania. Specifically:

- Companies listed on EU stock markets and EU banks must use IFRS reporting standards in preparing their consolidated financial statements.
  - Europe: More than 230 banks (banks of significant importance)
- Asia, Americas (excluding the US), Oceania, and Africa will be implementing IFRS either through a local-endorsement process or convergence of the respective country-specific standard.
  - Asia and the Middle East: More than 370 banks (banks of significant importance)

Institutions in the US will not be subject to IFRS 9 (GAAP is mandatory for those institutions). However, FASB will introduce a similar analytical framework (CECL) if the current proposal is approved under the proposed form without major modifications.

### Industry Snapshot: Current State

With all eyes on IFRS 9, Moody's Analytics carried out our first IFRS 9 survey to help practitioners better understand how their peers are preparing for the implementation. Overall, banks that participated in the survey are accelerating their planning, budgeting processes, and road-mapping activities for full-scale implementation projects, given the finalization of the IFRS 9 standard.

### Survey Results

The survey consolidates the views of 28 banks regarding how they are approaching the challenges that IFRS 9 poses. Banks answered 22 questions across five main areas:

1. Data
2. Analytics
3. Calculation
4. Reporting
5. Business uses

**Basel**

More than 40% of respondents plan to integrate IFRS 9 requirements in the Basel infrastructure

**Data**

Is a major challenge when implementing and designing an IFRS 9 solution

**80%**

Of respondents will include scenario analysis in the IFRS 9 calculation

**Deal Level**

85% of respondents plan to run facility-level granularity for wholesale portfolios

## Section 1 – Participants

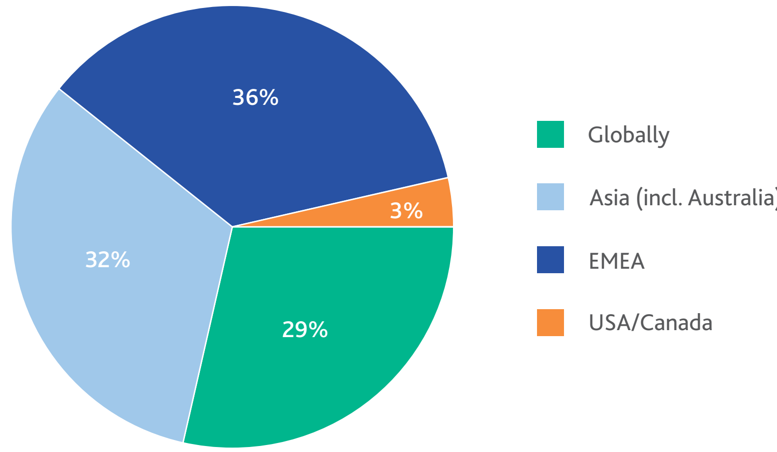
Key findings:

- We gathered our survey results from a significant cross section of institutions of all sizes, proof that IFRS 9 implementation is on the agenda, regardless of the size of the bank.
- More than 60% of the institutions have operations in the EMEA and APAC regions where IFRS 9 will be mandatory. Institutions in the US will not be subject to IFRS 9 (GAAP is mandatory for those banks).
- More than 72% of the respondents are from the risk and finance divisions at banks who will also be the major users of IFRS 9 (from an impairment-calculation and financial reporting perspective, respectively).
- Finance is the main stakeholder given the financial reporting implications of IFRS 9. However, the risk division closely follows finance given its role in the credit-impairment calculation.

**Question 1: What are the total assets of your bank?**

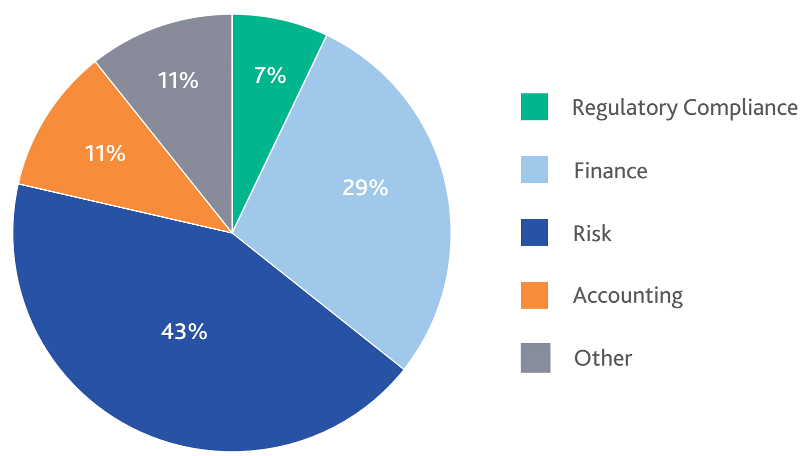

Source: Moody's Analytics

**Question 2: In which region(s) does your bank operate?**



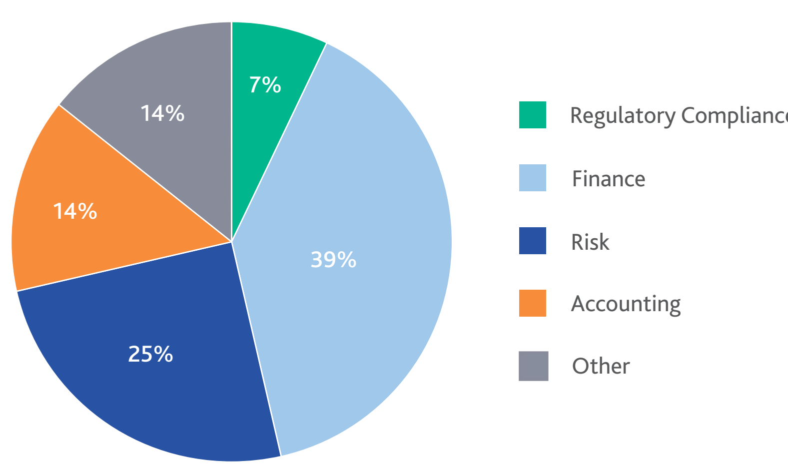

Source: Moody's Analytics

**Question 3: What is your role in the organization?**




Source: Moody's Analytics

**Question 4: Who is the key stakeholder responsible for IFRS 9 in your organization?**



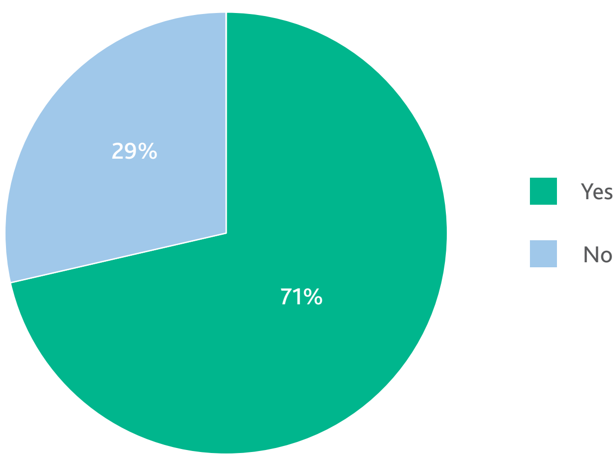

Source: Moody's Analytics

## Section 2 – Preparing for 2018

Key findings:

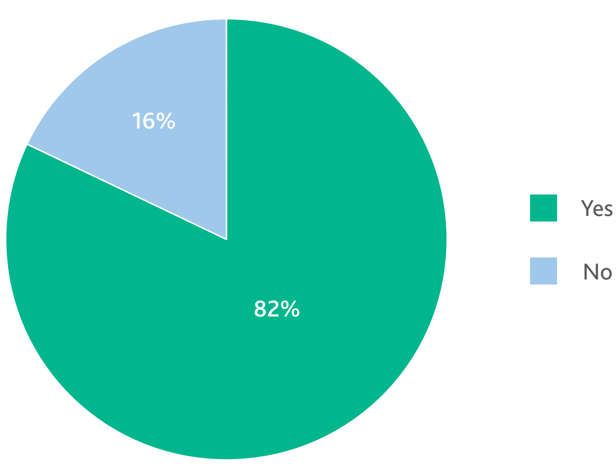
- More than 82% of banks surveyed have a formal roadmap in place and plan to carry out a parallel run ahead of the implementation deadline.
- More than 85% of banks surveyed plan to have an operational IFRS 9 solution by 2017 (one year before the mandatory date to be IFRS 9 compliant).
- More than 40% of the respondents are planning to integrate IFRS 9 requirements in the Basel infrastructure.
- More than 43% of the respondents have allocated a budget of more than $2 million to meet the IFRS 9 requirements and improve their infrastructure and analytics.

**Question 5: Do you have a formal IFRS 9 implementation roadmap at your organization?**



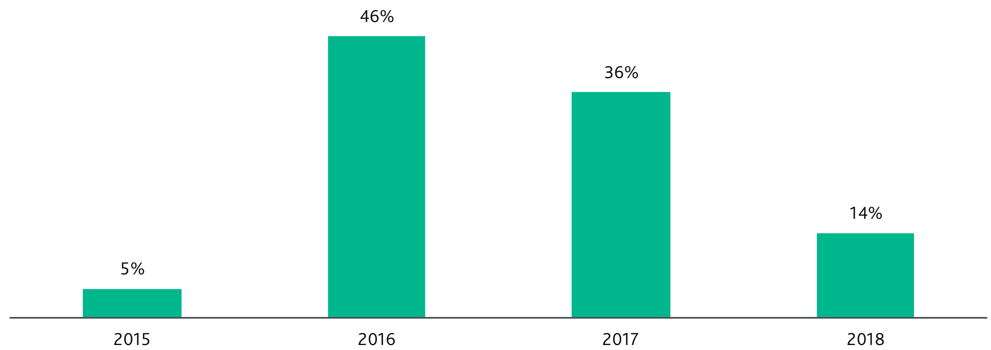

Source: Moody's Analytics

**Question 6: Are you planning a parallel run ahead of the deadline for implementation?**



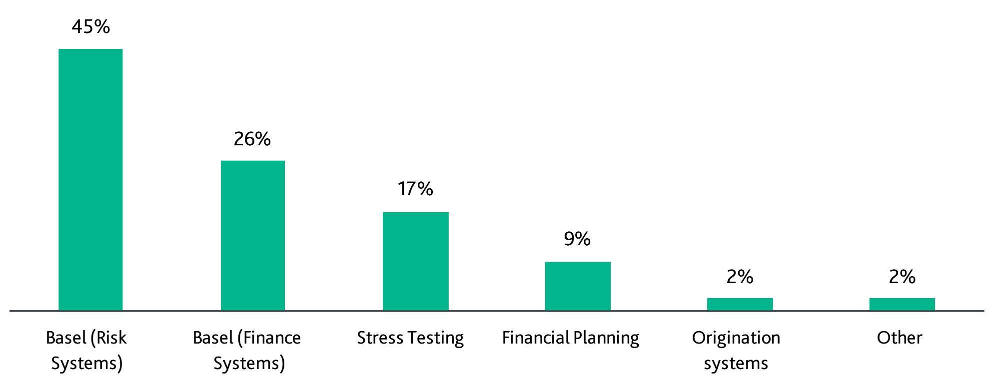

Source: Moody's Analytics

**Question 7: If you are going to be conducting a parallel run ahead of the deadline, when will you need an IFRS 9 solution?**



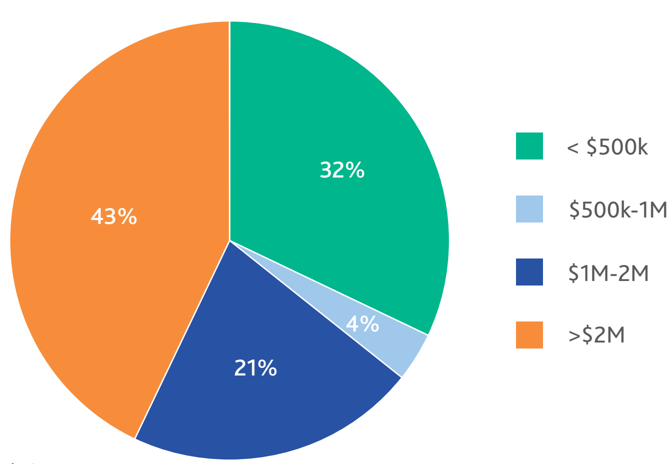

Source: Moody's Analytics

**Question 8: Are you planning to integrate your IFRS 9 compliance with other initiatives? Please state which initiatives.**



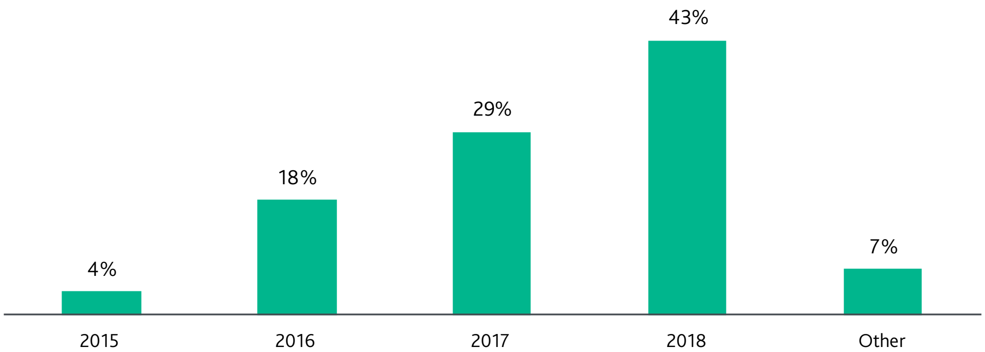

Source: Moody's Analytics

**Question 9: What is the allocated budget for IFRS 9 implementation?**



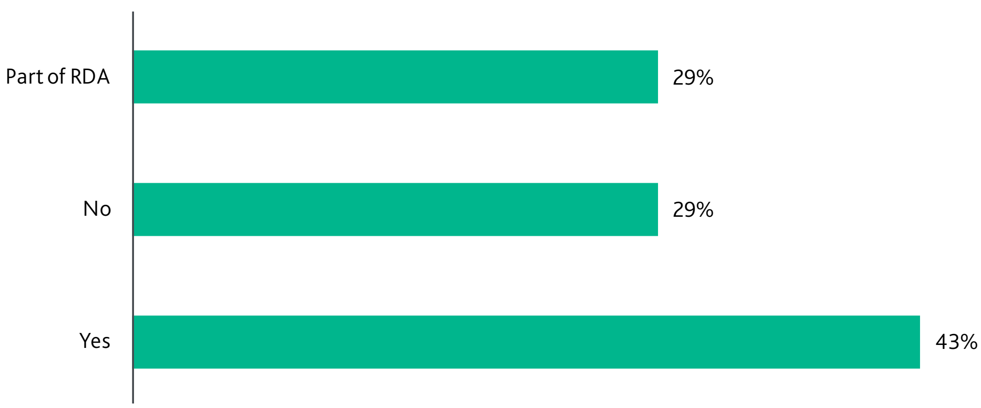

Source: Moody's Analytics

**Question 10: What is your timeline to be IFRS 9 compliant?**




Source: Moody's Analytics

**Question 11: Are you planning to invest in data reconciliation and aggregation platforms for IFRS 9 provision calculation, reconciliation, and reporting?**



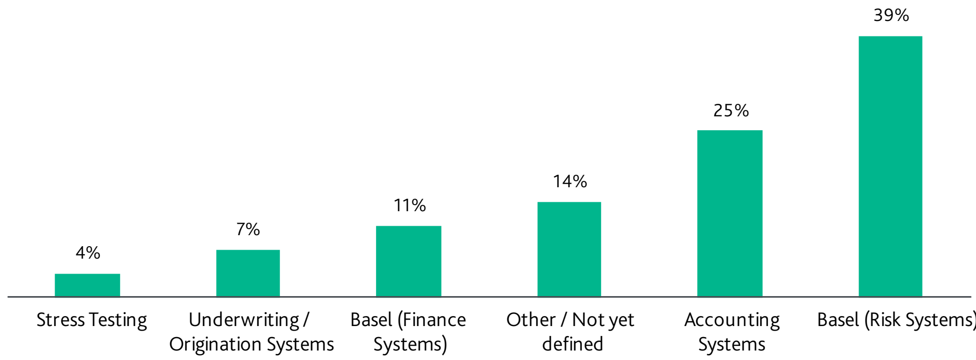

Source: Moody's Analytics

## Section 3 – Data and Calculation

Key findings:

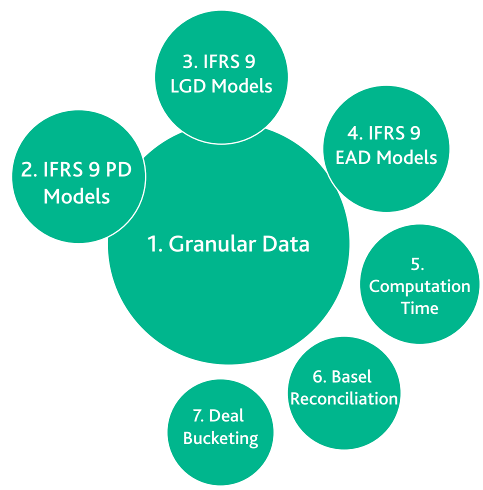
- Gathering granular data and developing PD and LGD IFRS 9-compliant models are the major challenges to designing and implementing an IFRS 9 solution.
- More than 40% of the respondents plan to add the credit impairment and expected loss calculation engine to their Basel risk systems.
- More than 82% of the respondents plan to leverage their ALM systems to compute amortizing balances.
- More than 63% of the respondents plan to leverage their Basel IRB models for the credit-loss impairment calculation.
- More than 50% of the respondents plan to run facility-level calculations for the retail portfolio; more than 85% of the respondents are planning to run this level of granularity for the wholesale portfolio.

**Question 12: If you plan on investing in an IFRS 9 Provisions Engine, to which system will it be an add-on?**



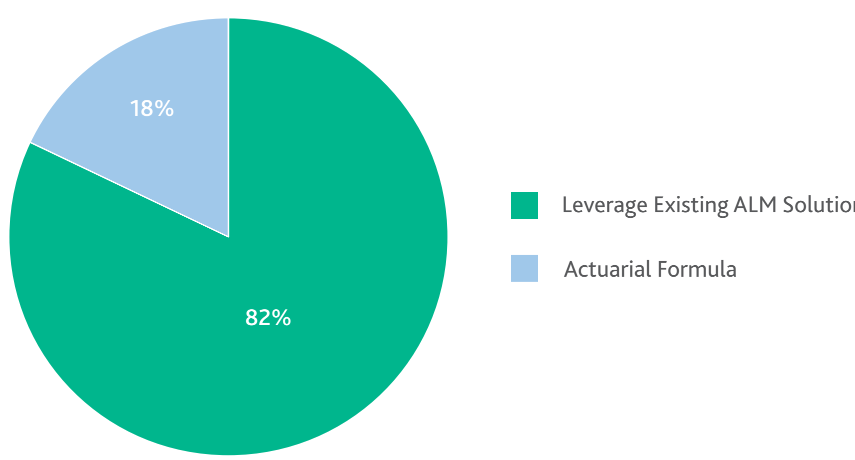

Source: Moody's Analytics

**Question 13: Please rank the following in order of difficulty (encountered or expected) when designing and implementing your IFRS 9 provision and impairment solution.**



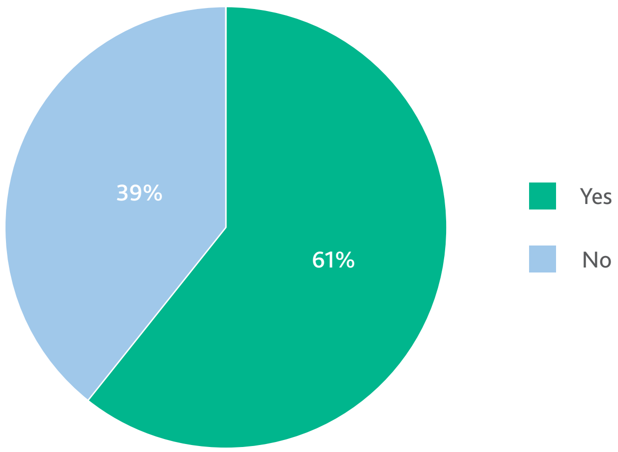

Source: Moody's Analytics

**Question 14: How do you plan on computing amortizing balances?**



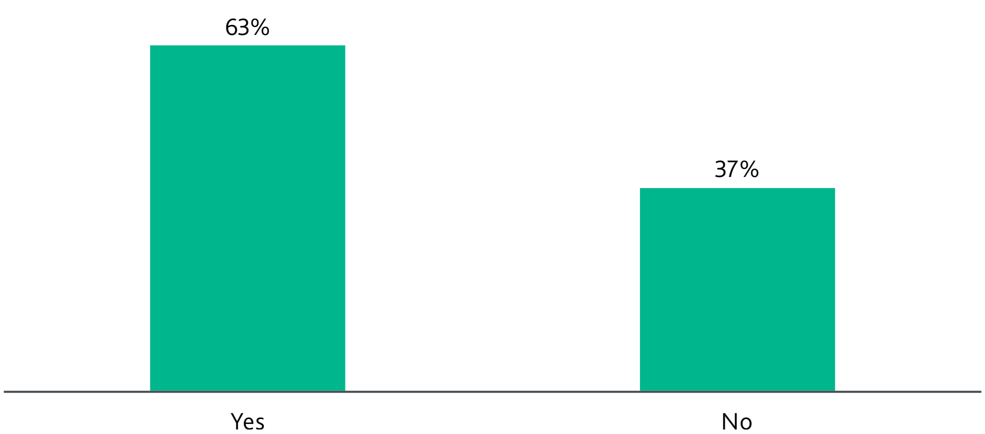

Source: Moody's Analytics

**Question 15: Do you plan on building dedicated IFRS 9 provisioning models in addition to Basel models?**



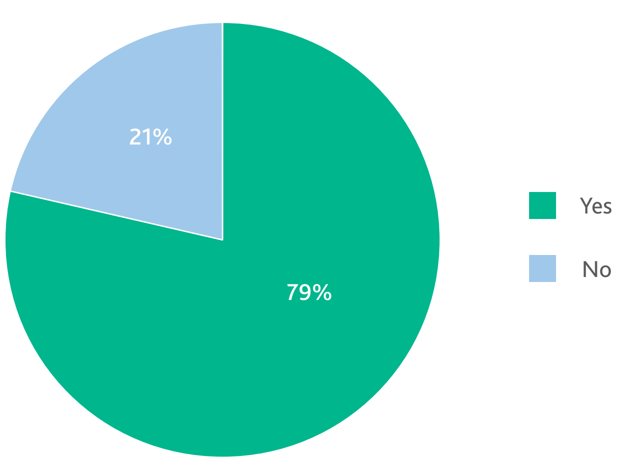

Source: Moody's Analytics

**Question 16: Do you plan on using an Advanced Internal Rating Model for IFRS 9 provision calculation?**



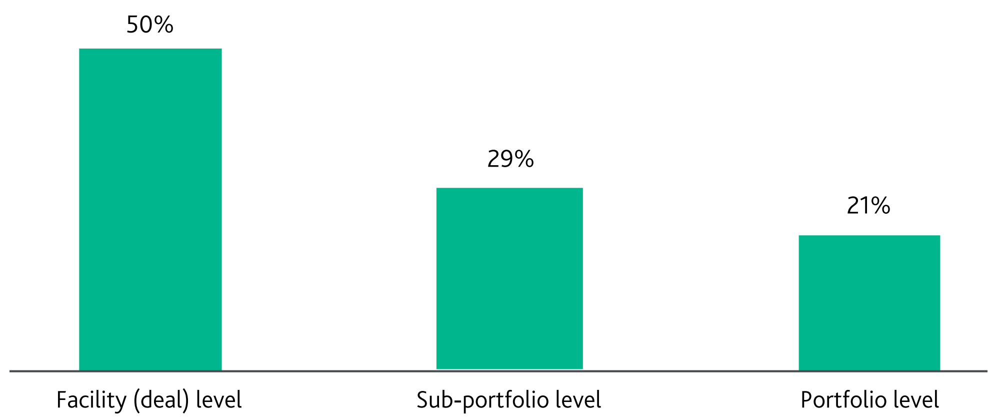

Source: Moody's Analytics

**Question 17: Do you plan on incorporating scenario capabilities in the IFRS 9 provision calculation?**



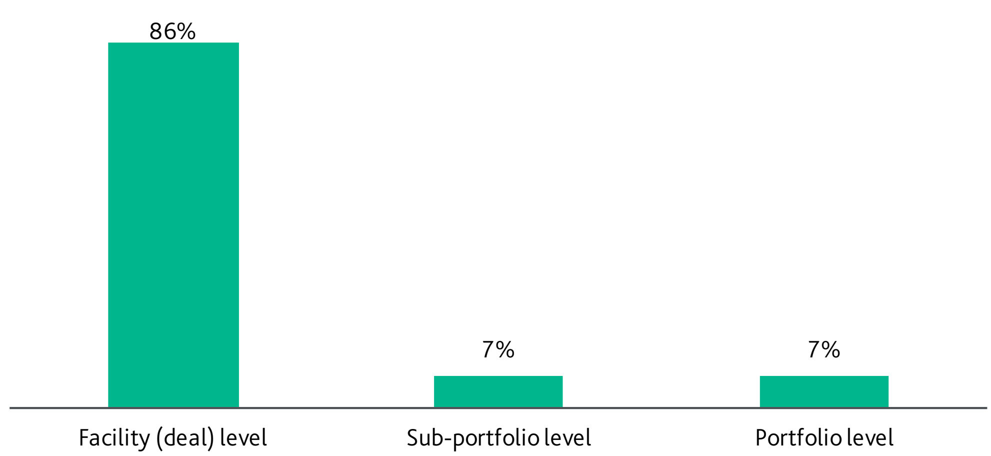

Source: Moody's Analytics

**Question 18: What is the planned bucket allocation and provisioning calculation granularity level for retail?**




Source: Moody's Analytics

**Question 19: What is the planned bucket allocation and provisioning calculation granularity level for wholesale?**



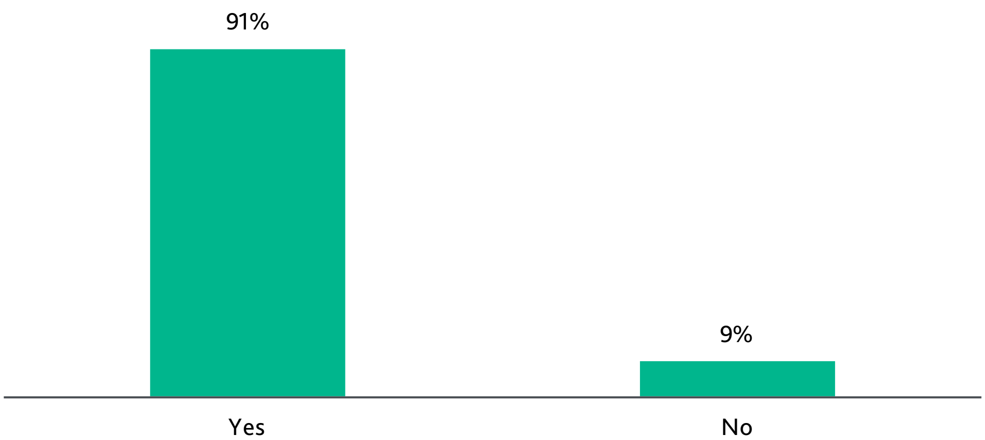

Source: Moody's Analytics

## Section 4 – Planning and Business Benefits

Key findings:

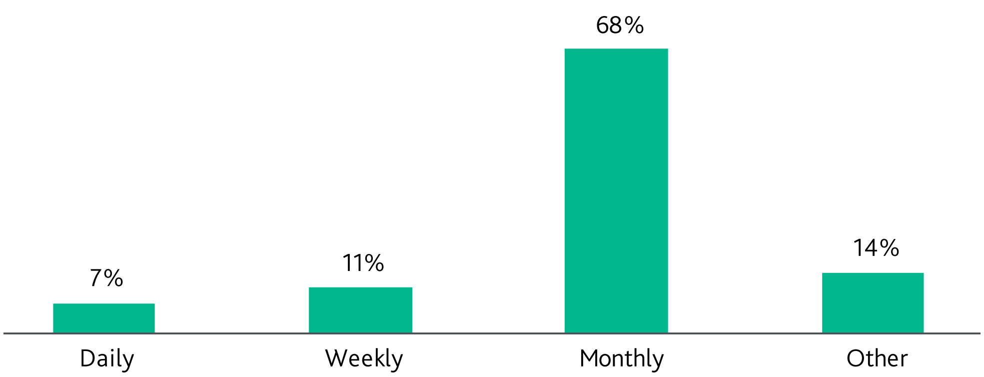
- Improved timely provisioning planning and better origination practices and capital planning are the major IFRS 9 benefits for the business.
- More than 68% of the respondents plan to run monthly calculations aligned with the frequency for Basel-related calculations (e.g., RWAs).
- More than 90% of the respondents are planning to integrate IFRS 9 scenario analysis into capital planning, stress testing, and origination activities.

**Question 20: Will you integrate IFRS 9 scenario capabilities into the origination, capital planning/optimization, and stress testing-related analytics or platforms?**



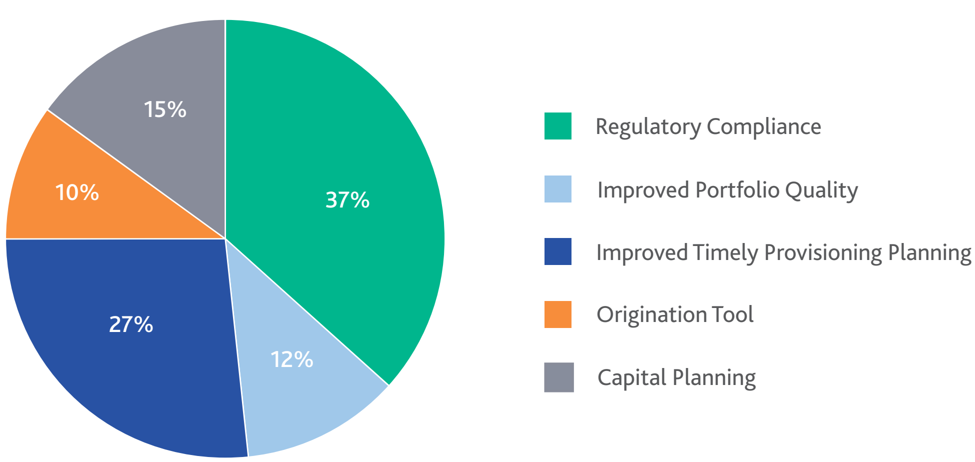

Source: Moody's Analytics

**Question 21: What is the planned IFRS 9 provisioning calculation system processing frequency?**




Source: Moody's Analytics

**Question 22: What do you consider the overall business benefits of undertaking an IFRS 9 initiative?**




Source: Moody's Analytics

# WHAT IF PPNR RESEARCH PROVES FRUITLESS?

By Dr. Tony Hughes

**Dr. Tony Hughes**
*Managing Director of Credit Analytics*

Tony manages Moody's Analytics credit analysis consulting projects for global lending institutions. An expert applied econometrician, he has helped develop approaches to stress testing and loss forecasting in retail, C&I, and CRE portfolios.

Banks must be savvy about all the forces at work before trusting their PPNR models. This article addresses how banks should look to sources of high-quality, industry-level data to ensure that their PPNR modeling is not only reliable and effective, but also better informs their risk management decisions.

While most banks can now produce decent stress tests for credit losses, research continues in the important area of pre-provision net revenue (PPNR). Even though PPNR is an important part of a bank's proactive stress testing regime, researchers must consider all the factors before trusting the accuracy of their models – or expecting bank executives to trust them.

### Where does PPNR fall short?

Regulators require banks to produce forecasts of loan and deposit volume, fees collected, and interest rate spreads (both paid and received), thus generating stress predictions of interest and non-interest revenues and expenses. These factors play an important role in determining a bank's financial position should a dire economic scenario start to unfold.

PPNR should complement stress testing, but the models it produces may not be as trustworthy as they seem. For one thing, many bank portfolios contain either scant or noisy PPNR data. It is not atypical for a bank to be forecasting, say, commercial loan origination volume with only 30 or 40 time-series observations at their disposal.

Within this context, modelers need to account for a number of other key factors that may influence business volume. Though the main aim of PPNR modeling is to identify robust macroeconomic drivers, managers would surely feel slighted if their actions were dismissed as irrelevant to the portfolio's projections. Indeed, if a business experiences strong growth, how do they know that the upswing is a result of general economic improvement and not a manager's improved sales procedures?

If the latter explanation has even a grain of truth (and if portfolio-specific factors are excluded from the model), the underlying effect of the economy on volume will be distorted and projections drawn from the model will be dangerously misleading.

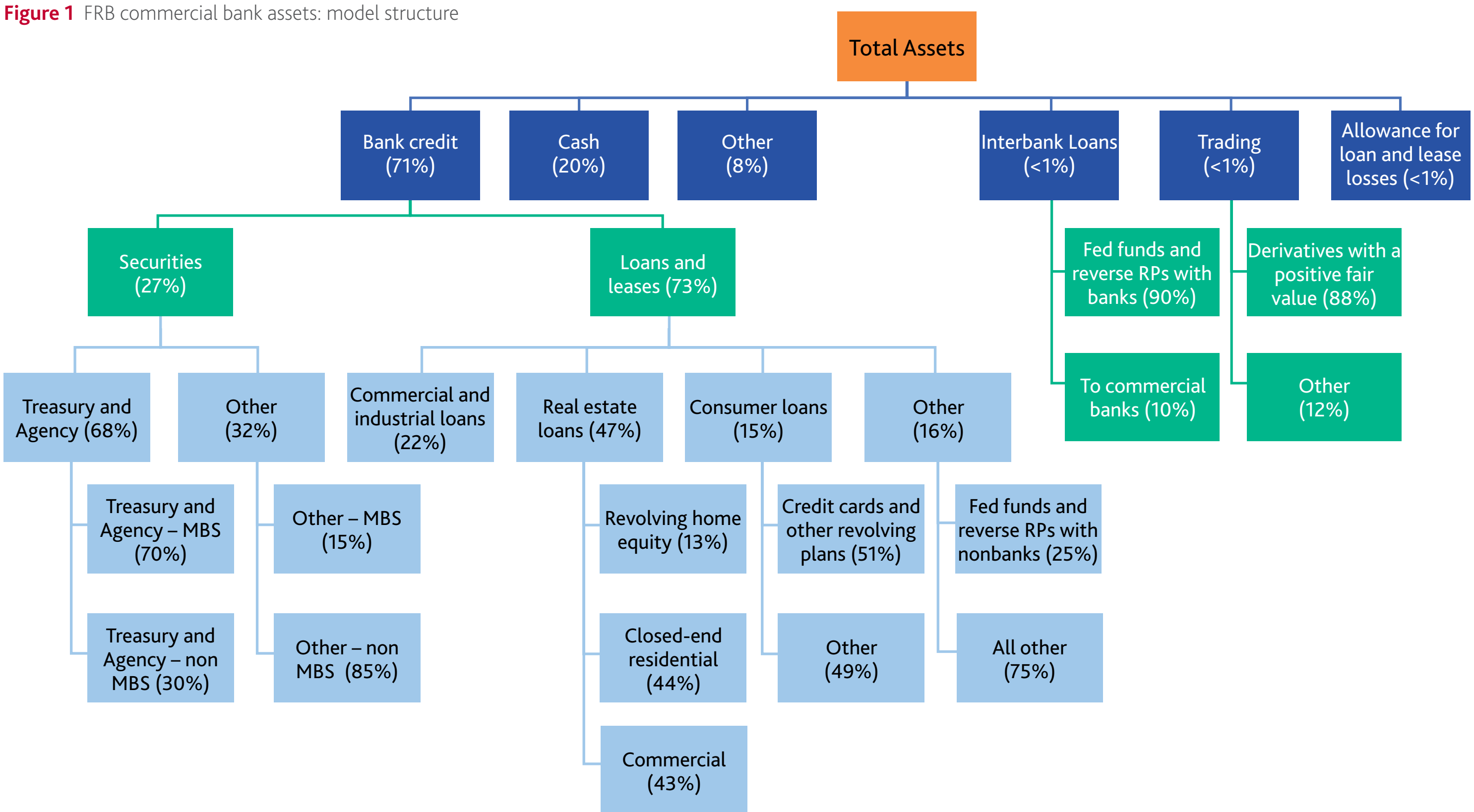
### When macro factors are mutable

Sometimes even diligent, well-designed research finds nothing. With a huge array of macro factors influencing the observed behavior of a portfolio, even focused research may not lead banks to a concrete destination.

Suppose banks diligently and intelligently produce the best possible model given this situation. They try to be parsimonious, using simple but powerful techniques and employing an intuitive behavioral framework. They then carefully consider any statistical issues that arise as they produce their models.

What happens, then, if the model produced by this process – the best possible model – is demonstrably unreliable or fragile?

**Figure 1** FRB commercial bank assets: model structure




Source: Moody's Analytics

When quantitative research falls short, the solution is invariably the same: collect more data! But in the case of PPNR modeling, it is often impossible to source more information from within the bank. Origination volume, the example used, is inherently a time-series concept. Stress testers, though highly skilled, have yet to unlock the secrets of time travel.

PPNR should complement stress testing, but the models it produces may not be as trustworthy as they seem. For one thing, many bank portfolios contain either scant or noisy PPNR data. Indeed, if a business experiences strong growth, how do they know that the upswing is a result of general economic improvement and not a manager's improved sales procedures?

## A time to turn to external sources

The only sensible alternative is to look for data from external sources. In the case of commercial loan volume, for instance, the Federal Reserve Board has quarterly data stretching back to the late 1940s. Using such a long series makes it easy to identify macroeconomic relationships through many distinct business cycles.

This data is not specific to any one bank, meaning that modeling the effect of management actions is not possible at this level. Despite this drawback, this method provides the best possible avenue through which a diligent modelers could find appropriate macroeconomic drivers of activity in the commercial lending space. Individual bank actions, under some reasonable assumptions, simply do not impact industry dynamics. This means that banks can focus their attention on identifying pertinent macro factors without having to worry about acquisitions, customers switching banks, staffing shifts, or changes in management strategy.

Modeling 30 or 40 bank-specific observations becomes much easier when stressed industry variables are already in hand and the right macro variables are understood with a high degree of confidence. Now, stress testers can focus almost exclusively on bank-specific drivers of observed portfolio behavior.

A researcher might notice, for example, that his portfolio has been growing at a faster rate than the broader industry and that the bank's market share is rising as a result. He can then interrogate relevant managers on the business side of the bank to find out why this is happening and whether the trend is likely to continue. More formally, he could seek quantitative drivers that explain the bank's growth anomaly and thus project the bank's performance under a number of alternative scenarios. The research is now usable and relevant.

### Is PPNR worth the effort?

Banks may wonder whether the current approach to PPNR modeling is very informative. Most banks, relying on scant internal data, have to cut corners or mine the data to find macro linkages that are likely to be spurious or, at best, fragile. The relationships they do find are unlikely to last through the next downturn.

Taking a realistic and holistic approach to PPNR modeling, then, risk modelers should look to the many sources available for high-quality, industry-level data for PPNR components. Only by using these data will PPNR stress testing be the basis of reliable risk management decisions and be taken seriously by bank executives.

# IMPLEMENTING THE IFRS 9'S EXPECTED LOSS IMPAIRMENT MODEL: CHALLENGES AND OPPORTUNITIES

By Eric Leman

The International Accounting Standards Board (IASB) has devoted considerable effort to resolving issues that dramatically emerged during the financial crisis – particularly the delayed recognition of credit losses on loans. As many believed that the incurred loss model in IAS 39 contributed to this delay, the IASB has introduced a forward-looking expected credit loss model. In this paper, we focus on the impairment aspect of the IFRS 9 standard, and how banks should now calculate credit losses to comply with the new IFRS 9 rules by 2018.

**Eric Leman**
*Director, Solutions Specialist*

Eric specializes in banking compliance and risk management – Basel II capital adequacy (credit risk, market risk), ALM, stress testing, and credit risk monitoring.

The IASB published the IFRS 9 *Financial Instruments* in July 2014, completing its response to the financial crisis by improving the accounting and reporting of financial assets and liabilities. It replaced the IAS 39 *Financial Instruments: Recognition and Measurement* with a unified standard that covers three areas:

1. Classification and measurement: determines how to account for financial assets and liabilities in financial statements and their ongoing measurement.
2. Hedge accounting: launches a reformed model for hedge accounting, with enhanced disclosures about risk management activity.
3. Impairment: introduces a new expected loss impairment model that will require more timely recognition of expected credit losses.

Impairment is the biggest change for banks moving from IAS 39 to IFRS 9. Forecasting expected credit losses instead of accounting for them when they occur will require institutions to greatly enhance their data infrastructure and calculation engines. The timeline given by regulators – compliance by 2018 – presents a considerable challenge, especially given the complexity of the new systems and workflows to be put in place.

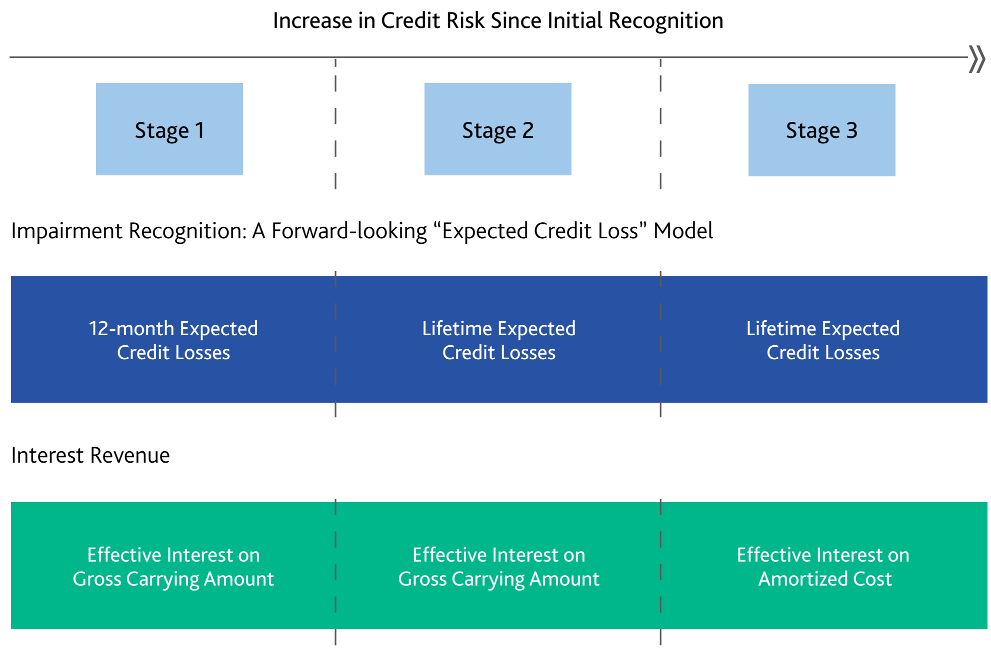
### Understanding the new impairment model

Under IAS 39 accounting standards, credit losses were taken into account when the loss occurred; hence the term "incurred loss." With the new IFRS 9 standards, impairment recognition will follow a forward-looking "expected credit loss" model.

According to the new model, credit exposures will be categorized into one of three stages, depending on the increase in credit risk since initial recognition (Figure 1). IFRS 9 requires that when there is a significant increase in credit risk, institutions must move an instrument from a 12-month expected loss to a lifetime expected loss. In making the evaluation, the institution will compare the initial credit risk of a financial instrument with its current credit risk, taking into consideration its remaining life.

In stages one and two, the interest revenue will be the effective interest on gross carrying amount; in stage three it will be the effective interest on amortized cost.

**Figure 1** Increase in credit risk since initial recognition: three stages




Source: Moody's Analytics

## Determining expected losses

In order to calculate 12-month and lifetime expected losses, banks should apply models on credit risk (PD, LGD), balance sheet forecast (prepayments, facility withdraws), and interest rates (discount factors).

- Includes forward-looking economic forecasts
- Existing internal ratings-based (IRB) Basel models can be reused but particular attention should be paid to point-in-time versus through-the-cycle models

> To overcome those challenges, banks should set up a dedicated group of subject matter experts and facilitate close collaboration between the architecture team – to ensure availability of data and infrastructure – and the modeling team – to ensure models are accurate and can rely on available data.

On the credit risk side, PD and LGD models are needed to satisfy the new impairment model.

**PD models**: IFRS 9 standards require an estimate of probability of default (PD) that is consistent with the following principles:

- Considers all relevant information
- Reflects current economic circumstances (i.e., it is a best estimate rather than a conservative estimate)
- Provides the likelihood of a default occurring within the next 12 months or during the lifetime of the instrument

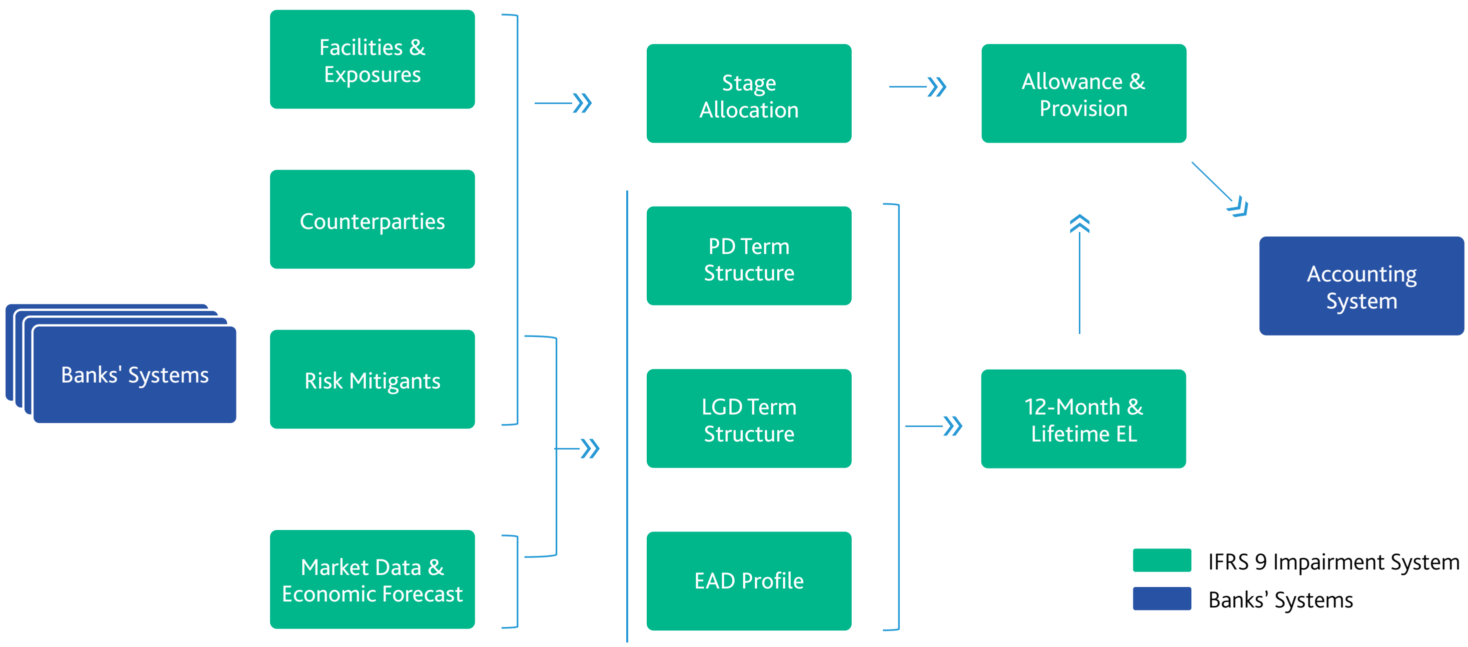
**LGD models**: IFRS 9 requires an estimate of loss percentage that is consistent with the following principles:

- Considers all relevant information and includes a forward-looking element
- Reflects current economic circumstances (i.e., is a best estimate rather than an economic downturn estimate)
- Considers only costs directly attributable to the collection of recoveries

## Complying with IFRS 9 requirements

Financial Institutions will face some challenges

**Figure 2** Calculation process workflow




Source: Moody's Analytics

to fulfilling these IFRS 9 requirements, including:

- Retrieval of old portfolio data, especially for the transactions that originated before the advanced internal ratings-based (A-IRB) models were introduced.
- Classification of the transactions at origination. Products will need to be categorized a priori (contractual cash flow test) or create a workflow to capture the classification and initial credit worthiness. An additional effort could be required to identify those products that can be considered out of scope (e.g., short-term cash facilities and/or covenant-like facilities).
- Management of standardized approach portfolios (if no model is available and/or data is not available)
- Flexibility of implementations (e.g., on models and thresholds) according to asset classes and model availability. For instance, a granular approach may be needed for one part of a portfolio (e.g. wholesale portfolio), while another portfolio (e.g., retail) may require provisioning.
- Historization of data for the new transactions.

To overcome those challenges, banks should set up a dedicated group of subject matter experts and facilitate close collaboration between the architecture team (to ensure availability of data and infrastructure) and the modeling team (to ensure models are accurate and can rely on available data).

Banks may either enhance existing solutions or use brand new products to achieve compliance. In either case, they should plan and execute an implementation project in the next two years.

## Implementing a rigorous workflow

Financial institutions should ensure that their systems can handle such granularity of data while maintaining high quality standards. They should use a rigorous workflow to produce these outputs consistently (Figure 2).

Figure 2 illustrates how banks should gather data on:

- Exposures
- Counterparties
- Credit risk mitigants

From this data, banks can implement models on PD, LGD, and exposure at default (EAD) profiles, using market data and macroeconomic forecasts to get 12-month and lifetime expected loss forecasts (discounted at current interest rates).

Then, based on exposure and counterparty characteristics, allocation between stages 1, 2, and 3 sends the final EL provision to accounting systems.

An example of such a calculation process would include:

- » The interest rate of each loan is used to calculate the discount rate.
- » EAD is calculated monthly for the next 360 months, based on the amortization of the contractual balance of the loan, plus up to six months of arrear payments.
- » The PD is derived from a default curve calibrated for the portfolio. The age of the loan will give the starting point on the default curve. This PD is then scaled to the loan, using the Basel point-in-time PD.
- » The LGD is derived from the loan-to-value (LTV) using a lookup table. The LTV uses the value of the property covering the loan and takes into account EAD from all other loans eventually covered by this property.
- » The expected loss for each of the next 360 months is the product EAD*PD*LGD divided by the discount rate.
- » The EL is then summed up for the first 12 months and for the full life of the loan. These two figures can then be used by accounting systems.

## Conclusion

IFRS 9 is the next regulatory "tsunami." Like Basel II and Basel III, it requires banks to make huge investments in models, data, and infrastructure for long-term implementation.

The output of IFRS 9 will be a more resilient financial system, capable of forecasting losses instead of accounting them after they occur, which will give the investor community greater confidence and add transparency to credit losses forecasts. Furthermore, banks will leverage such an implementation to manage, in a more accurate manner, their risks and forecast their capital and profit and loss.


Stress testing that fits.
Moody's Analytics complete and integrated stress testing solutions are tailored to your needs.
To learn more please contact:
MoodysAnalytics.com/stresstestingthatfits
AsiaRisk TECHNOLOGY RANKINGS 2014
fin tech FORWARD
2014 TOP 100 SOLUTION PROVIDER
RiskTech 100
2015 Top 10
Structured products
TECHNOLOGY RANKINGS 2015

# APPROACHES TO IMPLEMENTATION

Highlights best practices for effectively applying risk data management to your organization, including improving stress testing, commercial lending efficiency, and risk appetite management.

# ENHANCED DATA MANAGEMENT: A KEY COMPETITIVE ADVANTAGE FOR JAPANESE BANKS

By Yuji Mizuno


**Yuji Mizuno**
*Director, Business Development Officer*

Yuji leads the product and consulting areas of the firm in Japan and has extensive knowledge of regulations and risk management practices among financial institutions. He provides clients with insight on regulatory compliance, ALM, liquidity and ERM frameworks.


As mass amounts of data meet ever-increasing regulation in the world of finance, sophisticated data management has never been more important. How a bank handles this complex problem will make or break its position as a global player.

## Japanese banks face a pivotal moment in data management

With global regulatory bodies continually introducing new banking regulations, the burden to be fully compliant has significantly increased. Some regulations require banks to prepare new sets of data,[1] while liquidity regulations, such as the Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR), compel banks to source data for their balance sheets. New regulatory concepts, such as the risk appetite frameworks and stress tests, will inevitably require banks to improve their data management systems even further.

In response, most large Japanese banks are currently building data management platforms – constructing large-scale data infrastructures that address every potential business and regulatory need. While a multi-purpose data platform is a step in the right direction, these ambitious projects sometimes fail at that very task due to their sheer scope and "do everything" strategy.

This complex problem has caused the industry to experience a paradigm shift from a "bigger is always better" mindset to a more functional and flexible data infrastructure design – an especially attractive approach for Japanese banks as they aim to both quickly respond to regulations and position regulatory compliance as a profit-making strategy.

## The more effective use of risk capital

Improving low profitability has long been the biggest challenge to Japan's slow-growth economic environment. After years of rebuilding following the global financial crisis, Japanese banks are finally redirecting their strategies.

> Banks are now asking themselves, "If we are already spending an enormous amount of time and money, why don't we make it more useful for senior management as well?" By developing effective management platforms, they can take risks in a more aggressive but reasonable manner, ultimately gaining the strength they need to compete with other global banks.

Large banks are pursuing new means of gaining revenue: expanding outside of Japan, such as making acquisitions in foreign countries, or merging with other banks in Japan. To increase their revenue, they are also taking more risks under a reasonable risk control regime, rather than simply containing the risks under a conservative limit framework.

Banks tend to regard regulatory compliance as an annoyance, as they believe it does not generate revenue in and of itself. New stress testing requirements have prompted many banks to ask, "Why do we have to use so many resources to analyze when and how we will die?" Beyond simply maintaining a banking license, though, regulatory compliance can help increase a bank's profitability – if the data is effectively managed. Japan serves as an ideal case study to this point.

### Optimizing revenue, risk, and regulatory compliance: a complex puzzle

The risk appetite framework was introduced to Japan in 2011. Initially, many banks did not know how to reconcile their need to take more business risks with the framework's ostensible purpose of reducing them.

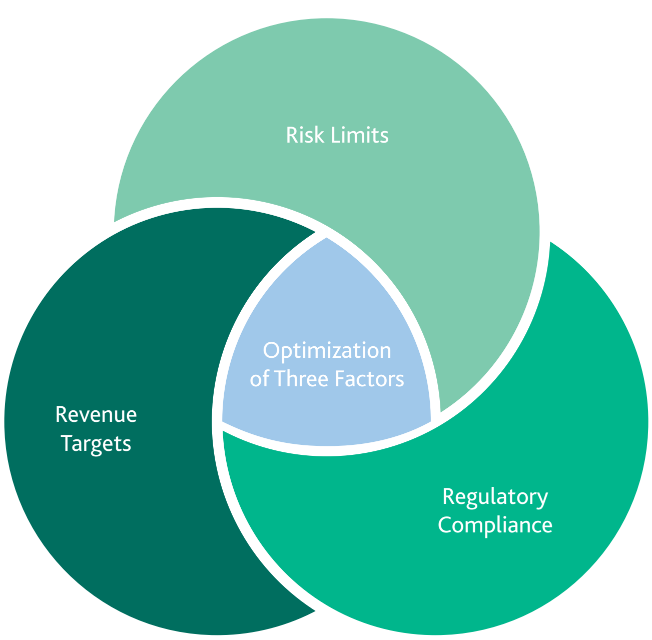
After all, the major objective of Japanese banks was to achieve revenue targets, not just reduce risk. As banks realized that the quest for additional revenue sources would not be as simple as it was previously, they gradually "Japanized" their implementation of the risk appetite framework so that it fit their challenging environment. This shift became apparent in 2013-2014. As more complex and stricter banking regulations were released, however, they realized that optimizing revenue, risk, and regulatory compliance at the same time was a puzzle they needed to address.

Large banks now know that they have to find the best mix of solutions for these three factors. Making matters difficult is the fact that they tend to work against each other – trying to achieve higher revenue may cause higher risk and capital requirements. Moreover, new banking regulations may not be fully consistent with one another. For example, holding too many liquid assets to achieve the LCR could work against the leveraged ratio. With all of these contradictions, regulatory compliance can resemble a frustrating game of whack-a-mole.

In attempting to win this "game," Japanese banks found that what had historically been their strength – their effective organization into necessary functions and departments – was actually their Achilles heel. If they worked separately on those three factors, it would be almost impossible to attain an optimal solution, especially if they stayed in departmental silos.

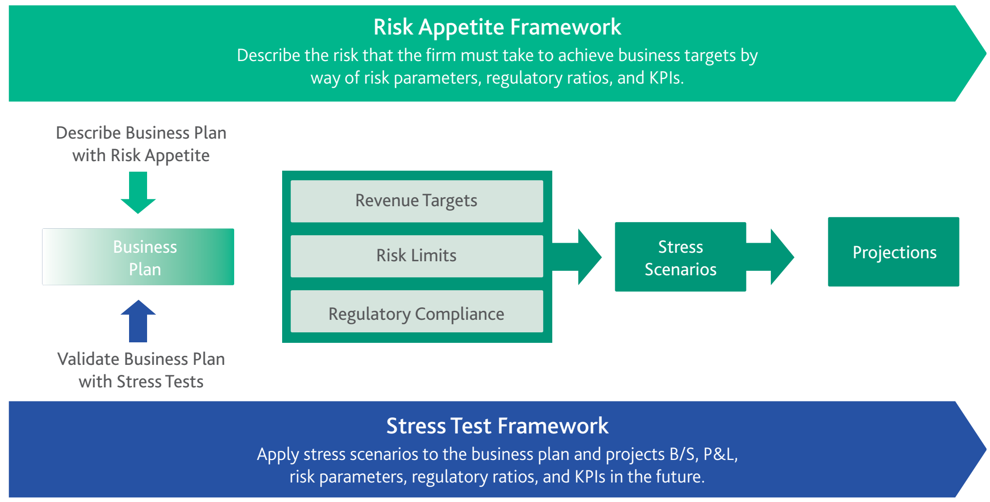
Banks discovered that risk appetite frameworks could, in fact, be a solution. They began implementing these frameworks as a platform for senior management to discuss how they

**Figure 1** Optimization of three factors: revenue, risk, and regulation




Source: Moody's Analytics

Figure 2 Risk appetite frameworks and stress tests




Source: Moody's Analytics

could simultaneously optimize revenue, risk, and regulatory compliance.

At the same time, stress testing was also changing significantly. More banks began to use stress testing as a tool to verify their risk appetite and establish whether or not a proposed plan could withstand stress events and still achieve the three targets. This also helped senior management better understand their strategy's weaknesses and adjust it if necessary.

### Data management in Japan: a changing mentality

Japanese banks have begun to view regulatory compliance and data management as an opportunity to enhance their business and increase revenue, rather than as a mere cost of maintaining their licenses. Along with regulatory challenges, data management has emerged as a critical issue for Japanese banks.

Banks typically handle data management by using a management information system (MIS). An MIS is a series of IT platforms that are used for all stages of the process, from aggregating data to reporting to senior management. All banks must build this as a foundation for a risk appetite framework.

Japanese banks typically share three common data management challenges:

1. **Aggregating all the data at a group level:** As some large banks expand their businesses globally, it has become more challenging to gather risk data in the same formats from all of their global entities and business units.
2. **Identifying new risks throughout the group:** It is important to identify and quantify a global organization's hidden risks and incorporate them into its existing risk management framework. Japanese regulators expect these emerging risks to be used for stress testing scenarios.
3. **Reporting those risks to senior management:** Senior management cannot effectively use risk appetite indices or stress test results for improving the management of their bank unless they are reported accurately and promptly. An MIS should incorporate a highly automated "dashboard" system to quickly share all the risk appetite indices.

By overcoming these three challenges, Japanese banks can build a comprehensive data platform that lets them gather all the data, identify emerging risks at early stages (with stress testing results), and swiftly report Key Risk Indictors (KRIs) to senior management. Banks are now asking themselves, "If we are already spending an enormous amount of time and money, why don't we make it more useful for senior management as well?" By developing effective management platforms, they can take risks in a more aggressive but reasonable manner, ultimately gaining the strength they need to compete with other global banks.

### The strengths and weaknesses of centralized IT organizations

While a strong data platform is the foundation for achieving risk management objectives, Japanese banks tend to deal with all the data issues at the same time by planning one huge IT project – making the work much trickier and the risk of delays or failure much higher. Moreover, by the time such an ambitious project is completed, there may well be new banking regulations with different data requirements to contend with.

This method has resulted in part from the typically centralized organizational structure of the IT group at Japanese financial institutions, which controls the IT work for every business line. A centralized structure enables banks to build a consistent and comprehensive IT infrastructure, but it lacks speed and flexibility in implementation.

There is a general distaste in Japan for IT environments that involve many different systems commingling like "spaghetti" or multiple overlapping data warehousing systems. This is probably due to Japan's bitter experiences in the 1990s, when it struggled to integrate different IT systems after mergers. Therefore, data integration projects in Japan are commonly comprehensive in scope and enormous in scale, usually requiring many years to complete. But with the extensive, complicated, and ever-changing requirements of the current regulatory regime, this centralized IT model falls short.

### Why is data management so challenging?

The Basel Committee on Banking Supervision issued a report in January 2015 called *Progress in adopting the principles for effective risk data aggregation and risk reporting*, which contains an interesting lesson about Globally Systemically Important Banks (G-SIBs). Surprisingly, 14 out of 30 G-SIBs revealed that they will not be fully compliant with at least one of the Basel Committee's regulatory principles by the deadline in 2016. Some banks noted in the report that this is partly due to delays in initiating or implementing large-scale IT projects and the complexity of those projects.

> Banks do not need to expand the project's scope to encompass a rebuild of the entire database – a potentially endless project – but can instead simply channel the existing data into a relay station. A data relay station is more cost efficient, too, as it is often completed within a much shorter time frame than a large IT project.

This structure is often contrasted with the "federal" organizational style, which global banks outside Japan frequently use when they have multiple legal entities or business units in a group. In a federal style, each entity or unit has some level of independence in designing and introducing IT platforms. To maintain order throughout an organization, a senior IT officer at a holding company level controls all those activities. (With regards to data management specifically, some large US banks have assigned a Chief Data Officer, or CDO, although it is still rare for Japanese banks to have a CDO.) A federal style's strengths and weaknesses are the opposite of those of a centralized style: what it offers in speed and flexibility, it lacks in consistency and comprehensiveness.

Banks meet roadblocks when they try to accomplish multiple objectives when they have only one core challenge. A data infrastructure usually has more than one purpose, such as integrating all data locations, cleansing/reconciling data from different sources, constructing data flows to calculation engines, and adding calculation results to an MIS reporting flow to senior management/regulators. Even a simple project like constructing data flows between several IT systems could become delayed if managers decide to expand its scope. Maintaining focus on the most important project task is therefore paramount.

In addition to regulations requiring banks to source new data directly, the current focus of data management for Japanese banks lies in the following two areas, which may involve the use of data beyond regulatory compliance:

- Calculation of risk appetite indicators and reporting by an MIS
- Automation of a stress testing calculation

Determining risk appetite requires banks to collect data throughout a business unit to calculate multiple risk indicators, such as KPIs, and to report them to senior management/ regulators through an MIS. Several steps of data processing are required, including aggregation, calculation, and reporting. Stress testing regimes also require banks to automatically and promptly conduct multiple calculations.

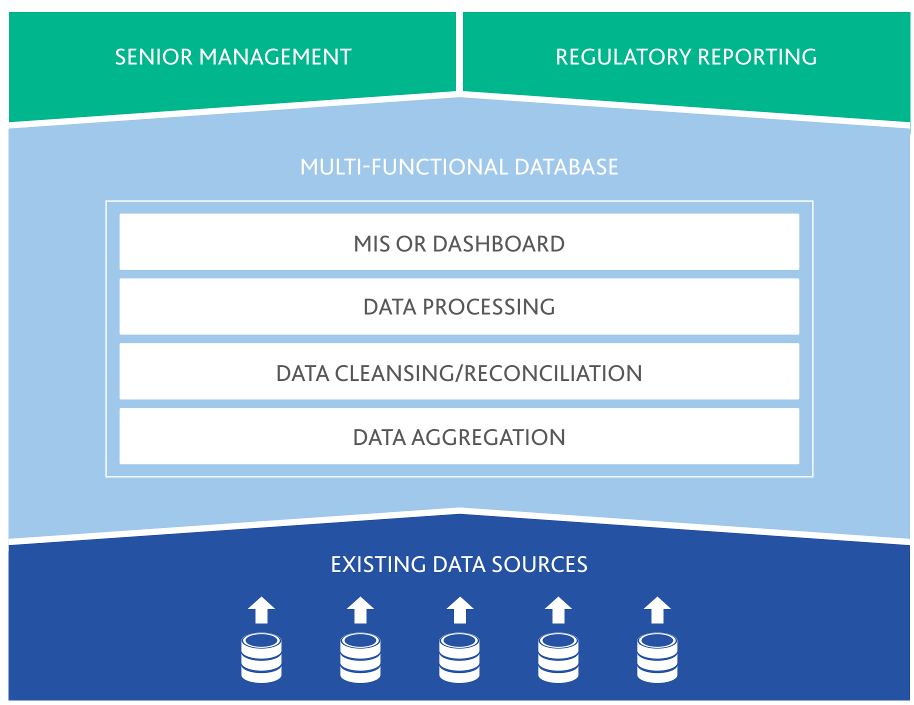
Recent trends show Japanese banks create multiple scenarios and conduct sensitivity analyses on a single indicator. For example, they simulate many patterns of LCRs based on several different data inputs, which are typically provided in a matrix. This helps senior management understand the nature of the LCR more effectively – how it behaves under stressful conditions and how it affects the firm's liquidity. The results should be shown in a more intuitive way if stress testing results are to be used to improve the bank's management.

### Meeting the IT challenge: focus, flexibility, and speed

There are two specific data challenges to which Japanese banks should pay the most attention. First, the data warehouse system has to be flexible, as the requirements for data management often change. Second, a data management platform needs to be implemented quickly.

These two challenges are exactly where Japanese banks' method is relatively weak. They should instead seek a "lighter" IT system and focus on one task at a time by dividing the entire project into multiple task periods. By reasonably limiting a project's scope, it is much more likely to succeed.

**Figure 3** Functional database




Source: Moody's Analytics

Focusing on "data flow" rather than "data storage" is one way to implement an effective, efficient data platform. Banks can maintain existing data sources and create a data flow, which gathers the necessary data from those sources and sends them to a new "data relay station." Banks do not need to expand the project's scope to encompass a rebuild of the entire database – a potentially endless project – but can instead simply channel the existing data into a relay station. A data relay station is more cost efficient, too, as it is often completed within a much shorter time frame than a large IT project.

One reason a data project encounters trouble is that all these functions are built into a single data platform. A data relay station can be used for multiple functions, including data aggregation, cleansing, processing, and reporting, which work separately from a bank's existing data platforms. Having a functionally separated data flow is less risky from an operational risk perspective, too.

Under this data management structure, existing data sources and a new data relay station are linked together. Data requirements based on regulations or management needs could be reflected in the data relay station, not at an existing data source level, which means banks can only work on the data relay station in a comprehensive way. Such a data relay station can be highly functional without necessarily covering all the banking activities that require data management.

Banks could also introduce this type of functional database into limited areas of business, such as stress testing. To do so, they would gather all the essential information, including balance sheet items and risk parameters, from all the existing databases. The functional database would then perform data processing to create consistent assumptions and send them to relevant calculation engines. The results would then be collected at the functional database again and reported to senior management/regulators through an MIS.

### Sophistication is the future of data infrastructure

Sophisticated data management is the foundation for both improving the management of a bank and increasing revenue in global markets. For many Japanese banks, imitating the best practices of foreign banks is not necessarily the best solution. While they struggle to find the appropriate direction, they have gradually succeeded in "Japanizing" some regulatory concepts while expanding their own concept of effective IT infrastructure beyond the cumbersome "centralized" approach.

Japan's banks are currently being challenged to significantly improve their data management systems, specifically for achieving flexibility and speed to continue growing revenues while meeting regulatory requirements. Accomplishing this will allow a bank to become a stronger, more competitive player on the global stage.

1 Basel Committee on Banking Supervision, *Principles for effective risk data aggregation and risk reporting*, 2013.

# MEASURING SYSTEMIC RISK IN THE SOUTHEAST ASIAN FINANCIAL SYSTEM

By Dr. David Hamilton, Dr. Tony Hughes, and Dr. Samuel W. Malone

**Dr. David Hamilton**
*Managing Director, Stress Testing and Credit Risk Analytics, APAC*

David is Managing Director, Head of Stress Testing and Credit Risk Analytics for the Asia Pacific Region, based in Singapore. With two decades of experience in credit risk modeling, credit ratings, and economic research, he helps provide insight into the practical challenges of credit risk measurement, management, and stress testing.

**Dr. Tony Hughes**
*Managing Director of Credit Analytics*

Tony manages Moody's Analytics credit analysis consulting projects for global lending institutions. An expert applied econometrician, he has helped develop approaches to stress testing and loss forecasting in retail, C&I, and CRE portfolios.

**Dr. Samuel W. Malone**
*Director of Economic Research*

Sam is Director of Economic Research in the Specialized Modeling Group (SMG). A systemic risk expert, forecaster, and former academic economist, his primary focus is developing systemic risk solutions that are actionable by individual financial institutions. He also contributes actively to SMG consulting projects, such as model validations and bespoke research.

Systemic vulnerabilities are an important, if often overlooked, aspect of a financial system's stress testing regime. This article looks back at the Asian financial crisis of 1997-1998 and applies new methods of measuring systemic risk and pinpointing weaknesses, which can be used by today's financial institutions and regulators.

## Assessing systemic vulnerabilities: East versus West

The ability of a country's financial system to withstand a severe negative shock has important implications for its general economic and social well-being. Following the global financial crisis and the sovereign debt crisis in Europe, stress testing has become one of the primary techniques for gauging the robustness of individual financial institutions and the financial system as a whole. Although officially part of stress testing mandates, such as the Federal Reserve's Comprehensive Capital Analysis and Review (CCAR), measuring systemic vulnerabilities has not been emphasized.

*In the West, that is*. In Southeast Asia, measuring and understanding the potential impact of systemic risk became imperative following the Asian financial crisis of 1997-1998. The crisis began in Thailand in July 1997 and quickly spread to Malaysia, Indonesia, Korea, and the Philippines. Singapore, a regional financial hub with an open economy, was also affected.

The impact of the crisis on these countries was staggering: in one year's time, a decade of extremely strong economic growth, the "East Asian miracle," risked being erased. Between June 1997 and March 1998, GDP contracted by nearly 6% in Korea, 9% in Thailand, and 14% in Indonesia. Equity valuations plummeted by 50% or more in most of the affected countries.[1]

Assessing systemic risk has been a key part of financial supervision in the region ever since. In addition to regulators' and central banks' increased focus on systemic risk in the wake of the crisis,[2] the International Monetary Fund and the World Bank jointly initiated the Financial Sector Assessment Program (FSAP) in 1999 to assess financial stability and perform stress testing of countries' financial sectors. These initiatives have been credited with helping Southeast Asia weather the worst of the global financial crisis (GFC) and avoid a repeat of the economic devastation caused by the Asian financial crisis.

"Contagion" is the word typically used to describe how the crisis spread so virulently throughout the region. But contagion is just another way of saying that these countries' economies were highly interconnected, and thus that systemic risk in Southeast Asia was high. Since the Asian financial crisis, new tools and techniques have been developed to better measure the multiple dimensions of systemic risk. In this paper, we describe a method for measuring the interconnectedness of financial institutions and apply it to the ASEAN-5 group of countries.[3] Our data allow us to go back to before the Asian financial crisis and to compare how the different shocks to the global financial system since then have impacted the systemic risk of financial institutions in the ASEAN-5 countries.

### Interconnectedness as a measure of systemic risk

Systemic risk refers to a shock that results in a broad-based failure of the financial system, which in turn threatens to jeopardize the economy. The initial shock(s) can be exogenous (an oil price shock, for example) or endogenous (the bankruptcy of a systemically important firm such as PT Bank Century, for example). Whatever the source of the shock, a high degree of systemic risk implies the potential for a cascade of distress or failure among financial institutions.

The word "potential" is important in this context. A high degree of connectivity among financial institutions is a necessary but not a sufficient condition for a systemic crisis. Indeed, the probability of a systemic crisis is another matter entirely. However, when the number and strength of the connections between financial institutions in an economy is high, contagion risk across firms will also be high. A market shock affecting one firm can quickly spread to others through sharp drops in market valuations and the mark-to-market impact on financial institutions' balance sheets. A credit event affecting one firm can spill over through on- and off-balance sheet exposures among banks and financial counterparties. When the tinder is piled sufficiently high, a small spark can ignite a conflagration.

The lines connecting Thailand, Singapore, and Malaysia also tend to be blue, meaning that the relationship between financial institutions in these countries is positive: an increase in credit risk among financial institutions in one of these countries has a high propensity to cause an increase in credit risk in the others.

Interconnectedness has traditionally been gauged using various quantitative measures such as the size of non-bank deposits, the size of domestic interbank borrowing, and the importance to the domestic payments system. The Monetary Authority of Singapore, for example, used these measures of systemic risk when it participated in the 2002 FSAP stress tests.[4]

Although these traditional, descriptive measures of systemic risk are useful and important, size measures do not necessarily uncover the risks resulting from a high degree of interconnectedness. Size is an imperfect measure of systemic risk. It is vital to know which firms occupy important nodes in the financial network – for example, those that may be a near-monopolist in market making for a particular asset class, regardless of size. Hence, measuring too-connected-to-fail is as important as measuring too-big-too-fail.[5]

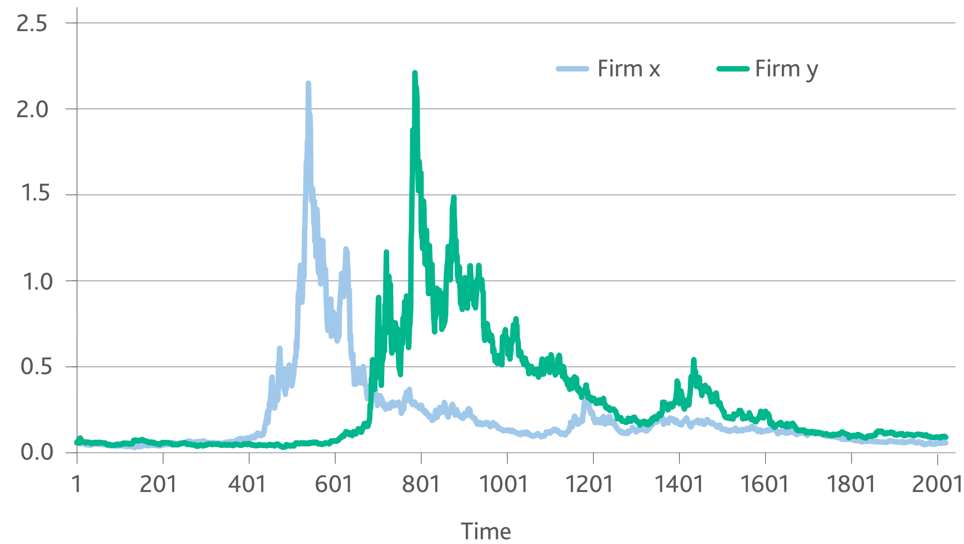
The lines connecting Thailand, Singapore, and Malaysia also tend to be blue, meaning that the relationship between financial institutions in these countries is positive: an increase in credit risk among financial institutions in one of these countries has a high propensity to cause an increase in credit risk in the others.

### Measuring financial firms' interconnectedness

In this paper, we analyze the interconnectedness and potential for contagion among financial institutions using Moody's Analytics Expected Default Frequency (EDF™) measures. EDF measures are probabilities of default derived from a contingent claims model of credit risk.[6] Our systemic risk framework is built on a network analysis perspective. Using firm-level EDFs and the determinants of those PDs — market leverage and asset volatility — we measure dynamic linkages by estimating Granger causal connections among all pairs of large financial institutions in the ASEAN-5 countries.[7]

A time-series x is said to Granger-cause a time-series y if past values of x provide statistically significant information about future values of y. Figure 1 illustrates the concept, plotting the time-series of PD for two hypothetical firms, x and y. The default probabilities for these two firms look very similar, but they are out of phase;

Figure 1 Movements in the PD for firm x Granger-cause changes in the PD for firm y




Source: Moody's Analytics

changes in the PD for firm x precede changes in firm y's PD. Firms x and y are temporally interconnected – changes in the values of x are closely followed by changes in firm y. In this particular example, knowing past values of firm x's PD would lead to good predictions for y. The Granger causal link is positive and strong.

Formally, Granger causality means that the β and/or γ coefficients in the following bivariate vector autoregression (VAR) are

$$
\begin{aligned}
x_t &= \mu + \sum_{(i=1)}^{p} \alpha_i x_{t-1} + \sum_{(i=1)}^{p} \beta_j y_{t-j} + \epsilon_{xt} \\
y_t &= \omega + \sum_{(i=1)}^{p} \Upsilon_i x_{t-1} + \sum_{(i=1)}^{p} \delta_j y_{t-j} + \epsilon_{xt}
\end{aligned}
\quad (1)
$$

statistically significant:

If the relevant F-test of the γ coefficients is significant at the 5% level, x is said to Granger-cause y; whereas if the equivalent F-test of the β coefficients is significant at the 5% level, y Granger-causes x. If both sets of coefficients are significant, there is mutual influence between firms x and y.

Our approach to measuring systemic risk, which is described in more detail in Hughes and Malone, is an extension of similar approaches taken in the systemic risk literature.[8] Gray and Malone[9] and Gray, Jobst and Malone,[10] for instance, adapt and apply contingent claims-based methods to the measurement of systemic risk, although they do not take a network approach to estimating the dynamic linkages across financial institutions. Billio et al. estimate systemic risk measures based on Granger causality networks derived from linkages identified on the basis of bivariate VAR models for pairs of entities in the financial system under consideration.[11] Their unit of study was equity returns, however, rather than PD measures derived from a structural credit risk model and historical data on default events such as EDF measures.

The paper most closely related to the approach taken here is Merton et al., which applies the Granger causality network technique of Billio et al. to the expected loss ratio (ELR)[12] of firm debt for major sovereigns and global financial institutions.[13] Our analysis can be seen as complementing theirs, in the sense that we study network linkages among expected default frequency measures, as well as asset volatilities and leverage ratios, which drive EDFs (and ELRs) in asset value-style credit risk models.

One of the advantages of the network approach to measuring systemic risk is that we can estimate both the direction and strength of the connectedness between financial institutions.[14] The direction of connectedness is determined by the statistical significance of the VAR coefficients, as described previously. The strength of the linkages between financial institutions is measured by calculating the degree of Granger causality (DGC) described in Billio et al. DGC is simply the fraction of statistically significant Granger-causality relationships among all N(N-1)/2 pairs of financial institutions at any given point in time. Each unique pair of financial institutions can have zero, one, or two Granger-causal connections, thus implying a maximum of N(N-1) possible connections that can be active in the system. The DGC measure, therefore, lies between zero and one. The higher the ratio, the higher the systemic risk.

The DGC measure captures both upstream and downstream Granger causal linkages in the system. In order to "share down" the DGC to individual institutions, we follow Billio et al. in computing what is known as the "Out measure" for each institution. The Out measure is equal to the percentage of the rest of the other N-1 institutions in the network that are Granger-caused by the institution in question. We can think of the Out measure as capturing an institution's contribution to systemic risk in the form of dynamic downstream linkages to other institutions.

EDF measures have also demonstrated they exhibit superior power, compared with equity returns, for predicting future credit events such as defaults and restructurings.[15] We can also calculate DGC measures on market leverage and asset volatility, the two primary drivers of the EDF model, to gain insight into whether credit risk contagion is being driven by volatility or leverage spillovers.

### Empirical results

The results of our empirical analysis are based on a dataset of financial institutions (SIC code between 6,000 and 6,799) domiciled in the ASEAN-5 group of countries: Indonesia, Malaysia, the Philippines, Singapore, and Thailand. We limit our dataset to financial institutions with at least US$1 billion in book assets observed at some point over their available histories. The only other selection constraint placed on our data is that financial institutions are required to have traded equity and public financial statements with which to calculate Expected Default Frequency measures over the time interval of our study, which begins in 1995 and runs through October 2014. Our study includes 201 unique financial institutions in the ASEAN-5 countries: 36 in Indonesia, 49 in Malaysia, 30 in the Philippines, 46 in Singapore, and 40 in Thailand.

> Size is an imperfect measure of systemic risk. It is vital to know which firms occupy important nodes in the macro-financial network – for example, those that may be a near-monopolist in market making for a particular asset class, regardless of size. Hence, measuring too-connected-to-fail is as important as measuring too-big-too-fail.

There are many advantages to using Expected Default Frequency metrics and their drivers as the basis for calculating the DGC and Out measures. EDF measures are forward-looking PDs; in this paper, we use EDFs with a one-year time horizon. That allows us to kill two analytical birds with one stone: we can measure the forward-looking likelihood of the default of a firm (or of a financial system by aggregating EDFs across firms), and calculate the level of systemic risk using the EDF-based DGC measure.

Figure 2 shows the top 10 financial institutions with the highest Out measures as of October 2014. TMB Bank Public Co. Limited, based in Thailand, exhibits the highest Out measure of the ASEAN-5 firms. The Out measure indicates that the bank's EDF movements Granger-cause EDF movements in 30.6% of the other financial institutions in the network. **Notably, the statistics shown in Figure 2 suggest that systemic risk (measured by Out) bears little correlation with either the probability of default or with firm size on average.** The

**Figure 2** Top 10 firms ranked by Out measure as of October 2014, with EDF level and firm size

| | Out | | EDF | | Book Assets | |
|---|---|---|---|---|---|---|
| Financial Institution | Value | Rank | Value | Rank | Value ($ mil) | Rank |
| TMB Bank Public Co. Limited | 0.306 | 1 | 0.283% | 42 | 24,568 | 25 |
| OSK Holdings Berhad | 0.281 | 2 | 0.087% | 4 | 880 | 115 |
| Bank of the Philippine Islands | 0.264 | 3 | 0.387% | 72 | 28,868 | 24 |
| UOB-Kay Hian Holdings Limited | 0.256 | 4 | 0.304% | 49 | 2,079 | 77 |
| CIMB Thai Bank Public Co. Limited | 0.248 | 5 | 0.333% | 60 | 7,798 | 49 |
| CitySpring Infrastructure Trust | 0.240 | 6 | 0.107% | 11 | 1,513 | 94 |
| Bangkok Land Public Co. Limited | 0.240 | 7 | 0.081% | 3 | 1,697 | 87 |
| Hong Leong Capital Berhad | 0.231 | 8 | 0.339% | 62 | 951 | 113 |
| Bangkok Life Assurance PCL | 0.231 | 9 | 0.343% | 64 | 6,259 | 55 |
| Bangkok Bank Public Co. Limited | 0.231 | 10 | 0.237% | 28 | 78,431 | 7 |

Source: Moody's Analytics

EDF-Out correlation exhibits significant and informative time variation, however, as Figure 5 shows.

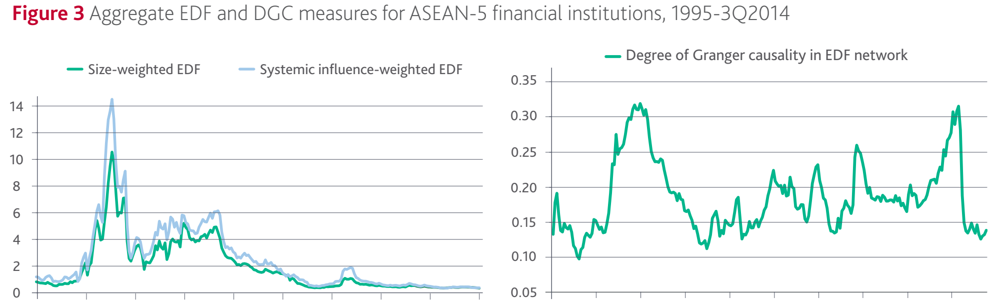
The EDF rank column shows the firm's EDF rank (sorted in increasing order) out of the 122 firms present in the network in October 2014; book-asset rank is measured in descending order. Half of the top 10 firms with the highest systemic risk measures as of October 2014 are based in Thailand and are about average with respect to their EDF levels and book-asset size. Most of the firms in the top 10 list are banks, but the rest are in the broker-dealer, real estate, infrastructure, and insurance sectors.

**The results shown in Figure 3 bring the impact of the 1997-1998 Asian financial crisis into sharp focus.** The graph on the left side shows the weighted average EDF level for the ASEAN-5 countries over time. We weight the historical EDF values using book assets (size) and by Out (systemic influence) . By either measure, the risk of default reached a historic peak during the Asian financial crisis. It is also notable that the peak in the systemically weighted EDF measure occurs one to two years prior to the peak in the size weighted EDF measure. The average risk of default dropped sharply after 1998, but trended higher during the early 2000s as the dot-com bubble burst, resulting in a recession in the United States, and Argentina defaulted on its foreign debt.

The global financial crisis, as severe as it was in the West, is a relatively minor blip in the time-series for the ASEAN-5 nations. These results suggest a potentially useful and powerful way of monitoring the future likelihood of systemic crises.

The right side of Figure 3 shows the 12-month moving average of the DGC measure for the network at each point in time. The right side of Figure 3 shows the DGC measure for the network at each point in time. In this one graph, we get a

**Figure 3** Aggregate EDF and DGC measures for ASEAN-5 financial institutions, 1995-3Q2014




Source: Moody's Analytics

panoramic view of how systemic risk has evolved for ASEAN-5 financial institutions over the past 20 years. The strength of interconnectedness among financial institutions and the high risk of contagion that characterized the Asian financial crisis is captured by the peak 0.31 DGC measure.

The graph also shows that it took at least four years for systemic risk to subside to levels that prevailed before the Asian financial crisis. **Although economic growth in the countries most affected by the crisis bounced back strongly after 1998, our results on systemic risk corroborate other macro-financial indicators that show that their financial systems and economies took a number of years to fully heal.**

The DGC time-series in Figure 3 attests to the fact that the risk of credit risk spillovers arising from the global financial crisis was virtually a non-event for the ASEAN-5 group of financial institutions. Although registering a brief spike, the DGC measure continued to fluctuate around the 0.18 average that prevailed after the Asian financial crisis. In contrast, the DGC measure for large US financial institutions reached a peak of 0.61 at the height of the global financial crisis. Intriguingly, systemic risk as measured by the DGC reached its highest level since the Asian financial crisis in July 2013. However, systemic risk has subsided considerably since that date, falling to its lowest level in 20 years.

**Figure 4 reinforces our historical understanding of the role of leverage as one of the key causes of the Asian financial crisis.** Here, leverage is defined as the ratio of a firm's default point to its market value of assets.[18] As in Figure 3, we calculated two weighted measures of leverage: using book assets (size) and the Out measure (systemic influence).

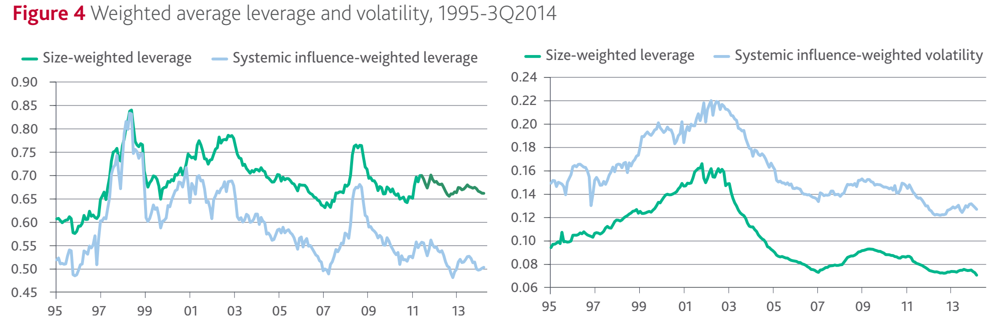
Size-weighted leverage is nearly always higher than systemic influence-weighted leverage, and by a considerable margin in some time periods. The implication is that larger financial institutions lever up more, a finding consistent with data for US financial institutions. A second, and perhaps more important, implication is that a firm's size is not perfectly correlated with the spillover dimension of systemic risk contribution.

The graph on the right side of Figure 4 shows size- and systemic influence-weighted average asset volatility over time. Unlike average EDF levels and leverage values, the weighted volatility measures rise throughout but peak well after the Asian financial crisis, around the time of Argentina's default. Systemic influence-weighted volatility is everywhere above size-weighted volatility: firms that exhibit a relatively high Out ratio, and therefore have a high potential for contagion, also exhibit higher asset volatility.

The global financial crisis exerts a stronger effect on leverage than on volatility for ASEAN-5 financial institutions. Weighted volatility rises and persists through the European sovereign debt crisis, but the magnitude of the increase is relatively small. Weighted leverage spikes to levels that persisted during the early 2000s but then falls sharply to pre-global financial crisis levels.

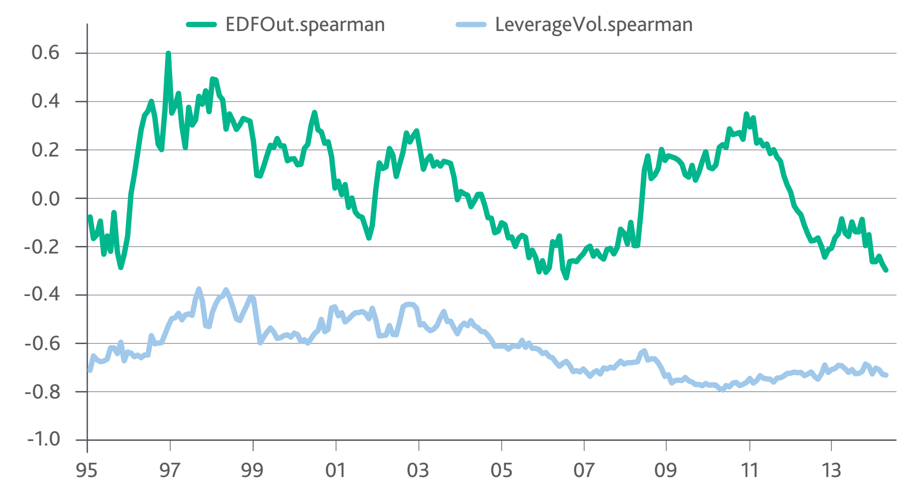
Tracking cross-sectional correlations over time can yield additional insights into system dynamics. Figure 5 displays two Spearman (rank)

**Figure 4** Weighted average leverage and volatility, 1995-3Q2014




Source: Moody's Analytics

**Figure 5** Cross-sectional correlations over time: EDF-Out and leverage-volatility




Source: Moody's Analytics

correlations: the EDF-Out measure correlation and the leverage-volatility correlation. At each time point, the correlations shown are computed using only the cross section available at that time point for the system. EDF levels and systemic influence correlations tend to be negative during calm periods and positive during crisis periods. Leverage and volatility correlations are always negative.

During times of crisis, the EDF-Out correlations increase, as do the leverage-volatility correlations. The interpretation is that riskier (that is, higher default probability) financial institutions increasingly drive the system during crises and that the negative relationship between leverage and volatility underlying optimal leverage theories in corporate finance (for example, the trade-off theory of the capital structure) becomes weaker in the cross section of firms during crises. **Figure 5 also shows that the EDF-Out correlation tends to spike at the beginnings of crisis episodes, a pattern that is also apparent in data for US financial institutions around 2007-2009.**[19]

Thailand was the epicenter of the Asian financial crisis in 1997. The devaluation of the baht set off a cascade of financial distress throughout the ASEAN countries. Our study of Granger causal connections among EDF measures reveals that financial institutions in Thailand still represent a concentration of systemic risk in the ASEAN-5 network. Financial institutions in Singapore and Malaysia also stand out as having a high concentration of positive (that is, forcing) Granger causal relationships.

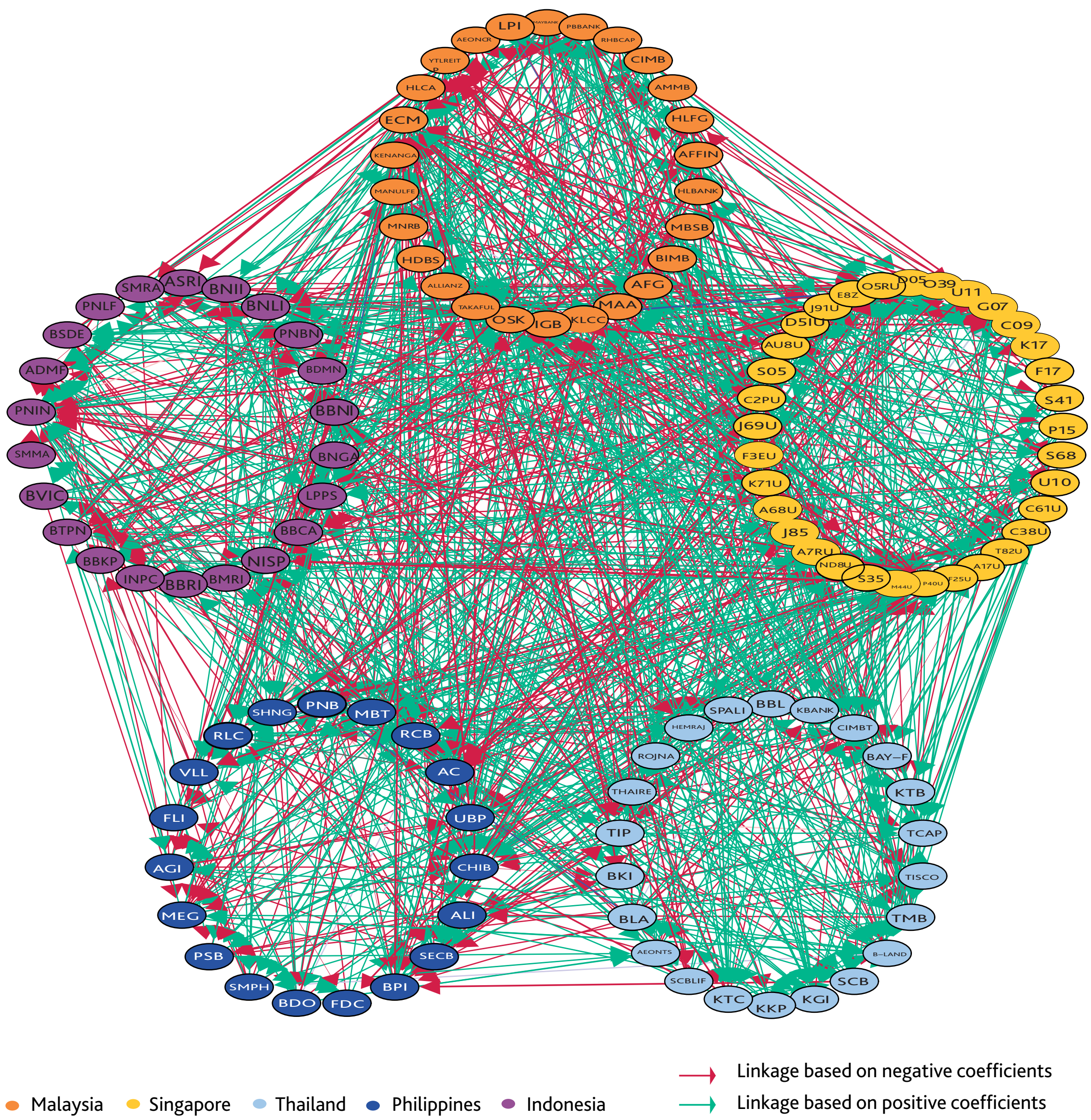
**Figure 6 shows the complete network map of Granger causal connections as of October 2014.** Circles represent financial institutions, and are color coded by country of domicile. This graph displays linkages based on the coefficients at lag 1 in the VAR models using EDF measures (equation 1 above). Red lines correspond to negative coefficients (damping effects), and blue lines correspond to positive coefficients (forcing effects).

The sets of lines connecting financial institutions in Thailand (green), Singapore (yellow) and Malaysia (red) are numerous, giving the graph a very dense appearance on the right side. The lines connecting Thailand, Singapore, and Malaysia also tend to be blue, meaning that the relationship between financial institutions in these countries is positive: **an increase in credit risk among financial institutions in one of these countries has a high propensity to cause an increase in credit risk in the others**.

## Conclusion

The experience of the Asian financial crisis sparked an intense interest in measuring systemic risk among regulators in Southeast Asia, with the aim of developing policy tools to mitigate its reoccurrence. That interest has

**Figure 6** Network map based on Granger causal connections as of October 2014




Source: Moody's Analytics

been further reinforced by the global financial crisis, which, while not having a serious effect on Southeast Asia, served as a salutary reminder that a systemic crisis can arise in one part of the world and spread to others.

Going forward, we expect that regulators will require financial institutions subject to supervisory stress tests to pay greater explicit attention to systemic risks. In order to do so, they must be able to quantify systemic risk in real time. Our empirical results showed that Granger causal measures captured the contagion risk of the Asian financial crisis to the greater region extremely well. Financial institutions in the ASEAN-5 nations experienced historic levels of interconnectedness and default risk during the Asian financial crisis. They were, however, relatively immune to the effects of the global financial crisis.

The tools we have explored in this research note can be of indispensable use to both financial institutions and regulators for estimating the current and future level of systemic risk and for identifying the sources of its changes. Regulators can, at a glance, obtain tangible signals indicating which institutions are most strongly connected in the network and thus pinpoint weaknesses in the broader financial system.

Managers of financial institutions, meanwhile, can assess their counterparty risks more fully via consideration of joint and conditional default likelihoods calculated using network-based simulations. In an environment where financial institutions are less likely to be bailed out, managers must take steps to guard against failures caused merely by being in the wrong place at the wrong time.

We described a useful measure of interconnectedness using a network approach whose implementation is straightforward and whose outputs are intuitive and easily interpretable. Granger causality networks address one of the key aspects of systemic risk: the extent of dynamic spillovers between institutions. By using expected default frequency measures as the fundamental unit of observation, we are able to relate statements about the likelihood of default for particular institutions to measures of systemic risk exposure and contribution.

1 Andrew Berg, International Monetary Fund Working Paper, WP/99/138, *The Asian Crisis: Causes, Policy Responses, Outcomes*, 1999.

2 Masahiro Kawai and Peter J. Morgan, Asian Development Bank Institute working paper, No. 377, *Central Banking for Financial Stability in Asia*, August 2012.

3 The Association of Southeast Asian Nations is an association for regional social and economic cooperation consisting of ten Southeast Asian countries. ASEAN was formed in 1967 by Indonesia, Malaysia, the Philippines, Singapore, and Thailand (the ASEAN-5 countries). Five additional countries joined later.

4 Chan Lily and Lim Phang Hong, The Monetary Authority of Singapore, Staff Paper No. 34, *FSAP Stress Testing: Singapore's Experience*, August 2004.

5 This fact has been recognized by the central banks in the ASEAN-5 nations. Much interesting research on systemic risk from a too-connected-to-fail perspective has been generated by the central banks of Indonesia, Malaysia and Thailand, including: Ayomi and Hermanto (2013), Bank Negara (2013), Hwa (2013), Nacaskul (2010). Sheng (2010) also studies systemic risk using a network approach.

- » Sri Ayomi and Bambang Hermanto, Bank of Indonesia Bulletin of Monetary, Economics and Banking, *Systemic Risk and Financial Linkages Measurement in the Indonesian Banking System*, October 2013.
- » Bank Negara Malaysia Financial Stability and Payment Systems Report (2013): 46-51, Risk Developments and Assessment of Financial Stability in 2013, *External Connectivity and Risk of Contagion to the Malaysian Banking System*, 2013.
- » Tng Boon Hwa, Bank Negara Malaysia working papers, WP1, *External Risks and Macro-Financial Linkages in the ASEAN-5 Economies*, 2013.
- » Poomjai Nacaskul, Bank of Thailand working paper, *Toward a Framework for Macroprudential Regulation and Supervision of Systemically Important Financial Institutions*, December 24, 2010.
- » Andrew Sheng, World Bank working paper, No. 67, *Financial Crisis and Global Governance: A Network Analysis*, 2010.

6 Zhao Sun, David Munves, and David T. Hamilton, Moody's Analytics Model Methodology, *Public Firm Expected Default Frequency (EDF™) Credit Measures: Methodology, Performance, and Model Extensions*, June 2012.

7 Clive C. W. Granger, Econometrica Vol. 37, No. 3, 424-438, *Investigating causal relations by econometric models and cross-spectral methods*, July 1967.

8 Tony Hughes and Samuel W. Malone, Moody's Analytics white paper, *CCA Financial Networks and Systemic Risk: Concepts and Outputs*, October 2014.

9 Dale Gray and Samuel W. Malone, Chichester, England: John Wiley & Sons, *Macrofinancial Risk Analysis*, 2008. Dale Gray and Samuel W. Malone, Annual Review of Financial Economics Vol. 4, No. 1: 297-312, *Sovereign and Financial Sector Risk: Measurement and Interactions*, 2012.

10 Dale Gray, Andreas Jobst, and Samuel W. Malone, Journal of Investment Management Vol. 8, No. 2: 90-110, *Quantifying Systemic Risk and Re-conceptualizing the Role of Finance for Economic Growth*, 2010.

11 Monica Billio, M. Getmansky, A. Lo and L. Pelizzon, Journal of Financial Economics Vol. 104, No. 3: 535-559, *Econometric Measures of Connectedness and Systemic Risk in the Finance and Insurance Sectors*, June 2012.

12 ELR is defined as the expected loss, or implicit put option, component of the debt divided by its promised (or risk-free) value.

13 Robert C. Merton, Monica Billio, Mila Getmansky, Dale Gray, Andrew W. Lo, and Loriana Pelizzon, Financial Analysts Journal 69 (2): 22-33, *On a New Approach for Analyzing and Managing Macrofinancial Risks*, 2103.

14 Although we do not discuss it in this paper, Granger-causality networks also allow us to identify whether the relationship between financial institutions is positive ("forcing") or negative ("dampening"), depending on the signs of the $\beta$ and $\gamma$ coefficients in equations (1). Hughes and Malone (2015) estimate the forcing and damping effects for U.S. financial institutions.

15 Zhao Sun, Moody's Analytics ViewPoints paper, *An Empirical Examination of the Power of Equity Returns vs. EDFs for Corporate Default Prediction*, January 2010.

16 To be precise, the systemic influence weights are an equally weighted average of weights based on Out, Out.plus, and Inverse Closeness; the latter two measures are described in Hughes and Malone (2015).

17 Hughes and Malone, 2014

18 In the expected default frequency model, the default point is defined as the notional value of liabilities that would trigger a credit event. For corporates, it is calculated as short-term debt plus half of long-term debt. For financial institutions, it is calculated as 75% of reported total liabilities.

19 Tony Hughes and Samuel W. Malone, Moody's Analytics ViewPoints paper, *Systemic Risk Monitor 1.0: A Network Approach*, forthcoming, 2015.

# EFFECT OF CREDIT DETERIORATION ON REGULATORY CAPITAL RISK WEIGHTS FOR STRUCTURED FINANCE SECURITIES

By Vivek Thadani and Peter Sallerson

**Vivek Thadani**
*Director, Structured Finance Valuations & Consulting Group*

Vivek is primarily responsible for developing and maintaining analytical models for various asset classes across the structured security space. Prior to his current role, Vivek supported investor and asset manager clients at Wall Street Analytics across CLO and RMBS asset classes.

**Peter Sallerson**
*Senior Director, Structured Analytics and Valuation*

Peter focuses on the CLO market at Moody's Analytics via the further development of our Structured Finance Portal's CLO section and related research. He has worked in many aspects of the CLO market for over 25 years.

With regulatory stress testing becoming more entrenched in general risk management, the need to understand the credit-specific drivers of regulatory risk weights has become an important function of risk management. This article aims to illustrate the general impact of credit deterioration on regulatory capital risk weights in a large dataset of multiple structured finance asset classes. For investors and risk managers, any asset class-specific trends can help in the investment evaluation process.

## Criteria for the analysis portfolio

To understand the actual impact of credit deterioration on regulatory capital risk weights across the universe of structured finance securities, we chose a large cohort of comparable securities that would broadly illustrate trends and effectively represent the universe as a whole, based on the following:

1. The current outstanding notional amount as of September 30, 2014 was at least US$1 million.
2. We excluded interest-only or combination tranches, which would have made the portfolio less uniform across asset classes. Excluding these tranches also removed the effect of cross-tranche referencing, a feature of combination tranches.
3. To study the effect of credit deterioration on regulatory capital, we excluded resecuritizations that would have required using a higher Simple Supervisory Formula Approach (SSFA) supervisory calibration,[1] so that we could observe the effect of credit deterioration in isolation. Further details on the supervisory calibration parameter and its impact on the SSFA formula can be found in the Appendix.
4. For student loan securities, we excluded the Federal Family Education Loan Program (FFELP) government-guaranteed transactions because the impact of credit deterioration on these securities can be affected by policy decisions. This would have introduced another dimension that was out of the scope of this analysis.
5. We included only USD-denominated securities because credit quality can vary significantly between the USD-denominated securities in an asset class and similar non-USD-denominated securities.
6. The final portfolio for analysis comprised approximately 43,700 securities, which effectively represent the structured finance universe of non-agency transactions.[2]

As we expected, RMBS made up the largest segment analyzed (by number of securities and outstanding notional amount), owing to the large size of the non-agency RMBS market. Student loan ABS (SLABS) made up the smallest segment.

By vintage range, the portfolio reflects broad trends in issuance, with the large majority of securities having been originated before the crisis. For this analysis, "pre-crisis" covers

**Figure 1** Analysis portfolio by asset class


Source: Moody's Analytics

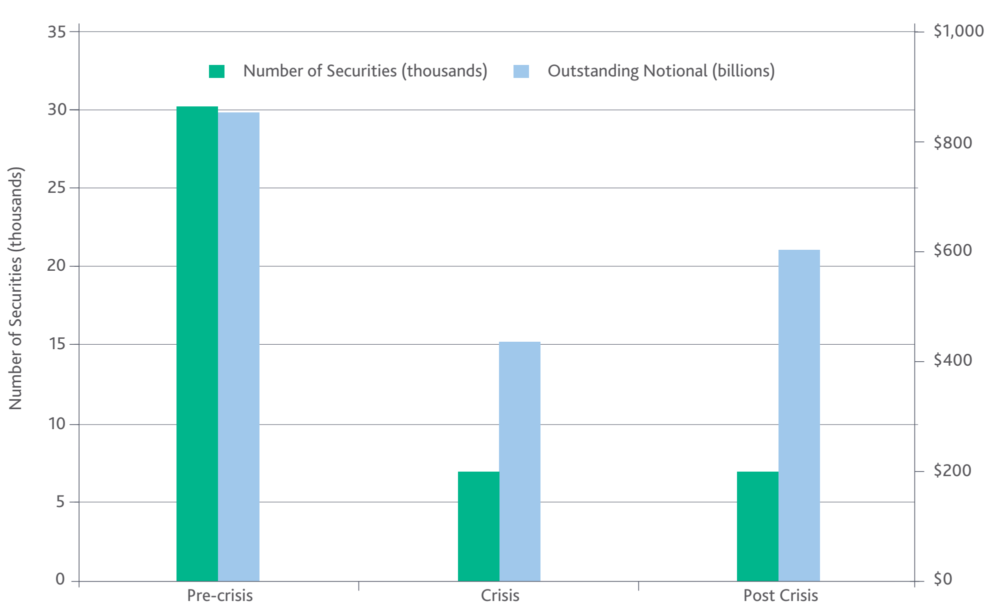
securities originated in 2006 and earlier; "crisis" covers 2007-09; and "post-crisis" covers 2009 to the present. The large outstanding notional for a smaller number of securities in the post-crisis bucket is due to the high bond factors (low seasoning) as compared to pre-crisis.

### Current W parameter levels

For the SSFA for regulatory capital, the W parameter represents the current delinquency and non-performing levels in a pool. As defined in the Federal Register,[3] the W parameter comprises loans that are:

1. 90 days or more past due
2. Subject to bankruptcy or insolvency proceeding
3. In the process of foreclosure
4. Held as real estate owned (REO)
5. Have contractually deferred payments for 90 days or more, other than principal or interest payments deferred on:
   - Federally guaranteed student loans, in accordance with the terms of those guarantee programs
     -Or-

**Figure 2** Analysis portfolio by vintage ranges




Source: Moody's Analytics

- Consumer loans, including non-federally guaranteed student loans, pursuant to certain conditions

6. Are in default

The SSFA formula requires normalization of a deal's structure to its attachment and detachment points, as well as normalization of the credit risk profile to its W parameter. Hence, for two identically structured deals – i.e., two deals with similar attachment and detachment points – the current non-performing level represented by the W parameter is the primary driver of regulatory risk weight.

The risk weight is divided by 1250% to convert it to a regulatory capital charge. For this analysis, we use the risk weight as the parameter to analyze shocks to W. We used the risk weight instead of the capital charge because the risk weight is the more common benchmark in general risk management.

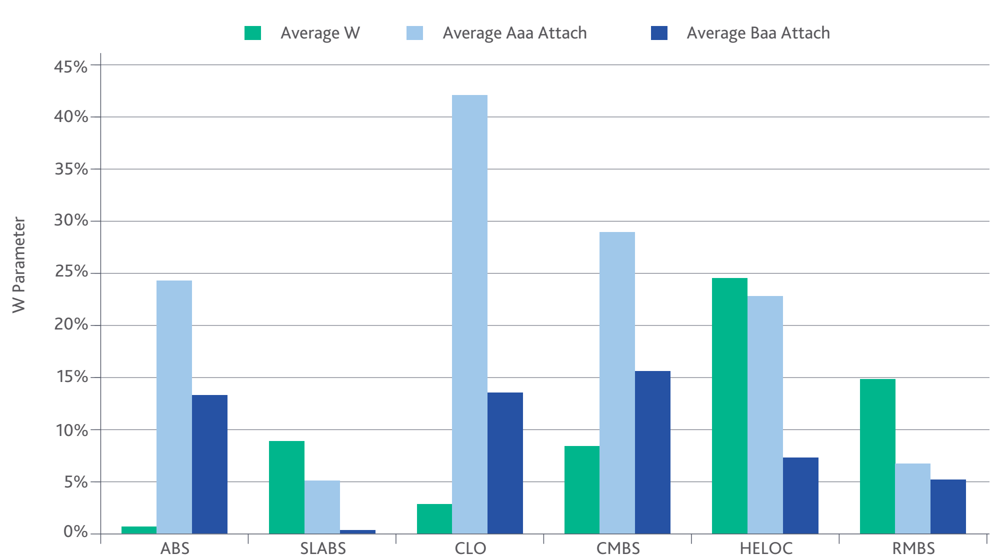
### Credit deterioration stresses to the W parameter

We stressed W instead of individual macroeconomic variables to exclude the dynamics of the different components of W to macroeconomic stresses, which allows for a comparable evaluation of the regulatory impact on an entire asset class, as opposed to deal-specific credit performance. For example, if we stressed only one macroeconomic variable, such as home prices, we would expect a sharp increase in the W parameter for an RMBS and HELOC security, but little change to a CLO security. There could be indirect effects to the macro-variable that drive corporate leveraged loan performance, but these effects would be minimal and likely delayed. Furthermore, such a macroeconomic shock would not affect all RMBS deals uniformly, because underlying credit quality differs. Stressing W directly illustrates the overall regulatory performance of an asset class.

For the analysis, we used average levels instead of medians. Although the median could be considered a good indicator of trends, the average better illustrates the broad trends of the stressed risk weights. Given that credit deterioration does not necessarily affect all

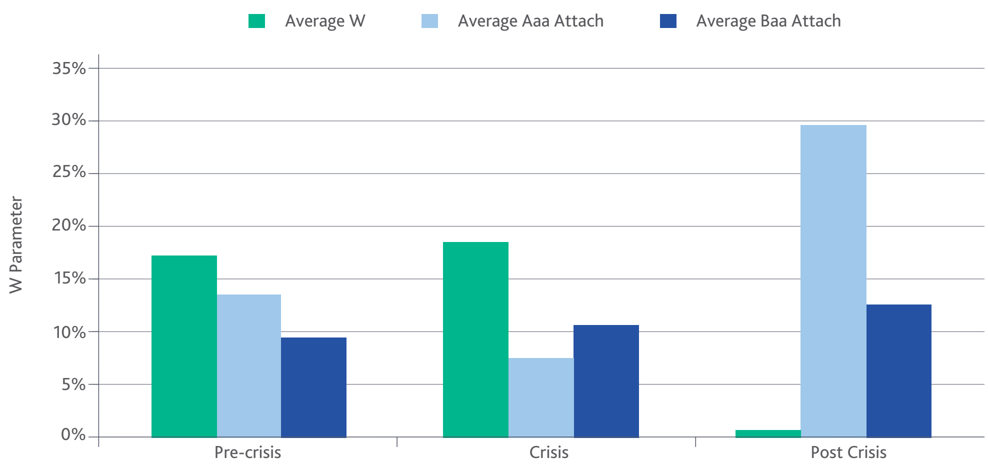
> One key observation is that the stresses do not affect all asset classes similarly; some can withstand such shocks across the rated structure better than others. This observation is in line with what we expected – that CLO and ABS securities have, on average, better credit protection.

**Figure 3** Average W levels and average Aaa and Baa attachment points by asset class




Source: Moody's Analytics

**Figure 4** Average W levels and average Aaa and Baa attachment points by vintage range



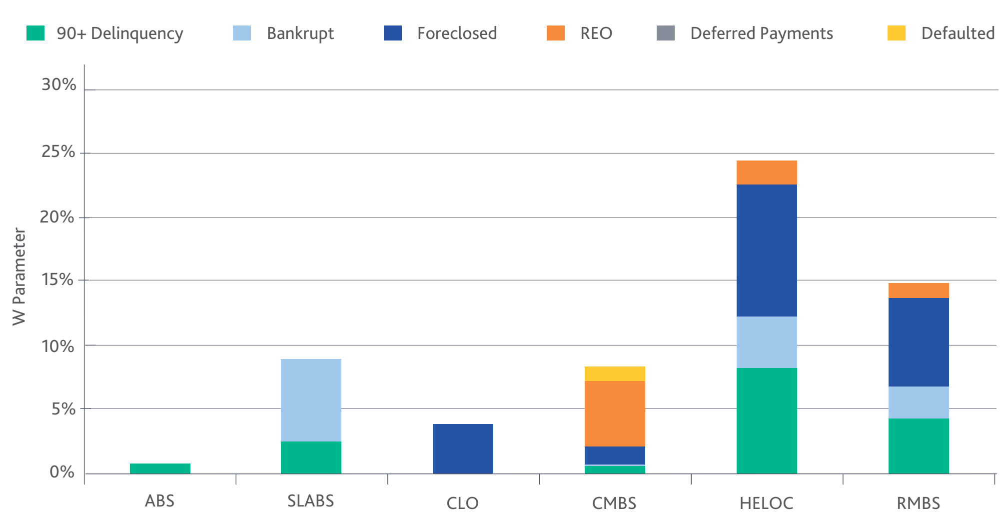

Source: Moody's Analytics

securities similarly, using a median would not demonstrate the true effect of the shock. The effects of a stress on credit quality can differ, such that the median value will remain unchanged but the risk weights of many securities will rise significantly. By using an average, the value will move in accordance with the segment overall and better demonstrate trends.

Figure 3 depicts the current average W levels for the entire analysis portfolio, along with the average attachment levels for Aaa- and Baa-rated securities. At a high level, it indicates current performance and credit enhancement for the asset classes. Specifically, the current average W level helps identify an expectation for credit deterioration shocks: changes to risk weight in the poorer performing asset classes should be greater than in the better performing asset classes.

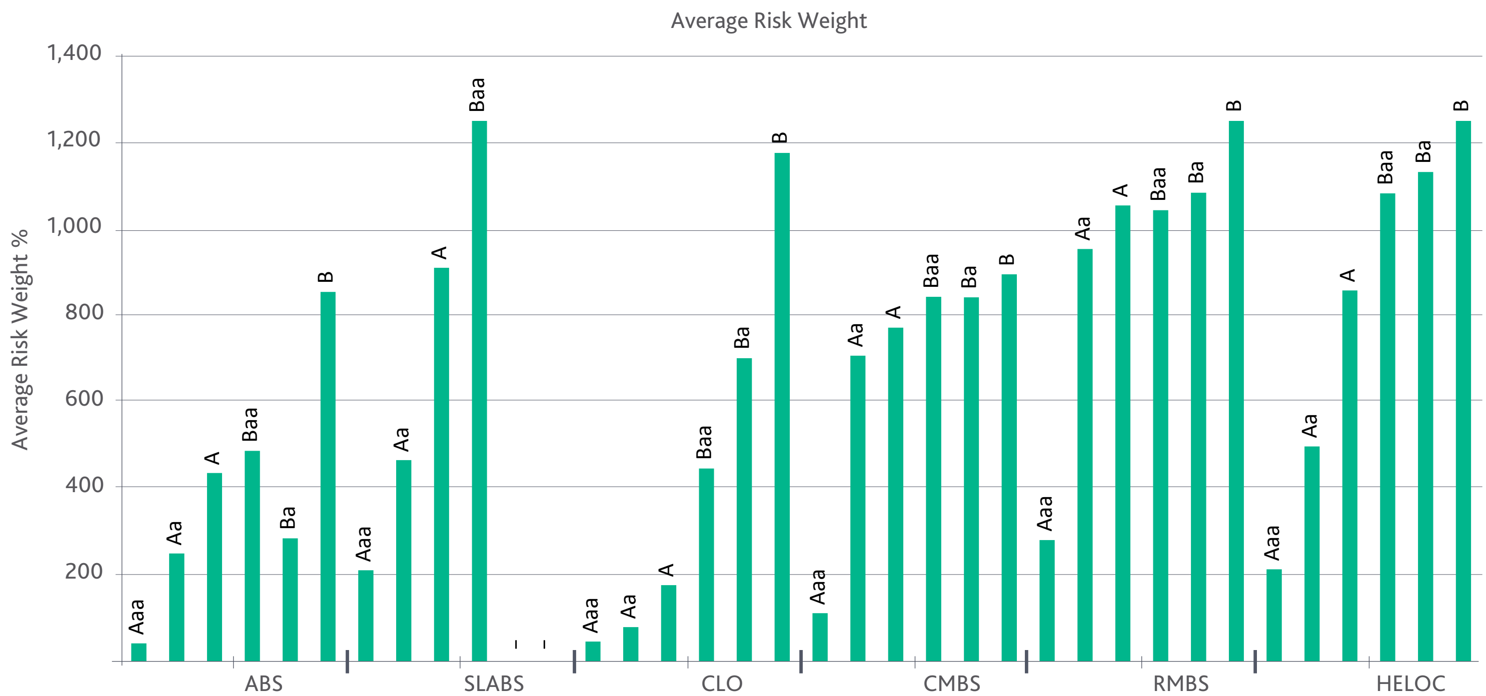
Given that the SSFA formula assumes a fixed severity for the W bucket (see the Appendix), an alternate way to use the data is to gauge a security's ability to withstand credit shocks by how much higher a security attaches (average Aaa attachment and average Baa attachment) than by the average W bucket size (average W).

**Figure 5** W parameter components by asset class



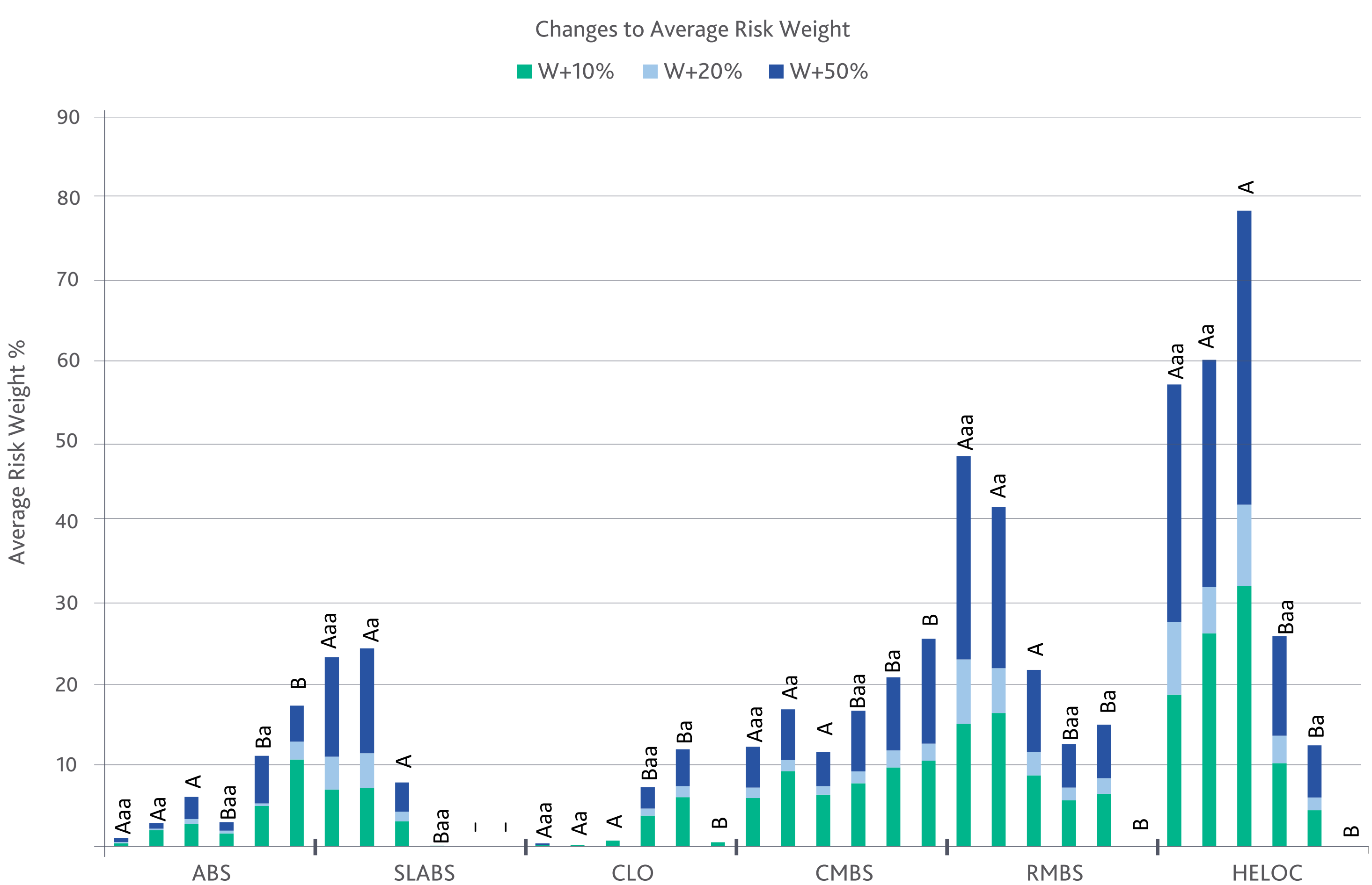

Source: Moody's Analytics

**Figure 6** Average risk weight levels by asset class and original ratings




Source: Moody's Analytics

**Figure 7** Changes to average risk weight levels owing to credit deterioration shocks




Source: Moody's Analytics

Such a back-of-the-envelope approach allows us to quickly determine that ABS and CLO are the only asset classes that have good credit protection at both the Aaa and Baa levels (Figure 3). These levels of credit protection are a function of how the transactions are structured and how their credit enhancement changes over time. Conversely, we can expect current HELOC and RMBS performance to be fairly poor because the average W levels are higher than the average Aaa attachment levels.

Similarly, the current credit performance of a vintage segment shows good credit protection levels for post-crisis securities, as compared to crisis and pre-crisis securities.

When reviewing the performance of an asset class as defined by the W parameter, breaking down the components of the level is also helpful. In Figure 5, the various components highlight the different makeup of the average W levels. This dispersion is the primary reason for the decision to shock credit quality uniformly rather than by independent macroeconomic variables.

To gauge potential credit deterioration, we analyzed the average risk weight by segmenting the portfolio by asset class and the original Moody's Investor Service rating levels, which ranged from Aaa to B. We did not consider sub-ratings (1 to 3).

Figure 6 shows the average current risk weight by the segments used in the credit shock.

As expected, the SSFA-based risk weights are on average higher for lower rating levels. For SLABS, there were no securities originally rated Ba or B that met the selection criteria. Also, for the ABS buckets, very few securities were originally rated Ba and B and the average level skews to a low and high value. This would not be the case for one transaction – the B security will always have a higher risk weight compared to the Ba security in the same deal.

For this analysis, we ran three credit deterioration scenarios using values of 10%, 20%, and 50% to shock the current W level. For example, if a transaction had a current W level of 5%, we used values of 5.5%, 6%, and 7.5% for the three credit deterioration scenarios. Using a proportional approach ensures that the stress affects deals progressively – i.e., better performing deals are shocked by smaller stresses while worse performing deals are affected by larger stresses. Figure 7 shows the results for the credit quality shocks.

Although the effects of the credit deterioration stresses may appear to be minimal at the current W levels, we note some interesting trends. **One key observation is that the stresses do not affect all asset classes similarly; some can withstand such shocks across the rated structure better than others.** This observation is in line with what we expected – that CLO and ABS securities have, on average, better credit protection. The changes to risk weight owing to credit quality shocks, therefore, are minimal. Also, the performance of these securities in the scenarios aligns well with actual performance during the crisis.

The absolute change in stressed risk weight for the poorer performing asset classes (such as HELOC and RMBS) are higher than the stress applied. Although this view compares the relative change in W to the absolute change in risk weight – a relationship that is not linear – it helps to put the risk weight changes into context. While the change in risk weights is higher for the poorer performing asset classes, within an asset class such as RMBS or HELOC, the change in risk weight is low for lower rated securities. This is not surprising given that the lower rated securities are closer to the risk weight ceiling of 1250%.

## Conclusion

There are a few different ways to interpret this analysis. From a regulatory perspective, the overarching theme is that credit deterioration affects different asset classes differently. This could be due to either the historical credit performance or the typical structure for an asset class or both. While risk management professionals can use different segmentations to analyze regulatory impact of portfolio changes, this analysis highlights high-level trends that should be considered at every step of the investment process.

## Appendix – SSFA Mechanics[4]

The Simplified Supervisory Formula Approach requires a simpler calculation and data collection process. The trade-off for this is conservative assumptions on the losses of the underlying exposures, which could result in potentially higher regulatory capital requirements. The SSFA calculation requires the following input parameters:

1. Kg, which is the weighted average total base capital requirements of the underlying exposures
2. Parameter W, which is the ratio of the sum of underlying exposures that are seriously delinquent or defaulted for regulatory purposes[4]
3. Parameter A, which is the attachment point of the security
4. Parameter D, which is the detachment point of the security
5. Supervisory calibration parameter p, which is set to 0.5 for securitization exposures and 1.5 for resecuritization exposures (For this analysis, resecuritizations were excluded and the p was set to 0.5 for the entire portfolio.)

**SSFA risk-based capital calculation:**

$$\text{Risk Weight} = \left[\left(\frac{K_A - A}{D - A}\right) \text{x } 1250\%\right] + \left[\left(\frac{D - K_A}{D - A}\right) \text{x } 1250\% \text{ x } K_{SSFA}\right]$$

| | |
|---|---|
| 1 | $K_A=(1-w).K_G+(0.5\times w)$ |
| 2 | $a = -\frac{1}{p \times K_A}$ |
| 3 | $u=D-K_A$ |
| 4 | $l=\max(A-K_A,0)$ |
| 5 | $K_{SSFA} = \frac{e^{a.u} - e^{a.l}}{a(u - l)}$ |

1 Although we excluded multi-tranche resecuritizations that would have required using a higher SSFA supervisory calibration parameter of p=1.5, we did include all single-tranche re-remics with p=0.5.

2 We analyzed the portfolio using the Regulatory Module in the Moody's Analytics Structured Finance Portal.

3 See Federal Register, Vol. 78, No. 198, October 11, 2013..

4 For more information, see Federal Register, Vol. 78, No. 198, October 11, 2013.

# FINDING ALPHA: SEEKING ADDED VALUE FROM STRESS TESTING

By Greg Clemens and Mark McKenna

**Greg Clemens**
*Director,*
*Stress Testing Solutions*

As a member of the Stress Testing Task Force at Moody's Analytics, Greg helps clients automate their stress testing processes – providing insight about architectures, data management, and software solutions for risk management.

**Mark McKenna**
*Senior Director,*
*Stress Testing Solutions*

Mark is responsible for business and relationship management for Moody's Analytics Stress Testing Solutions. Prior to his current role, he was with the Structured Analytics & Valuations Group, leading valuations and cash flow analytics projects. He has worked with many US financial institutions, providing risk management tools and loss estimation models for their retail portfolios.

How can banks measure the success of their stress testing efforts? This article explores where banks can look for the "alpha" in stress testing – that is, how they can measure the performance of their stress testing programs, identify weaknesses, and make the process more efficient and effective.

## Introduction

In sports, a team's success is measured by winning percentages, and an individual player's, by statistics such as batting average, yards gained, or points scored. In business, success is measured by profitability. For banks, that specifically means net profit from fees and interest and return on investments.

Portfolio managers use the concept of "alpha" to gauge their performance, which is a measure of how much better their return is versus a benchmark index. For example, if a benchmark index increases five percent, but a mutual fund generates a return of seven percent over the same period, that fund would have an alpha of two percent, meaning that it performed that much better than the underlying index.

But how can we measure the performance of a bank's stress testing efforts? Although it's not as simple as measuring a batting average, there are some best practices that banks can adopt to help them find quantifiable "alpha factors."

## Stress testing is more than a pass/fail exercise

For US banks subject to the Dodd-Frank Act Stress Test (DFAST), the results are pass/fail for each bank; that is, for the banks that pass the test there is no merit to being first, second, third, or last, for that matter.

If stress testing were like a ski competition, each skier (in this case, each bank) would race down their own individual course, there would be no clock, and each would be declared a winner if they just made it safely to the bottom of the course.

To assess a bank's stress testing performance, we need to measure how well the bank's stress test program succeeded beyond simply passing the test. Rather than compare one bank's performance to another's, it makes more sense to compare the bank's own performance from one year to the next.

To quantify how a bank's program is improving (taking for granted that it passed the DFAST test), we need to find the "alpha" in stress testing.

## Streamlining the stress testing process

In terms of an organizational framework, a typical stress testing process involves:

- Gathering data from across the firm – not just finance, risk, and treasury but all lines of business
- Preparing an initial balance sheet using the jump-off data
- Forecasting what the balance sheet will look like in the future in a variety of economic scenarios using models for projections of losses, net income, pre-provision net revenue,

**Figure 1** Stress testing process framework


Source: Moody's Analytics

cash flows, and other elements of the balance sheet

- Incorporating proposed capital plans, overlays, and expert judgment
- Preparing reports and supporting documentation to fully explain how the forecasts were derived

The process seems straightforward, but in reality it involves many stops and starts, revisions, and iterations.

### A strain on resources: the data challenge

Developing and running a stress testing process is a daunting challenge for most banks. Multiple regulatory reforms with complex oversight and compliance guidelines have added to the already difficult challenges of risk management for financial institutions.

Government urgency to ensure that financial systems are safe and stable has prompted continued enhancements to the relatively new regulations even as they widen in scope. This heightened regulatory expectation and intense scrutiny come at a time when organizations are already under pressure to improve their profitability and establish a competitive edge in a low-return market environment.

an enterprise-wide exercise. Organizations must access, validate, and reconcile data from across the enterprise, including all geographies, portfolios, and instruments, irrespective of the origin of the data.

On top of these data aggregation challenges, firms need to widen the scope and improve the accuracy and governance of their models and estimation processes for generating the forecasts needed for the stress tests. These challenges are straining firm resources even further.

To put the required effort in perspective: We believe that the largest US banks are running their stress testing programs year round, with upwards of four or five hundred full-time-equivalent resources engaged in the program for much of that time.[1]

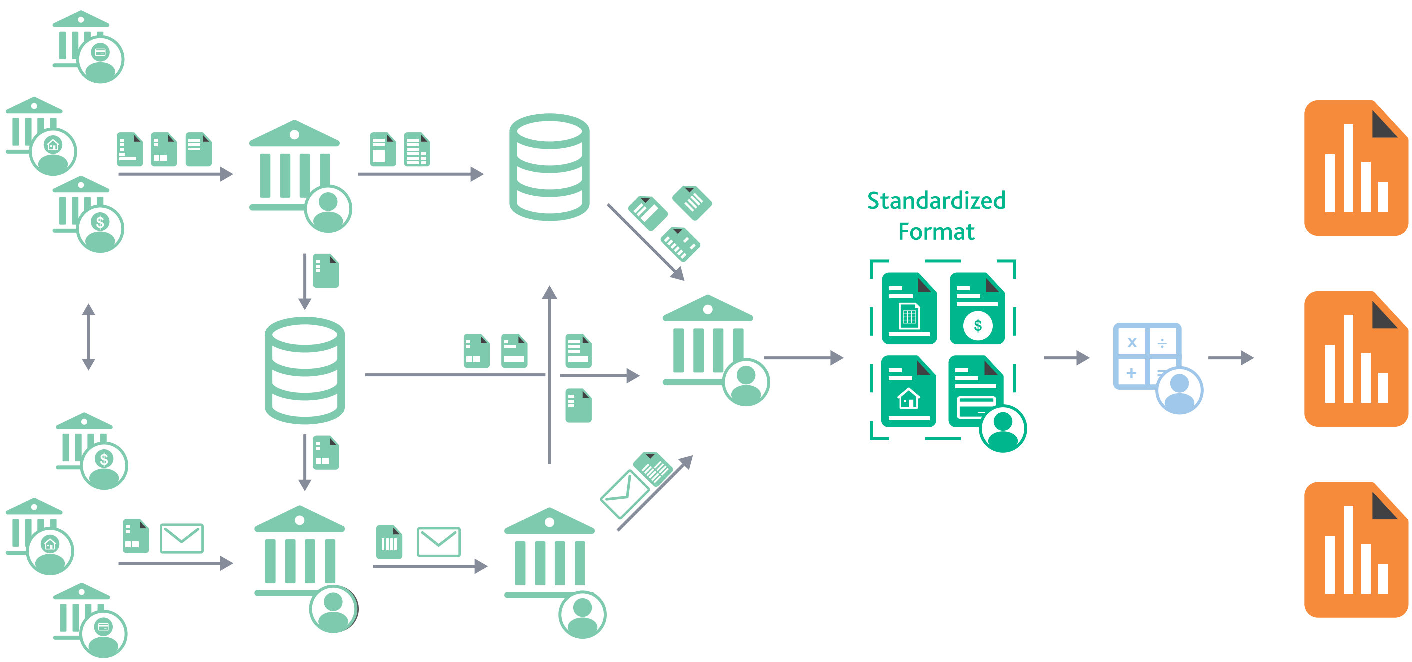
Thwarting the success of these efforts is the data itself. Data exists in many formats, such as paper records, desktop files, and other suboptimal data storage solutions, which adds to the difficulty of efficiently meeting reporting obligations. Organizations often need to build additional environments to pull data from different locations for reporting purposes, as shown in Figure 2.

To put the required effort in perspective: We believe that the largest US banks are running their stress testing programs year round, with upwards of four or five hundred full-time-equivalent resources engaged in the program for much of that time.

As a result, stress testing budgets at most financial institutions have soared. These regulations have one characteristic in common: They require that financial institutions set up processes and systems to manage an ever-growing amount of data and oversee

Primitive data systems, which are characterized by inconsistent standards, data duplication, and missing and conflicting data, lead financial institutions to make major and potentially erroneous assumptions about how to reconcile data. Firms must also contend with the challenge

**Figure 2** Challenges of data standardization

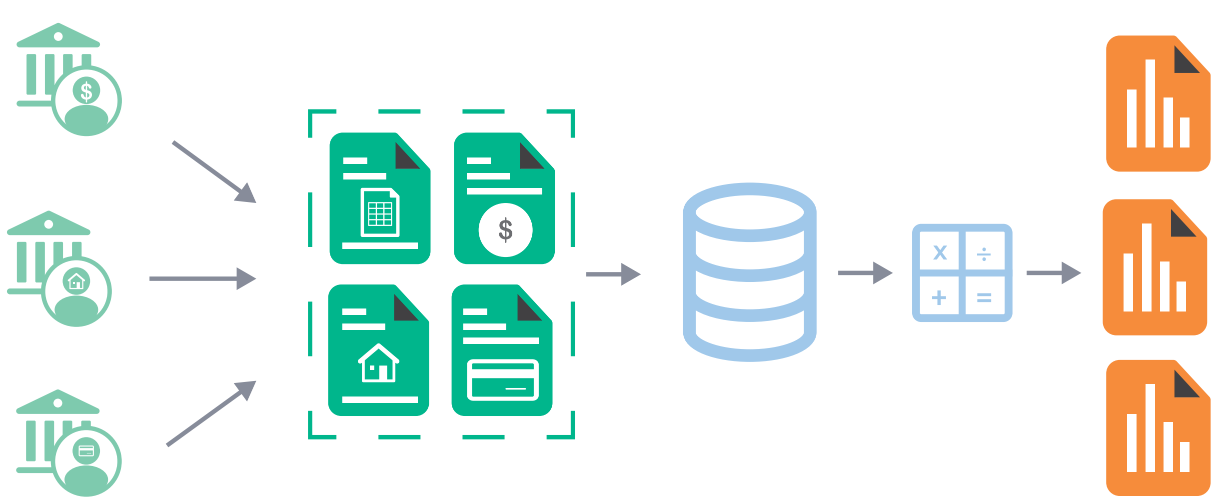



Source: Moody's Analytics

of ensuring consistency across reporting dates and between different reports.

One of the principles put forth by the Basel Committee on Banking Supervision (BCBS) states that organizations should strive to determine a single authoritative source of risk data for each type of risk. A firm must create a structure and processes that can aggregate risk data in a way that is accurate, complete, and transparent for its senior management, board of directors, and regulators – enabling these stakeholders to make informed decisions.

**Figure 3** A centralized datamart allows for a much simpler process



Source: Moody's Analytics

A centralized datamart that connects different pieces of information is key to mitigating the challenges of data management and can clear a path for banks to determine quantifiable stress testing performance measures.

### Striving for repeatability

The first step to passing regulatory requirements is to compile the numbers. The next is to ensure the transparency of the process, so that the bank can explain easily and clearly where the numbers came from and how the forecasts were derived. The final major step is to make sure the process is auditable: The bank needs to be able to make sure the process can be audited to show how everything came together, with clear and detailed documentation showing what estimates and models were used, what parameters and defaults were included, how they were validated, how overlays and expert judgment were applied, and how all decisions were made throughout the process.

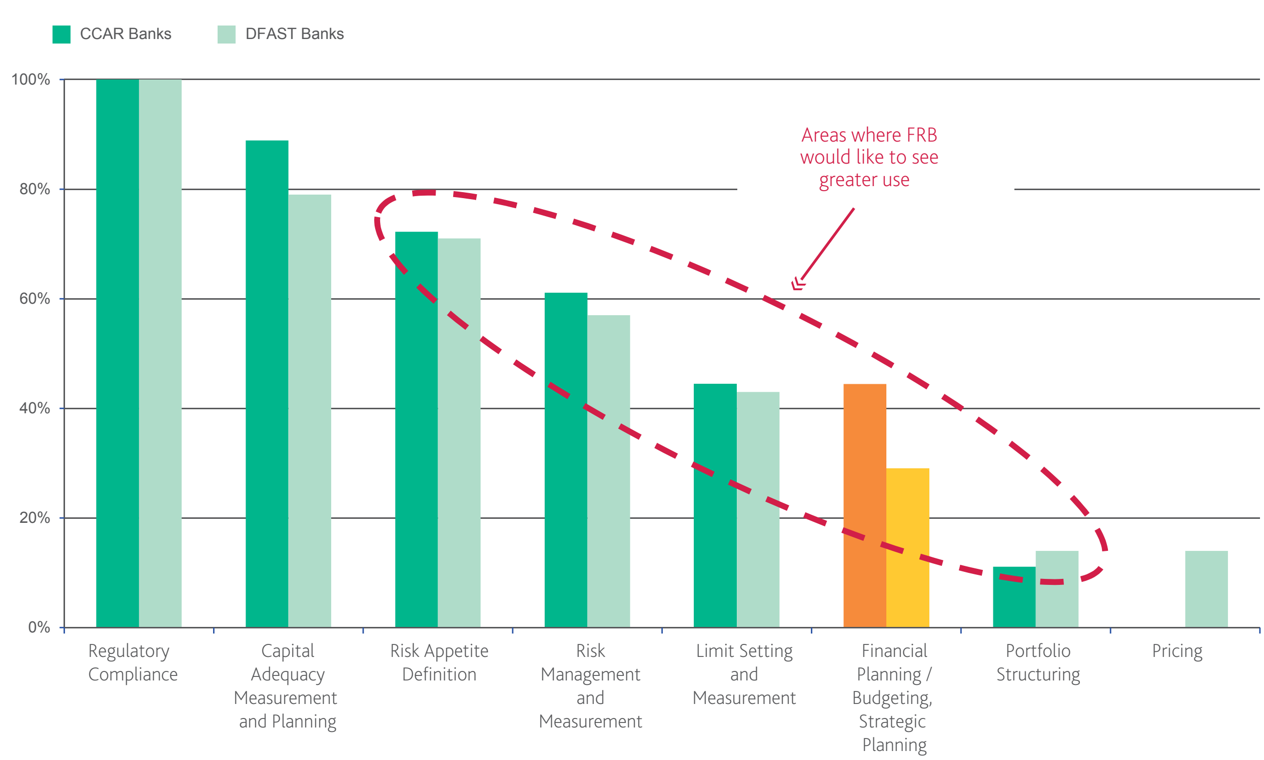
The tactical approaches many organizations use to meet such increasingly complex regulatory and accounting requirements don't necessarily include the strategic investments critical to delivering a more sustainable and cost-efficient business model. Compliance strategies that address only current needs could lead to unintended downstream consequences and additional costs. As we've shown, this process isn't straightforward; it is iterative and complicated, and requires substantial time and labor, all of which makes it hard for banks to see beyond the primary goal of satisfying regulatory requirements and thus to realize secondary benefits or find alpha in the process.

Making the process repeatable, in addition to streamlining it, will minimize the time and cost of the exercise. It also allows for more what-if and sensitivity analyses, which can provide more clarity into the bank's forecasts and improve its test results.

### Stress testing results: a missed opportunity

Stress testing should be seen within the wider context of the efforts banks put into improving their risk management capabilities. Banks face a number of common challenges, including the following:

**Figure 4** Uses of a stress testing program




Source: Moody's Analytics

- Significantly enhancing data and systems
- Improving risk governance and board oversight
- Integrating approaches to risk management
- Enhancing stress testing methodology
- Changing stress testing processes and operating models
- Extending reporting capability

Ideally, overcoming these challenges would allow banks to derive value from their stress testing programs beyond merely responding to regulatory requirements and passing tests – but this is seldom the case. Last year, we conducted surveys of large and mid-sized banks in the US. As Figure 4 shows, one question we asked was how the banks were using their stress testing programs.

When we asked the banks what they were using their stress testing results for, they all said regulatory compliance; most also said capital planning. But the degree to which banks use stress testing results quickly drops off after that. Not only did fewer banks mention that they were using stress testing for other purposes, such as financial planning and budgeting, but the ones that did were much less emphatic about how they used stress testing in these areas compared to compliance.

Regulators have indicated they would like to see banks use stress testing for other things, like risk appetite definition, limits, and risk management in general. Unfortunately, there seems to be a long way to go before banks start incorporating stress testing into their business in these areas. Many simply don't have the time or resources to go beyond the regulatory requirements.

If risk managers did see ways to derive insights from stress testing that could help them run the bank, this would be a form of alpha. But for the most part this isn't the case, and any value realized beyond satisfying compliance goals would thus be hard to quantify.

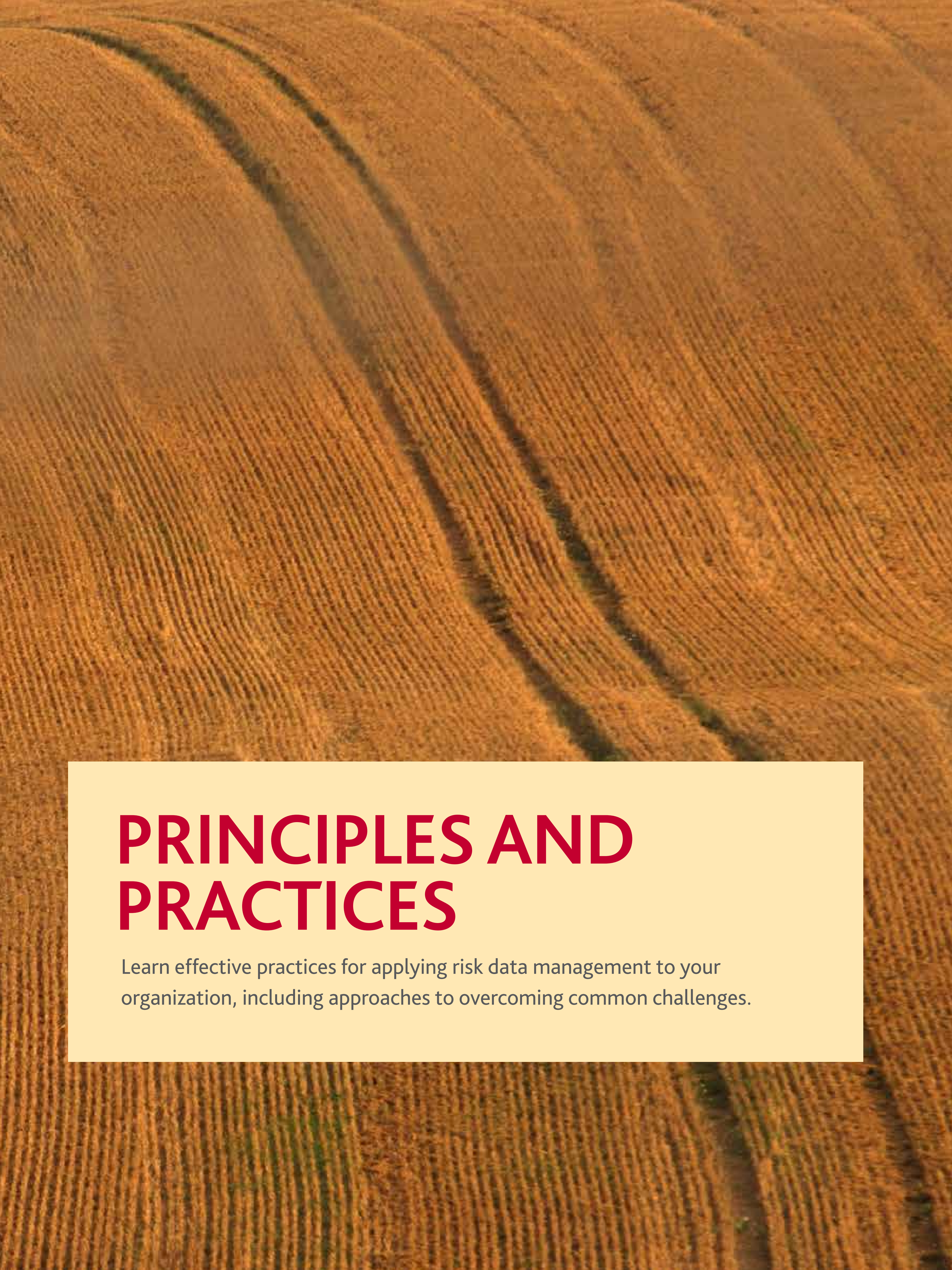
## Conclusion

Making the process more efficient – easier and less time-consuming – will mean that stress testing takes up less of a bank's resources. So perhaps this is where banks can start to look for alpha. Saving time for key resources by making the stress testing process more business-as-usual means a bank's key people can stop "working for the regulators" and have more time to be creative and focus on the business of the bank.

Developing automated, well-governed processes for stress testing will lead to better results with more transparency, auditability and repeatability, and in less time. Banks will be even better positioned to achieve the primary goal of compliance, with less cost and effort.

Integrating the best practices outlined in this article can help banks streamline their processes, freeing up time for key resources. That is, they may change their stress testing race course, making it easier and faster to run through, and find their stress testing alpha.

1 Jamie Dimon, ***Annual letter to shareholders***, p12, April 9, 2015. He mentioned the cost of stress testing at JP Morgan.



# PRINCIPLES AND PRACTICES

Learn effective practices for applying risk data management to your organization, including approaches to overcoming common challenges.

# MODELING TECHNIQUES AND TOOLS IN SCENARIO-BASED RISK APPETITE MANAGEMENT

By Pierre Gaudin

**Pierre Gaudin**
*Senior Director, Enterprise Risk Solutions, APAC*

Pierre is in charge of strategic initiatives in Asia-Pacific for risk appetite management, stress testing, and origination at Moody's Analytics, assisting with subject matter expertise, clients requirement analysis, and use case illustrations.

To get senior stakeholders to buy in to alternative macroeconomic scenarios, risk management and ALM teams must assemble risk models and risk-adjusted performance measurements in their simulation tools. Institutions must switch from a qualitative to a quantitative approach to analysis so they can effectively define risk appetite. This article addresses these issues, as well as building repeatable measurements, resolving data gaps, using data flow automation tools, and implementing processes to enforce and monitor such measurements.

## Introduction

The regulatory stress testing requirements that have been published in the US, Europe, and soon in Asia-Pacific are increasingly guiding financial institutions toward scenario-based governance and risk appetite management. From an internal practice perspective, management information reports are now expected to articulate a consistent set of profitability and risk forecasts for different time horizons. Governance practice is therefore shifting from a qualitative approach to a quantified framework, which evaluates the sustainability of the institution's compliance and ability to deliver value to its shareholders, through the cycle.

The overarching goal of a risk appetite framework is to provide senior management with a quantitative assessment of profitability, budget, and dividends in different macroeconomic assumptions. Such a framework outlines a variety of scenarios (e.g., US liquidity crisis, euro zone sovereign default, or a recession in China) and provides potential mitigation actions. Institutions can then make a decision, taking into account the cost of hedging compared to the likelihood and severity of the scenario. For example, the cost of a sovereign credit default swap may be measured against the probability-weighted losses incurred in a sovereign-default scenario.

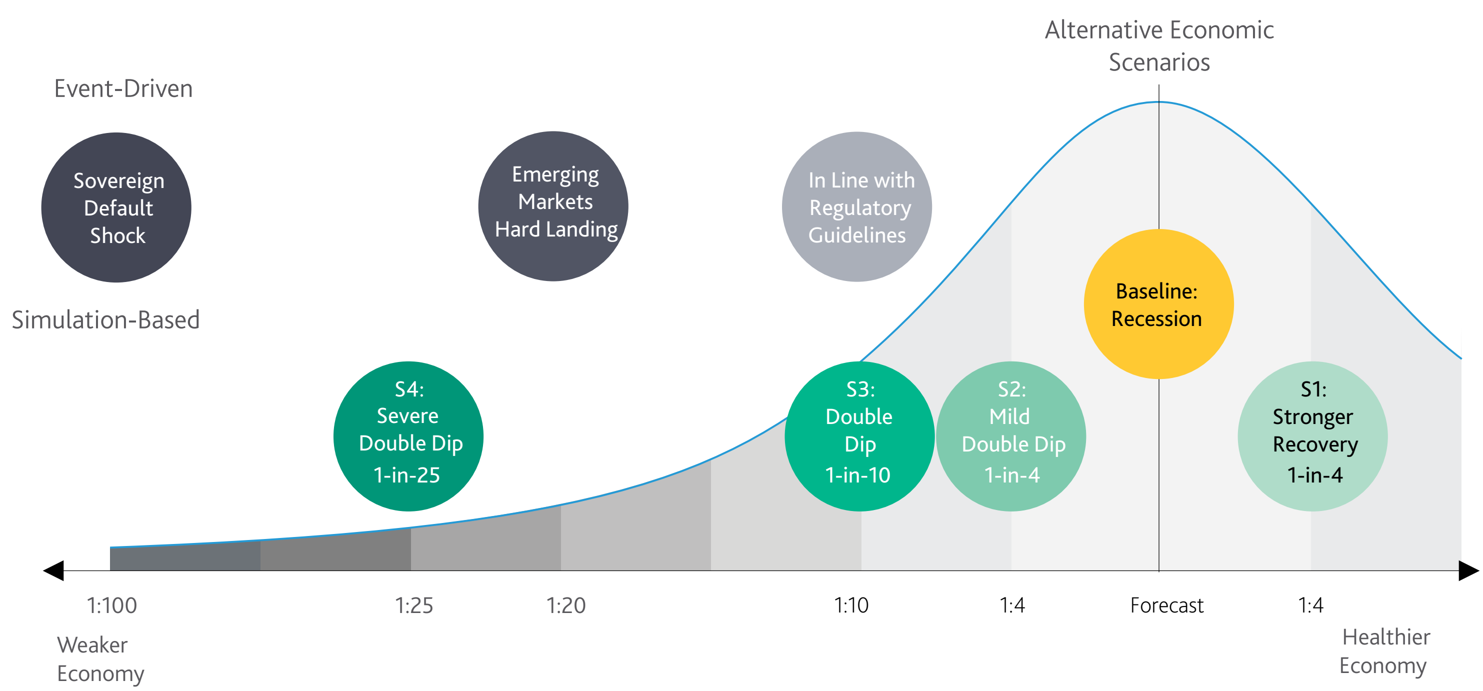
Synchronizing profitability with risk forecasts in a macroeconomic scenario presents a significant organizational challenge. Indeed, aside from combining simulations across risk management and asset and liability management systems, measurements need to account for the consistent effects on market factors, credit transitions, and transaction volumes across the usual organizational silos. This challenge sometimes attracts such focus that key project risks are overlooked, such as data gaps.

## Scenario narrative and likelihood calibration

Scenario narrative and severity have traditionally been expressed in terms of frequency, such as once-in-seven years market downturn, once-in-twenty-five years commodity crisis, or once-in-a-hundred years sovereign default. This practice, however, has reduced stress testing to a repetitive exercise, lacking the ability to account for the evolution of the economy from its current state, worldwide and locally.

A more informed approach consists of centering the construction of scenarios around a baseline

**Figure 1** Calibration of scenario likelihood around a baseline consensus




Source: Moody's Analytics

outlook, representative of the economists' consensus, increasing the relevance of the stress testing exercise to the current situation. Revisited monthly or quarterly using the latest macroeconomic data and economists' opinions, alternative macroeconomic scenarios are then built using stochastic analysis, whereby shocks are applied throughout global macroeconomic models and measured against the contours of previous business cycles. As a result, each scenario is calibrated in terms of likelihood against the distribution (Figure 1).

portfolio indicators, scenario definitions need to be assorted with observable time-series of macroeconomic and market factors that can be drilled down geographically to country and city levels.

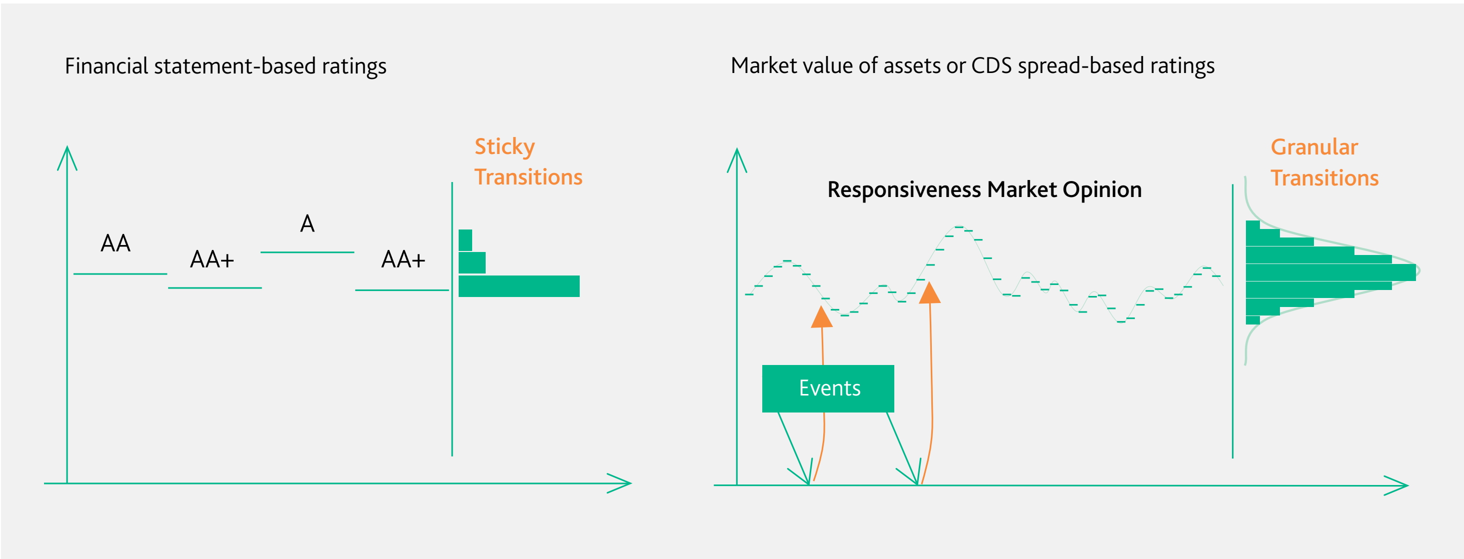
This framework can also be used for regulatory scenarios such as the Federal Reserve's Comprehensive Capital Analysis and Review (CCAR) scenarios, the Financial Services Authority's Anchor scenarios in the UK, the European Banking Authority's stress scenarios,

> Credit time-series augmentation techniques that use credit estimates based on market prices can significantly improve credit, liquidity, and profitability models leveraged in the risk appetite framework. These techniques are available not only for publicly listed firms, but also for private firms and small- and medium-sized enterprises, as well as sovereign entities.

With this method, each scenario deemed relevant by senior stakeholders can be extracted from the distribution, along with the economic narrative explaining the possible causes of the scenario compared with the baseline outlook. Ideally, to allow meaningful regressions to key

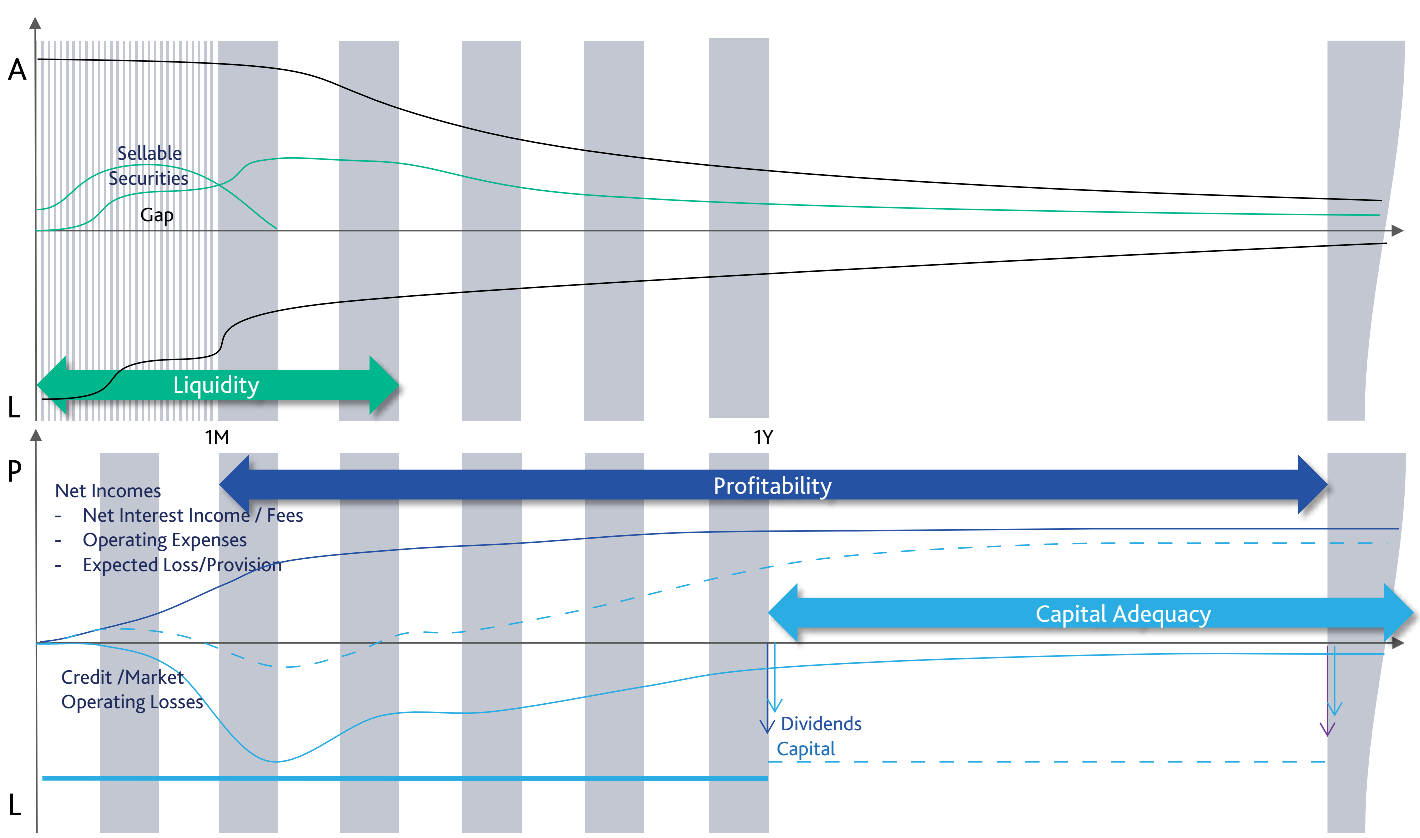
the International Monetary Fund's scenarios, as well as others proposed by local authorities. Using the same approach, banks can benchmark and leverage regulatory scenarios throughout the stress testing exercise using a single framework.

**Figure 2** Interpolating internal ratings with market-price-driven credit time-series




Source: Moody's Analytics

**Figure 3** Key portfolio indicators at different time horizons




Source: Moody's Analytics

### Resolving data gaps

A key aspect emerging from the practical application of regulatory stress testing is that risk and performance models need to establish how credit behaviors, liquidity cash flows, market risks, profitability, and budget forecasts are related to macroeconomic time-series, by leveraging the historical time-series observable in the portfolio. While most of this data can be well described, for most institutions the only source of credit data is related to their internal ratings practice, which is based on quarterly financial statements. With at most one point per quarter, the resulting credit time-series imply very static and insensitive credit behaviors, leading to significant noise both in the elasticity models of credit transitions and in the evaluation of correlations. This affects not only credit forecasts, but also the subsequent liquidity behavioral models, which are based on credit ratings, as well as profitability adjusted for credit losses.

Analysts often assume that the best data available inherently includes such data gaps and time-series deficiencies. However, experience in loss forecasting shows that under-sampled historical time-series have a significant impact on the consistency of model outputs. Practitioners faced similar challenges in modeling forecast losses in economic capital measurement. As a solution to data gaps, time-series augmentation techniques have proved efficient in delivering consistent reports over time. This is even more relevant considering that regulators have used this technique to calibrate current parametric regulatory functions.

Overall, project risks due to data gaps in credit time-series cannot be overstated. Traditional modeling and simulation practices for liquidity and risk-adjusted performance measurements need to be revisited so as to allow a proper scenario-driven forecast.

Credit time-series augmentation techniques (Figure 2) that use credit estimates based on market prices can significantly improve credit, liquidity, and profitability models leveraged in the risk appetite framework. These techniques are available not only for publicly listed firms, but also for private firms and small- and medium-sized enterprises, as well as sovereign entities.

Experience shows that this approach can deliver robust statistical regressions against macroeconomic assumptions, as well as correlations, providing for consistent forecasts over different time horizons. It ensures quality and repeatability, allowing senior stakeholders to understand trends, acquire reference points, and build trust in the numbers and practice.

> On the technology side, data flow automation is becoming increasingly necessary. Institutions are streamlining their computation flows for both internal and regulatory purposes, in areas of strategic planning, credit portfolio management, asset and liability management, and liquidity risk management.

### Forecasting key portfolio indicators

Scenario-based risk appetite management leverages multiple measurements according to different time horizons: short-term liquidity compliance, medium-term net revenue, income volatility, dividend sustainability and, in the long-term, capital adequacy (Figure 3). These reports require a comprehensive description of risks that examines the relationship between macroeconomic factors and key portfolio indicators.

In liquidity modeling, the behavior of a counterparty depends highly on its own credit situation. Therefore, forecasting behavioral cash flow demands a precise description of credit transitions. This is illustrated, for instance, in regulatory liquidity coverage ratio (LCR) calculations, in which the eligibility of bond positions for the liquidity reserve is tied to the credit assessment of the issuer, and in which inflows and outflows depend on the past-due status of the contracts. As a result, the accuracy of liquidity-monitoring models depends on the ability to evaluate realistic credit transitions over a time horizon as short as 30 days. The use of quarterly financial statements can lead to a significant underestimation of volatility. Overall, credit and behavioral models are reflected at each time horizon, impacting liquidity, then profitability, and – as a consequence – capital adequacy and dividend sustainability (Figure 4).

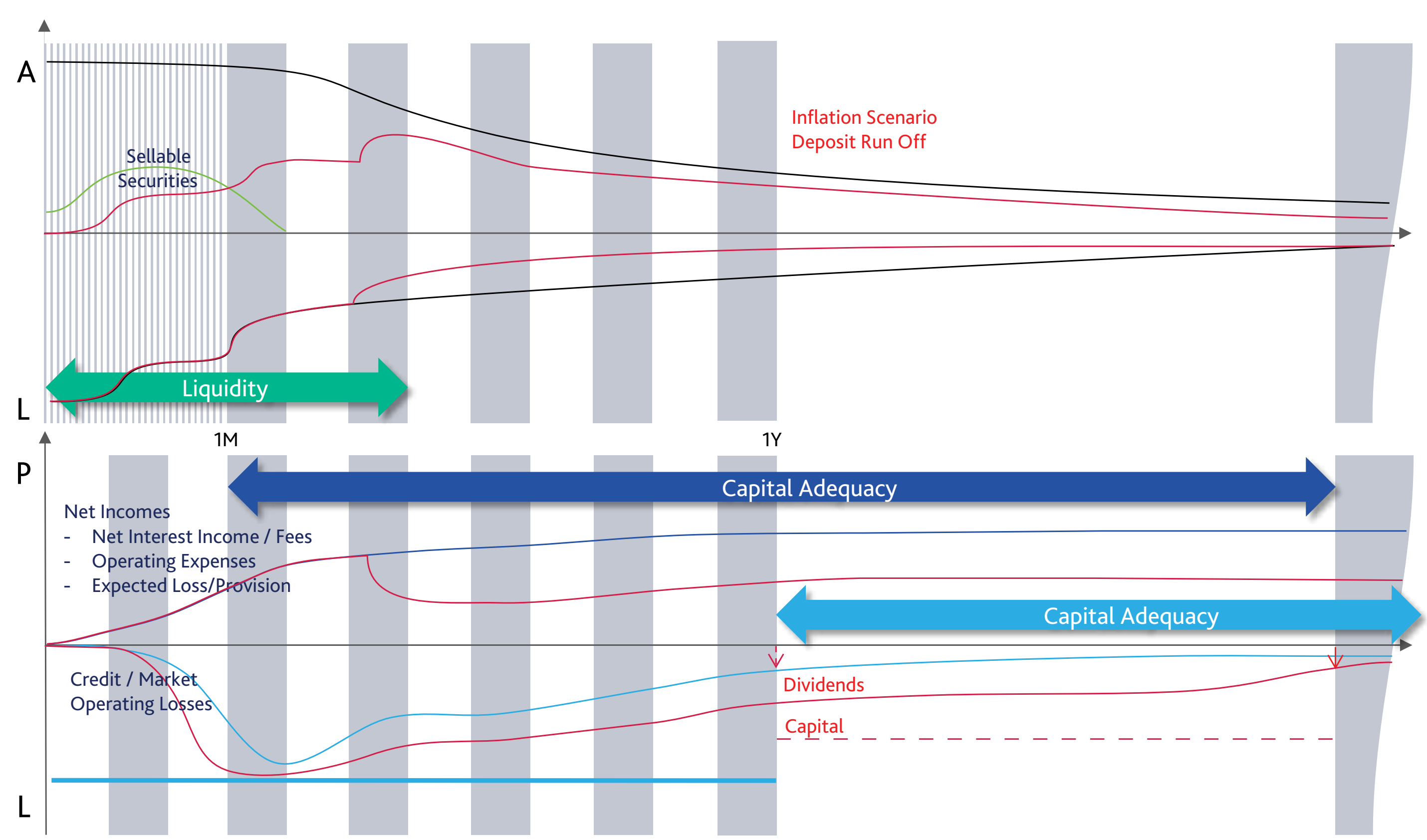
### Assessing volatility

Risk measurements in the current portfolio can generally be described as either an expected value or a value-at-risk within a risk distribution. Such a distribution is typically built on through-the-cycle assumptions, reflecting cyclical or long-run behaviors, while sensitivities are assessed by applying calibrated shifts on market data.

In stress testing, however, whether key portfolio indicators represent a median or a tail-risk assessment, forecasting models typically provide expected outcomes for each scenario assumption. In a recession scenario, for instance, an institution might forecast a decrease in the LCR to 105% within a year. In this case, a key risk managers would need to anticipate is how narrowly distributed security prices will be around the expected value, so as to gauge the likelihood that the liquidity compliance threshold will be breached, even though the expected LCR value is compliant.

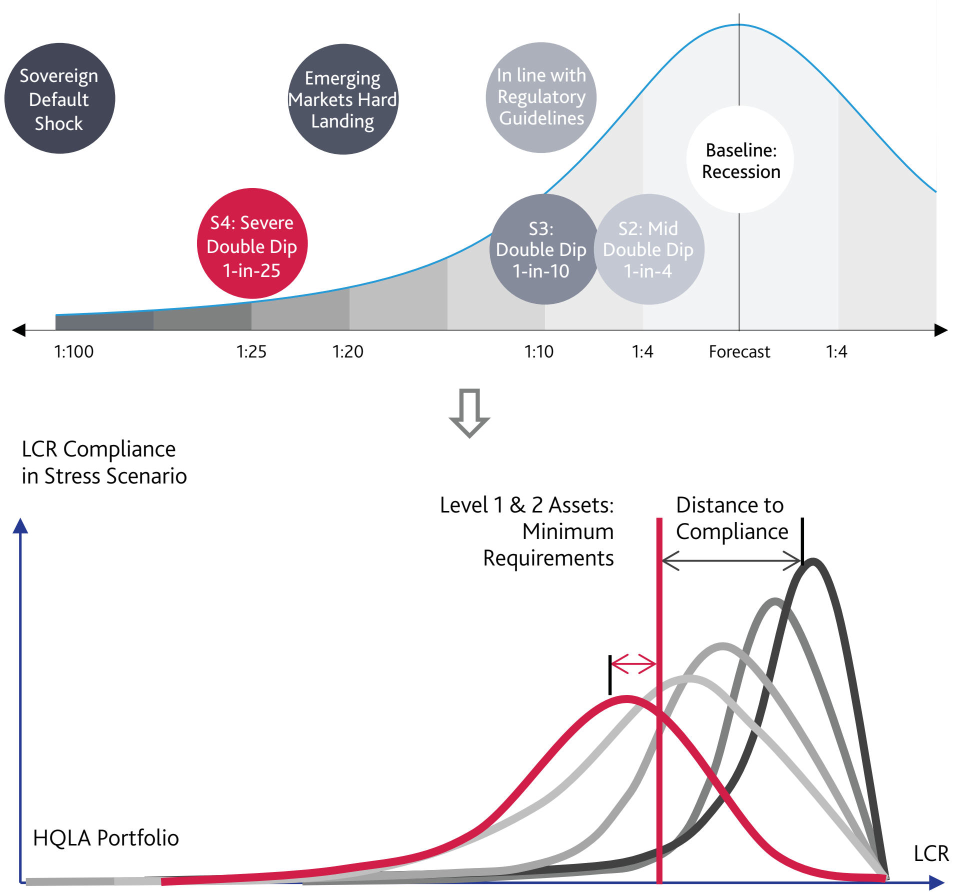
Providing this additional distribution through stochastic modeling might seem like a vast undertaking, given the wide range of simulation inputs (from macroeconomic and market factors to creditworthiness and budget figures).

**Figure 4** Key portfolio indicators under stress




Source: Moody's Analytics

**Figure 5** Impact of credit transitions on liquidity reserves volatility




Source: Moody's Analytics

However, undertaking a comprehensive Monte Carlo process across risks can lead to excessive or false precision, misaligned with the simulation time horizon and other key stress testing assumptions.

Because a key purpose of the stress testing framework is to identify and quantify outcomes of drastic but plausible situations, it is relevant to focus on the key contributors to volatility during a crisis. Spikes in market prices and credit downgrades explain a significant part of such volatility, so a stochastic simulation of macroeconomic-driven credit transitions can provide a good understanding of volatility for each risk and time horizon: short-term liquidity, mid-term profitability, and long-term capital adequacy.

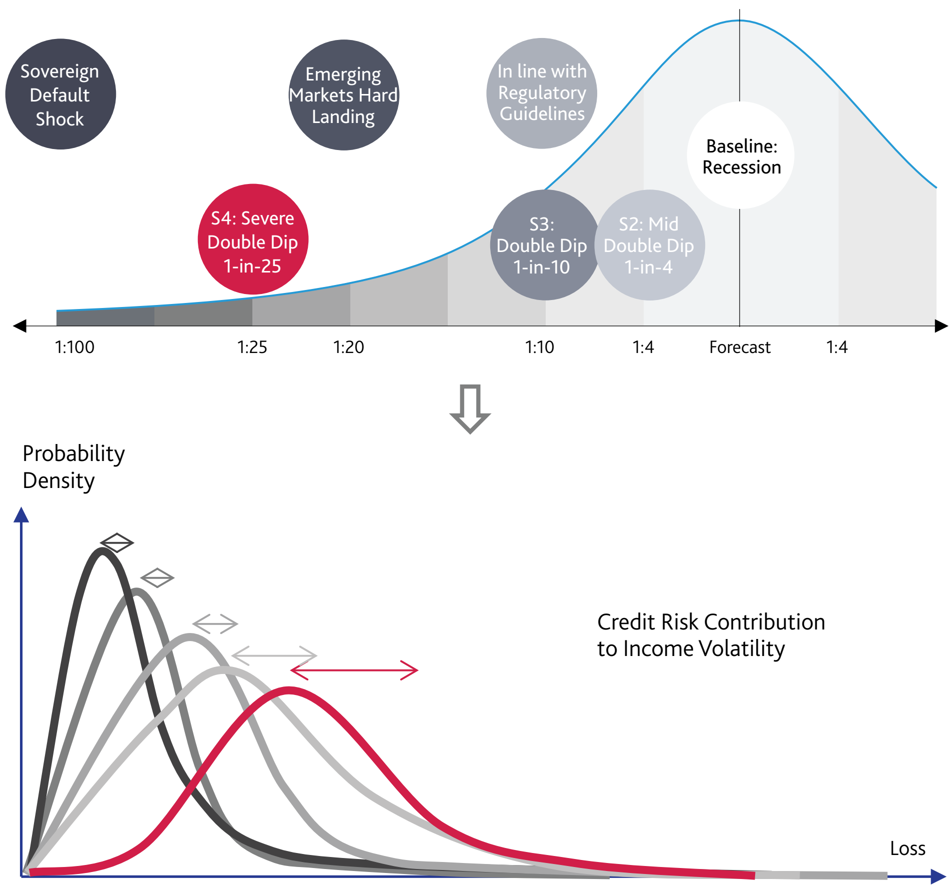
### Short-term forecasts

Credit transitions in the liquidity reserve explain a significant part of the volatility in the LCR. Even if high-quality liquid asset (HQLA) positions are replaceable, it is worth simulating how risk can build up by monitoring an extended set of positions and possible replacement issuers. For this purpose, running an analysis of credit value-at-risk on the HQLA portfolio (pre-haircut) provides a good gauge of the LCR forecast distribution (Figure 5).

### Medium-term forecasts

Analyzing earnings-at-risk traditionally encompasses gauging the adverse impact of interest rates and exchange rates onto net interest income forecasts. By adding the effect of unexpected credit losses to the earnings in each scenario, the simulation provides a comprehensive assessment of the volatility in forecast incomes (Figure 6).

**Figure 6** Impact of credit transitions on risk-adjusted earnings volatility




Source: Moody's Analytics

## Long-term forecasts

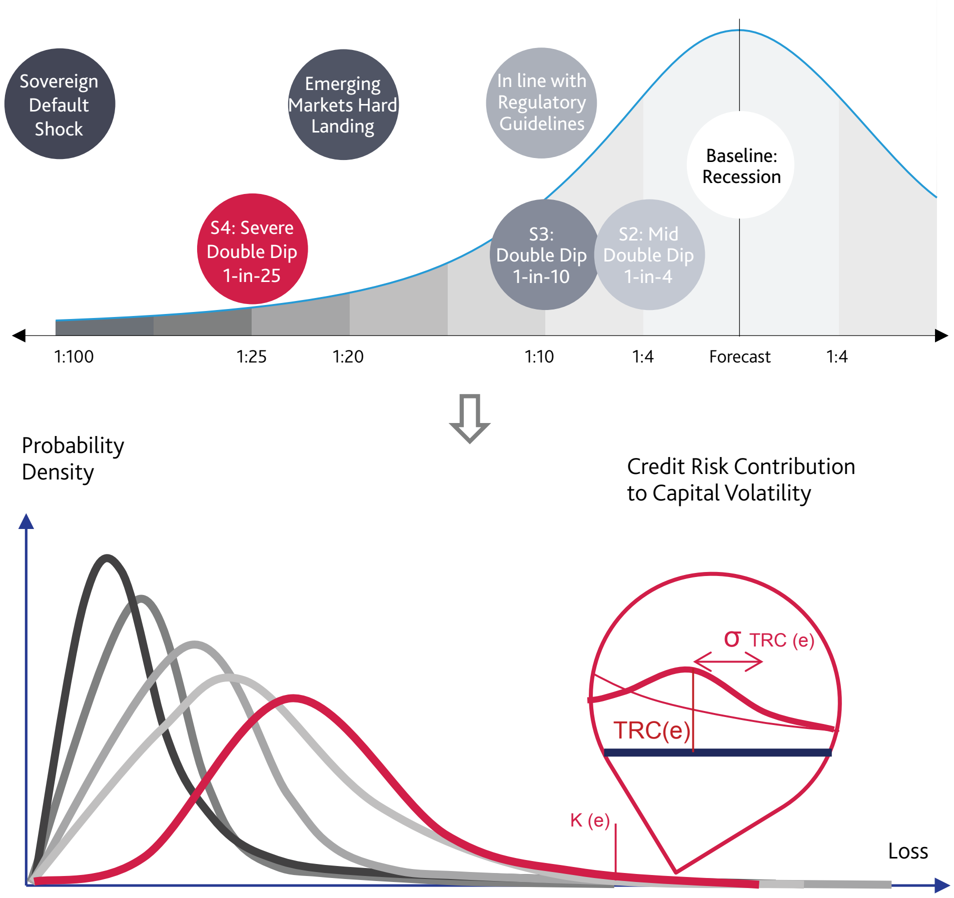
Capital adequacy is expressed through operational, market, and credit value-at-risk. Running a tail-risk simulation can help provide a credit loss tail distribution, thereby affording a clear understanding of volatility for the forecast of capital requirements.

## Conclusion

Overall, for the purpose of extending the dialogue with senior stakeholders to alternative macroeconomic scenarios, risk management and asset and liability management teams are required to work closely together to assemble risk models and risk-adjusted performance measurements in their simulation tools. Key stakeholders and supervisors need repeatable measurements, ensuring that the assumptions in the forecasts are consistent over time and allowing them to understand trends, acquire reference points, and build trust in the numbers and the practice. This process then allows institutions to switch from a qualitative to a quantitative approach to risk appetite analysis. In the modeling exercise, data gaps have a significant impact, for which best practices in econometric augmentation are a proven solution.

On the technology side, data flow automation is becoming increasingly necessary. Institutions are streamlining their computation flows for both internal and regulatory purposes, in areas of strategic planning, credit portfolio management, asset and liability management, and liquidity risk management. They are taking advantage of data flow automation tools that help institutions with regulatory and internally driven stress testing initiatives, handling scenario libraries, driving inputs for each

**Figure 7** Impact of credit transitions on capital requirement volatility




Source: Moody's Analytics

computation engine, and running parametric regression models from macroeconomic scenarios into key indicator forecasts.

The final consideration, related to a quantitative formulation of risk appetite, is the need for processes to enforce and monitor such measurements. Concentration monitoring and risk appetite limit-setting are excellent starting points. After leveraging a data aggregation initiative, a logical next step is to implement an enterprise-wide and consistent limit-monitoring framework that translates risks into exposure limits in different business lines and units, market segments, industries, geographies, and currencies. This allows risk managers and front offices to improve performance and control the build-up of risk in the portfolio at the point of origination.

# THE BENEFITS OF MODERNIZING THE COMMERCIAL CREDIT DECISIONING PROCESS

By Buck Rumely

**Buck Rumely**
*Senior Director, Client Management*

Buck leads the Americas team of credit and technology specialists at Moody's Analytics. He has helped design credit and risk management systems for a variety of financial, governmental, and energy firms throughout North and South America. He has published papers on credit risk, including *Risk Magazine*.

Regulators and auditors expect banks' data submissions to be more detailed than ever before. However, many banks still labor under outdated credit decisioning systems – black holes in which valuable loan data disappears and can no longer be used for critical processes such as stress testing. This article explains the benefits of an online decision system to deliver higher returns on risk while making regulatory compliance easier and cheaper.

## Introduction

Commercial bankers understand that granting a loan is an iterative and dynamic process, not a distinct event with a simple "yes" or "no" outcome. It involves many data inputs and outputs, as well as examination of risk and revenue tradeoffs. A facility often evolves substantially before finalization.

Traditionally, a "loan file" was essentially closed once a bank finalized the facility, made the credit decision, and released the funds. Bank credit policies typically required an annual review, at which time the bank would update the borrower rating and close the loan file for another year. Periodically – and often haphazardly – the bank's staff checked the compliance status of the loan covenants (or, being overwhelmed, ignored them). Banks rarely placed enough clean, consistent, and quality data in a searchable system to determine covenant compliance without having to manually reopen a credit file.

Today, the data from the loan decisioning process for complex commercial credit facilities is still rarely aggregated in a searchable, reportable, and auditable system – even at sophisticated banks. Instead, this data is manually loaded into Excel or Word documents from various source systems and left in flat files where it can't be re-used for more critical processes, such as stress testing, covenant monitoring, or model validation.

The data on a typical commercial loan decision document comes from many areas, including customer relationship management (CRM), core systems, deposit and exposure systems, financial statement spreading systems, and scoring systems. This aggregated information is frequently used only to facilitate credit committee decisions and is not conveniently stored in one system. Banks thus lose invaluable opportunities to repurpose a rich dataset for meaningful activities that could ultimately increase revenues and greatly lower compliance and audit costs.

## Credit decision data can help answer regulators' questions

The recent financial crisis revealed that some banks did not electronically store data from the credit decisioning process and lacked systems to track covenant compliance. In addition, regulatory expectations for data retention, storage, and reporting have grown considerably – indeed, both regulators and auditors are increasingly requiring that banks capture and store all key data points and collateral information associated with making a commercial loan decision. Antiquated and standalone systems no longer meet these demands, much less optimize revenues.

The questions regulators ask banks might seem easy, but experienced bankers know that they can be difficult to answer, owing to the limitations of their systems. Among some of the simple but challenging regulatory and audit questions are the following:

- How many loans are guaranteed by the same guarantor, for example, by a high net-worth individual or real estate developer?
- How many loans comply with covenants? How many do not?
- What credit decisioning data does the bank have for model validation?
- What is the bank's direct and indirect exposure to a given customer or financial institution?
- Can the bank stress the inputs to its rating models for enterprise stress testing?
- Can the bank recreate its rationale for a commercial loan decision?
- How many loans are related to a specific customer?
- Why does the bank have multiple spreads or credit files for a given customer? Which one is correct?

> We know of one leading commercial bank that employs 20 full time workers to aggregate and clean data in preparation for the FR Y-14Q quarterly commercial data submission. What if the bank had a clean, aggregated, and reliable source of data? Both regulatory compliance costs and data error rates would decline, and the bank would be able to more meaningfully deploy resources to more profitable tasks.

### Enter the era of modern online commercial credit decisioning

Answering these questions is challenging, but improving the credit decisioning process will make it easier and will also provide banks a number of benefits, among them:

- Faster loan approvals, which will increase the bank's loan closure rate and throughput
- Automated covenant monitoring and reporting
- Lower regulatory compliance costs
- Ability to re-use origination data for stress testing and model validation
- More consistent underwriting and better return on risk

We will examine each of these benefits in detail, as well as some of the challenges that banks may encounter when switching their systems.

### Faster loan approvals increase loan closure rates and productivity

Loan approvals often face bottlenecks, whether from multiple approval requirements because deals exceed credit authority or a key credit officer is on vacation. Modern credit decisioning systems can assign approvals to the appropriate credit officer and reroute requests when resources are out of the office.

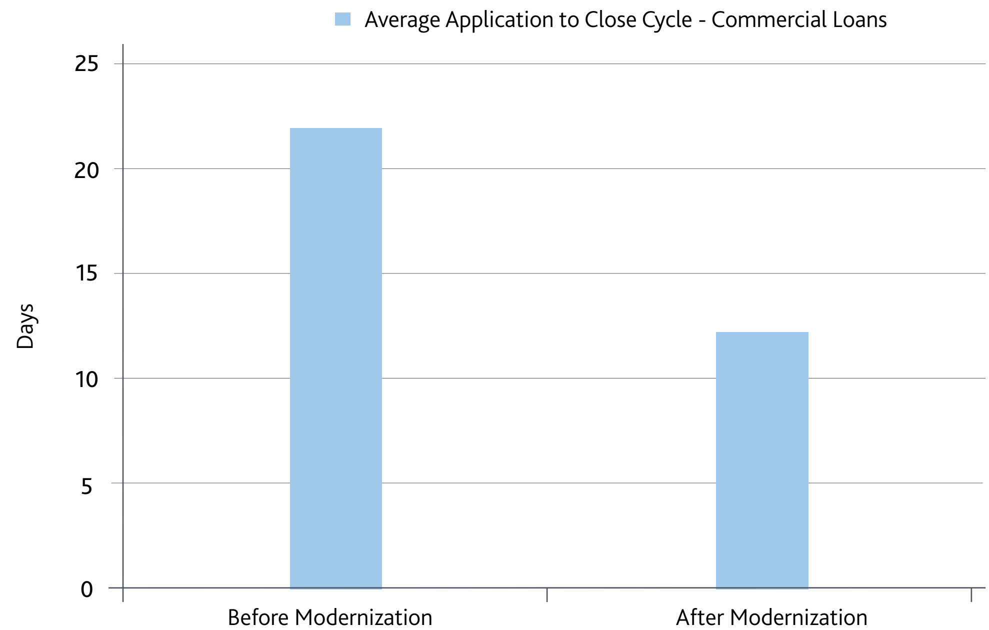
Bankers can use online technology to improve the speed and accuracy of their loan decision making process, earning them more business. Credit teams can add new approvers on the fly (or the system can do this automatically) and establish a "service level," or a schedule that outlines when the tasks required in the credit process have to be completed. For example, if the service level for financial statement spreading and analysis is four hours, the deal team can expect turnaround within that time span. Service levels can be tracked to identify bottlenecks and improve productivity.

These and other process efficiencies can shorten the cycle for credit decisioning. If a complex commercial credit decisioning process can be cut from 22 to 12 days, productivity and profitability will increase dramatically, which could boost loan throughput significantly.

### Automated covenants monitoring and reporting

Regulators and auditors have expanded their scrutiny of covenant monitoring and reporting. For example, regulators are increasingly

**Figure 1** Decision cycle length for large commercial loans: before and after modernization




Source: Moody's Analytics

issuing Matters Requiring Attention (MRAs) to commercial banks to improve systematic monitoring and compliance reporting for both financial and non-financial covenants.

An efficient credit decisioning process will automatically capture covenants at the point of credit underwriting and monitor them throughout the life of the loan. Banks can select from a library of standard covenants or customize them for a customer's specific risk attributes. Integration with the spreading process can automatically test financial covenants when a borrower's monthly, quarterly, or annual financial statements are analyzed. Portfolio- or business line-level reports can automatically identify customers who do not meet covenant requirements. Banks can track the entire covenant resolution process – granting customers a grace period, giving them the opportunity to cure the covenant, and monitoring the cure periods – so that they can determine how to improve or expedite the process.

Moreover, having this data and history at hand provides banks another powerful benefit: They can more quickly adjust their credit policies to eliminate covenants that do not result in a meaningful reduction of risk. Imagine a credit policy with fewer but more effective loan covenants!

### Decreased regulatory compliance costs

Historically, most banks stored credit decision data and documents in an unstructured or even imaged process. Given that regulators now require more information about the rationale and all of the data involved in a commercial lending decision, however, these systems are inadequate and unable to deliver the information in the format required.

Most underwriting and decisioning systems were designed for a single purpose – credit decisioning – and not for submitting data in bulk to the regulator. This has led to banks' hiring dozens of people to cut, paste, and audit underwriting data for consistency and de-duplication as they prepare information for submission to regulators.

We know of one leading commercial bank that employs 20 full time workers to aggregate and clean data in preparation for the FR Y-14Q quarterly commercial data submission. What if the bank had a clean, aggregated, and reliable source of data? Both regulatory compliance costs and data error rates would decline, and the bank would be able to more meaningfully deploy resources to more profitable tasks.

### Re-use of decisioning data for stress testing and model validation

One essential element required for both stress testing and model validation is good, clean, standardized data. A modern credit decisioning system can deliver this data in droves to stress testing and quantitative teams, which can then build and update more powerful and relevant models.

Banks can use data validation rules in the origination process so underwriters don't mistakenly enter incorrect data. The data from credit decisioning can be used to build bottom-up or top-down stress testing models. Historical data on a borrower's financial status, loan performance, and other key data elements can be quickly exported to model development environments to build more relevant models. This lowers the costs of ad hoc data requests from quantitative teams because the system provides the crucial data to the modeling teams on the back end.

### Delivering a higher return on risk

A modern credit decisioning system can help a bank identify trends, giving it a competitive edge and boosting its commercial portfolio profits. Readily accessible portfolio-level reporting can help banks spot performance trends in borrowers' financials and also regional or industry trends.

With reliable underwriting and loan performance data and an online decisioning system, a bank can segment its portfolio by region or industry and quickly analyze data and identify bright spots in the market. For example, during the financial crisis, many banks abandoned commercial real estate owing to the housing market crash; medical office loans, however, performed well – throughout the crisis. Banks can adjust their industry and regional portfolio composition to beat the competition in promising market segments.

### Conclusion

A modern, more powerful on-line credit decisioning process can help improve a bank's commercial portfolio performance, no matter the economic condition, through a combination of increased revenue, process efficiency, and lower regulatory compliance costs.

#### DATAMARTS OVER DATA WAREHOUSES

Many banks assume that an enterprise data warehouse will help with the creation of an online decisioning system. Despite heavy investments in data warehouse solutions over the last 10-15 years, however, these projects have achieved only a checkered success rate. Many were too ambitious in scope, attempting to place virtually all the bank customers' data into a warehouse. Although these projects may have succeeded in their main objective of consolidating data, they did not always succeed in delivering reportable aggregated information to commercial business leaders and risk managers. One of our customers calls its bank data warehouse the "data landfill"; still others think of their data warehouses as graveyards for data that is doomed never to be seen again.

Fortunately, new reporting tools and more focused "datamarts" have evolved to fill the voids left by the large data warehouses. Datamarts and data warehouses differ in a few key attributes. Data warehouses are quite expansive, containing data from dozens to sometimes hundreds of systems, while datamarts are highly specific means of aggregating and validating data for a specific purpose.

Datamarts also typically incorporate processes to clean and validate data. Rules can be built to automatically kick out data that doesn't meet specified criteria. For example, an exposure aggregation process may have to be put into common currency through an automated data aggregation and validation process before it enters the datamart.

The other major difference between a datamart and data warehouse is the reporting capability. Because datamarts are purpose-built, standardized reports and user-friendly reporting tools can be leveraged to deliver the meaningful information users demand from the system.

Banks should utilize a data warehouse as a source of data feeding a purpose-built datamart. This will enable more informative reporting supporting business decisions.

# MULTICOLLINEARITY AND STRESS TESTING

By Dr. Tony Hughes and Dr. Brian Poi


**Dr. Tony Hughes**
*Managing Director of Credit Analytics*

Tony manages Moody's Analytics credit analysis consulting projects for global lending institutions. An expert applied econometrician, he has helped develop approaches to stress testing and loss forecasting in retail, C&I, and CRE portfolios.

**Dr. Brian Poi**
*Director, Economic Research*

Brian develops a variety of credit loss, credit origination, and deposit account models for use in both strategic planning and CCAR/DFAST environments. He is equally adept at developing primary models and validating models developed elsewhere. He also provides thought leadership and guidance on the use of advanced statistical and econometric methods in economic forecasting applications.



Most readers will remember being somewhat perplexed back in their undergraduate days by a topic called multicollinearity. This phenomenon, in which the regressors of a model are correlated with each other, apparently causes a lot of confusion among practitioners and users of stress testing models for. This article seeks to dispel this confusion and show how fear of multicollinearity is misplaced and, in some cases, harmful to a model's accuracy.


### Is a fear of multicollinearity justified?

Multicollinearity is common to all non-experimental statistical disciplines. If we are conducting a fully controlled experiment, we can design our research to ensure the independence of all of the control variables. In bank stress testing, the Fed and the general public, not to mention shareholders, would likely not approve of banks running randomized experiments to discern bank losses under a range of controlled conditions. Instead, banks must do their best to piece together the effects of a range of performance drivers with the limited actual data they have.

Many people take a dim view of multicollinearity, but we don't belong in this camp. We feel that multicollinearity, rather than being a problem, is actually what keeps risk modelers gainfully employed and enjoying life. Not only would bank stress testing, and life generally, be banal if the phenomenon did not exist, but interrelations between variables would not be possible. Under these circumstances, there would be no need for expert statisticians – even bankers could conduct stress testing! (Personally, we wouldn't want to live in such a cruel dystopia.)

Multicollinearity makes estimating individual model coefficients imprecise. Say we have two highly correlated regressors. For some purposes it often suffices to include only one in our final model of the dependent variable, even if the unknown "true model" actually contains both. We are seeking to explain variations in the dependent variable using signals gleaned from variations in the independent variables of the regression.

If these signals are, for all intents and purposes, identical, we don't need both regressors to adequately capture the signal. Including both will lead to a "competition" between the variables, and they will crowd each other out. Though the estimates will be unbiased in the more liberally (and, indeed, correctly) specified model, the individual coefficient estimates will have high standard errors, and thus the probability of obtaining a coefficient that isn't statistically different from zero or else has the wrong sign would be high. If data are plentiful, on the other hand, we can more easily distinguish the subtle differences between the signals provided by the two variables and include both. Multicollinearity is, always and everywhere, a problem that occurs due to small sample size.

Note that we have talked only of the contributions of individual variables. If the aim of the exercise is forecasting – for which the loss function is specified solely in terms of forecast errors – multicollinearity can be rendered a second-order problem. If we have two highly correlated variables (say, r = 0.99), and we compare the model estimated using both with a model estimated using just one or the other variable, we will find that baseline projections from the models will usually be very similar. Although the individual contributions are estimated imprecisely, the joint contribution is not. If the sole aim of the model user is forecasting (of which stress testing is a recent but important sub-discipline), the choice between a one- and a two-variable model is largely immaterial. Unnecessarily including the second regressor leads to a small efficiency loss (i.e., one degree of freedom), but in the grand scheme of things this is hardly worthy of consideration.

Multicollinearity is more of a problem if the aim of the model is to conduct some form of structural analysis. If we are testing an assertion about the relationship between one of our correlated factors and the dependent variable of interest, too much multicollinearity will tend to drain away the power of the statistical test used for this purpose. Tightly specifying a model and leaving out variables that should be there will typically distort the test's size. The upside of this trade-off is that practitioners have more power in conducting their tests.

Validators and examiners should carefully consider the aims of the model when determining whether fear of multicollinearity is justified for model builders.

## Model risk and multicollinearity

Now let's consider cases where worrying about multicollinearity can increase the prevalence of model risk. We use "risk" here in the traditional statistical sense – the expected value of statistical loss across repeated samples. The risk function we use here, assuming squared error loss, is a variation of that discussed in Hughes (2012):

$$\lambda_{\mathrm{BL}} \left[\mathrm{E}_{\Theta} \left(y_{t+i} - \check{y}_{t+i}\right)^2 \right] + \lambda_{\mathrm{ADV}} \left[\mathrm{E}_{\Psi}\left(y_{t+i} - \tilde{y}_{t+i}\right)^2\right] + \lambda_{\mathrm{SA}} \left[\mathrm{E}_{\Omega}\left(y_{t+i} - \bar{y}_{t+i}\right)^2 \right]$$

where $\lambda_{BL} + \lambda_{ADV} + \lambda_{SA} = 1$ are a series of weights that indicate the relative importance of correctly projecting credit losses (or PDs, LGDs, volumes, etc.) in the various Fed's Comprehensive Capital Analysis and Review (CCAR) scenarios. Expectations are conditional on the relevant Fed scenario actually playing out, and the forecasts (conditional on the relevant scenario) produced are based on the information available at the time.

We view as reasonable the assumption that $\lambda_{BL} = \lambda_{ADV} = \lambda_{SA} = 0.33$, though, admittedly, the

Rather than considering multicollinearity to be a phenomenon that always increases model risk, validators should instead try to discern the optimal level of multicollinearity in models.

Stress testers may well be interested in conducting this type of structural analysis. For example, a bank may be interested in finding out the main driver of a portfolio's behavior, unemployment, or household income. **This function should, however, be considered separately from the broader problem of projecting future behavior under assumed stress.** There are, to our knowledge, no regulatory dictats against stress testers using a "horses for courses" approach to model selection and keeping a stable of models designed for different purposes (so long as these are well documented and well understood).

majority of banks tend to give the adverse scenario less weight than the severely adverse scenario under most circumstances. Fed examiners are well known to also give the baseline scenario considerable weight in their deliberations. (In reality, the risk function must also accommodate idiosyncratic scenarios designed specifically for each bank, but we are leaving that out of our analysis for clarity's sake.)

To further set the stage, assume that the true data generating process (DGP) is a function only of an unknown subset of the variables published annually by the Fed. In reality, of course, this process is likely to be infinitely more complex than implied by this simple assumption. Suppose, unbeknown to the modeler, that the correct specification includes only the unemployment rate, the rate of GDP growth, and the interest rate on ten-year treasury bills.

The following statements about this situation are all true:

1. A model that contains only the three variables in the DGP will minimize overall model risk.
2. Any model selection procedure established within this framework will have a non-zero probability of selecting an incorrect model.
3. If we select a model that includes not just the three variables, but also additional extraneous variables, our model will still produce unbiased forecasts in all three scenarios, but the forecasts will not be accurate, as discussed above.
4. If the selected model excludes one or more of the three variables, projections in all three scenarios will be biased and inconsistent. This situation could yield efficiency gains in parameter estimation, but these are likely to be modest, given that the efficiency of a biased parameter estimate is unlikely to be optimal.

simulations, later in this article.

The standard fix for multicollinearity is to drop some of the correlated regressors, but doing so is risky because it increases the probability of making errors like that described in (4). If we estimate a model and find that one variable, intuitively viewed as important, has an estimated coefficient with a p-value of 0.07, should it necessarily be dropped? In our view, removing the variable is riskier than keeping it. Does the universal application of a 5% significance level really minimize overall model risk when the ultimate goal of the model is to provide stress projections?

**Rather than considering multicollinearity to be a phenomenon that always increases model risk, validators should instead try to discern the optimal level of multicollinearity in models.** Models that are specified extremely tightly are next to useless when seeking to understand the effects of a range of idiosyncratic stresses on the portfolio. Likewise, models of the "kitchen sink" variety are unlikely to be very useful since many of the drivers will be found to be insignificant. The best model will be a liberally specified one, but where the liberty is not abused.

> Our small Monte Carlo study has demonstrated in the clearest way possible that extreme forecast bias is most likely when historical relationships shift and key variables are removed from regressions merely because they are insignificant.

In weighing up the relative costs of the errors made in (3) and (4), the risk of (4) is likely to exceed the risk of (3). From a forecasting perspective, this must also be considered alongside Hughes' (2012) observation that input forecast errors aren't possible when computing stress tests that are conditional on a stated macroeconomic scenario. The implication of these observations is that when high levels of multicollinearity are present, the practitioner should still tend to err, at the margin, in favor of the more liberally specified model. We will explore this question, using Monte Carlo

### Shifts in historical correlations

A more pressing issue has to do with scenarios involving shifts in historical correlations between variables. What we mean here are situations in which, for example, two variables have historically been positively correlated but where the Fed, in its infinite wisdom, gives us a scenario in which the two variables move in opposition to each other.

It is crucial that we know how to deal with these situations, as no one knows the nature of the next stress event. Stress test models should be able to cope, at least reasonably well, with unusual happenstances. Models that can only cope with a repeat of the Great Recession and nothing else are next to useless.

We do not need to look far to find a situation in which historical correlations shifted in this way. In recent years, during the 2000s and 2010s, the U.S. Phillips Curve has been modestly negatively sloped. Between January 2000 and November 2014, the correlation coefficient between the unemployment rate and the year-over-year rate of consumer price inflation has been -0.51. In the Fed's baseline scenario published in October 2014, the correlation between the two variables is -0.72 across the nine-quarter forecast window, and in the severely adverse scenario, the figure is -0.41. In these scenarios, the Fed is saying that Phillips Curve dynamics basically mimic those of recent history. The adverse scenario is completely different; in this case, the correlation is +0.97 across the nine-quarter scenario window. To put this into context, during the 1970s – considered the stagflationary nadir by most right-thinking economists – the correlation between the two variables was a mere +0.14.

Now suppose that the true DGP for the probability of default (PD) for a particular portfolio is a function only of inflation and the unemployment rate. We set the parameters of the model to be -2 for inflation and 2 for unemployment, and then simulate data for PD assuming a simple linear functional form and normal errors. Normally, in a model of the default likelihood of fixed repayment loans, we would expect the unemployment rate to be positively signed in our regression and the inflation rate to be negatively signed. Inflation, after all, reduces the burden of nominal principal and interest payments as nominal income rises at a fast clip. Inflation should therefore act to mitigate against the effect of stress, and projected real credit losses should be lower than expected because of increases in the actual unemployment rate.

Such a simple data generating process can throw off unrealistic results – like negative default rates – but we want to keep this exercise as straightforward as possible. We first fit the model containing both variables and exclude any that we find to be insignificant at the 5% level using a standard t-test; we labeled the model selected using this procedure "Chosen." We then compared the forecasting and stress testing performance of the chosen model with those based on a full model. Table 1 shows results for this simple experiment, assuming 5,000 replications.

**Table 1** Forecasting and stress testing performance: comparing the chosen and full models

| | CCAR Baseline | | | CCAR Adverse | | | CCAR Severely Adverse | | |
|---|---|---|---|---|---|---|---|---|---|
| | E(Bias) | E(RMSE) | E(MAPE) | E(Bias) | E(RMSE) | E(MAPE) | E(Bias) | E(RMSE) | E(MAPE) |
| Full | -0.006 | 0.142 | 1.133 | 0.000 | 0.635 | 1.368 | -0.004 | 0.467 | 1.310 |
| Chosen | -0.176 | 0.196 | 1.459 | 0.388 | 1.034 | 1.988 | 0.060 | 0.602 | 1.573 |

Source: Moody's Analytics

We found that the correct full model is chosen 59% of the time. Overall, the inflation coefficient is statistically significant in around 67% of cases, whereas the unemployment rate coefficient is significant 91% of the time. As might be expected, always choosing the full model yields forecasts that suffer no appreciable bias in any of the three scenarios. Zero bias here means that the conditional forecasts produced by the model are, on average across the nine-quarter forecast window, neither too high nor too low when compared to the expected outcomes of the target variable.

The situation changes quite noticeably when we look at the performance of the chosen model. Predictions from this model are too low under baseline conditions and too high in both stressed scenarios. In the severely adverse case, the bias is only slight, but in the adverse case the levels of overprediction are extreme. When we consider root mean squared prediction error (RMSE), whereby the improved efficiency of the smaller models may compensate for the effect of bias, we find that, in all cases, using the full model yields substantially smaller forecast errors than the selected model.

Because the historical correlation between the two variables is preserved in both the baseline and the severely adverse scenarios, we have a pretty good shot at getting decent projections using an incorrectly specified model that excludes one of the variables.

In the adverse scenario, however, the situation changes markedly. In Fed's adverse scenario, increases in the unemployment rate, which would normally be accompanied by declines in inflation, are now accompanied by rising inflation. Removing the inflation variable from the model means that the historical effects of inflation are conflated with correlated unemployment effects, and the coefficient on the unemployment variable is far higher than it should be as a result. We are powerless to capture the mitigating effect of inflation, and our projections suffer alarmingly as a result.

One could argue that the misspecified model here is more conservative but we think that misses the point. The idea of modeling should be to derive an accurate, unbiased view of reality. Users of models can always apply conservative assumptions to arrive at appropriately austere stress test results.

## A fuller exposition of the problem

In the preceding discussion, two features might have immediately jumped out at the reader. The first is that the framework is so simple that it bears no relation to the difficult task of CCAR-style stress testing. The second point is that the experimental set-up explicitly favors the larger model, as it is the only correctly specified model in the choice set.

We now address those points by extending our experiment to consider a true DGP that contains three factors and has five potential regressors in our variable selection choice set. The true model, as before, contains unemployment and inflation, to which we add GDP growth with a parameter of -2. The choice set contains these three variables as well as the Baa spread and the ten-year treasury interest rate.

As before, we select a model by excluding any variable that is found to be statistically insignificant at the 5% level and compare this with the strategy whereby the full model (containing all five variables) is used every time. Again, we are interested in the observed bias and RMSE of the calculated projections in the three Fed scenarios. The results are contained in Table 2.

In this case, the full model is potentially at a disadvantage because it always contains two extraneous variables. This has no effect on forecast bias, however, since the estimated model encompasses the true specification. In all scenarios, the full model suffers effectively zero bias.

**Table 2** Forecasting and stress testing performance: fuller comparison of the chosen and full models

| | CCAR Baseline | | | CCAR Adverse | | | CCAR Severely Adverse | | |
|---|---|---|---|---|---|---|---|---|---|
| | E(Bias) | E(RMSE) | E(MAPE) | E(Bias) | E(RMSE) | E(MAPE) | E(Bias) | E(RMSE) | E(MAPE) |
| Full | 0.028 | 6.308 | 5.143 | 0.035 | 6.767 | 5.538 | 0.018 | 7.507 | 6.197 |
| Chosen | -7.078 | 13.070 | 11.927 | -8.616 | 16.006 | 14.858 | -9.289 | 16.691 | 15.265 |

Source: Moody's Analytics

In this case, our simple model selection procedure yields the correct model (that which contains the three factors) only 15% of the time. More often, one or more of the true factors is missing from the selected model. In 50% of the simulations, one factor is missing; in 29%, two of the important factors are erroneously excluded from the model. This demonstrates a key result of model selection – that, as the choice set expands, the probability of correct selection declines rapidly to zero. In only 3% of the simulations does the model include too many factors. The full model, containing all five variables, is selected by this simple t-statistic-based procedure a mere 0.5% of times.

That the model selection procedure is so easily tricked into excluding important factors is a likely outcome in the presence of multicollinearity.

In this experiment, we find that the selection procedure yields models that produce projections that are consistently too high. Bear in mind that this is a function of our experimental design; we could have just as easily designed an experiment with bias of the opposite sign. Looking at RMSE, we find that the model selected on the basis of t-tests yields twice the forecast error of the "full model always" modeling strategy. Improved estimation efficiency does little to mitigate against the proximate threat of omitted variable bias caused by excluding key factors on the basis of an insignificant t-statistic.

## Conclusion

In an important sense, the results of this analysis will be unsurprising. That the issue of multicollinearity has little currency when the aim of the modeler is forecasting has been well-known for many decades. What could be an important issue for structural analysis using regression type models is, at the margin, irrelevant to forecasters.

This is not to say that practitioners should go wild and throw as many drivers into models as they have degrees of freedom available to model them. If our advice is taken to the extreme, efficiency losses will become large enough to outweigh any gain from a reduction in the threat of omitted variable bias. At the margin, however, looking at a t-statistic of 1.7, or even 1.2, should hold few fears for model validators, so long as inclusion of the variable is logical and intuitive.

If our aim was only to conduct baseline forecasting, multicollinearity would be, at best, a second-order concern. Here, though, we are interested in stress scenarios, in which regulators and senior managers will regularly throw curveballs involving shifts in historical relationships. In this case, a fear of multicollinearity can be positively harmful. **Our small Monte Carlo study has demonstrated in the clearest way possible that extreme forecast bias is most likely when historical relationships shift and key variables are removed from regressions merely because they are insignificant.** To capture nuanced scenarios like the adverse and severely adverse CCAR events, or bank-specific idiosyncratic happenstances, models need to be specified quite liberally.

Ignoring this advice will not decrease model risk. Rather, it will raise that risk to potentially extreme levels.

# MULTI-PERIOD STOCHASTIC SCENARIO GENERATION

By Dr. Juan Licari and Dr. Gustavo Ordoñez-Sanz

**Dr. Juan Licari**
*Senior Director, Head of Economic and Consumer Credit Analytics for EMEA*

Juan and his team are responsible for generating alternative macroeconomic forecasts for Europe and for building econometric tools to model credit risk phenomena.

**Dr. Gustavo Ordonez-Sanz**
*Director, Stress Testing Specialist Team*

Based in London, Gustavo advises financial organizations on the different aspects of stress testing scenario analysis at the firm-wide level. This includes: scenario generation; risk, revenue, and capital modeling and forecasting; embedding scenario analysis in the firm's decision-making processes (risk appetite, portfolio management, pricing, etc.); and governance, infrastructure, and reporting.

Robust models are currently being developed worldwide to meet the demands of dynamic stress testing. This article describes how to build consistent projections for standard credit risk metrics and mark-to-market parameters simultaneously within a single, unified environment: stochastic dynamic macro models. It gives a step-by-step breakdown of the development of a dynamic framework for stochastic scenario generation that allows risk managers and economists to build multi-period environments, integrating conditional credit and market risk modeling.

## Introduction

Dynamic stress testing and multi-period credit portfolio analysis are priority areas for risk managers and academics. New methodologies and techniques are being developed across the globe, mainly focusing on building robust models that translate macro scenarios into conditional risk parameters (so-called satellite models). But a significant challenge emerges when it comes to building stochastic multi-period environments. Dynamic simulations can quickly get out of control when a modeler starts increasing the sources of uncertainty and the out-of-sample periods.

In this article, we develop an innovative framework to handle multi-period stochastic simulations. The proposed methodology hinges on macro models as the starting point in the scenario generation process. Once we obtain the simulations from the econometric model, we need to embed these paths with a probability structure. To this end, we develop a rank-ordering mechanism that considers several dimensions of economic performance to produce an overall score for each scenario. With the scenarios and their probabilities in hand, we can run these forecasts through stress testing satellite models. This step provides us with forward-looking, multi-period, scenario-specific simulations for all relevant risk parameters. We illustrate this process with two leading examples: default risk for a lending portfolio (US mortgages) and mark-to-market risk for a traded credit portfolio (rate and credit spread risks).

The structure of the article is consistent with the steps required to build the proposed framework. It starts with the econometrics needed to build dynamic stochastic macro simulations (Step 1). Next, it describes our methodology for embedding the forecasted paths with probability metrics (Step 2). Satellite models are then used to compute path-specific forecasts for credit and market risk parameters (Step 3).

The combination of conditional risk parameter realizations and their probabilities provides the modeler with the necessary inputs to address dynamic stress testing questions (such as probabilities of losses for a given stressed scenario) and to build a stochastic framework for multi-period credit portfolio management.

### Step 1: Simulations using a Dynamic Stochastic General Equilibrium (DSGE) model

To overcome the challenge of building multi-period scenarios, we propose the use of dynamic stochastic macroeconomic models. The main advantage of this family of models is the ability to simulate millions of time-series of economic shocks that are linked to each other through general equilibrium conditions. In other words, the simulations are consistent within periods (alternative macro series must satisfy equilibrium conditions), and the connection across subsequent periods comes from inter-temporal optimal behavior and pricing. This is the reason why these types of models are usually referred to as "macroeconomic models with micro-foundations."

At the core of their set-up are optimality and arbitrage-free pricing conditions. The following sub-steps can be used to produce millions of simulated stochastic paths.

#### Step 1.A: Find the equilibrium conditions that solve the selected DSGE model

In practice, this requires the modeler to solve dynamic stochastic optimization problems. Recursive methods are leveraged in order to obtain the so-called "Bellman Equations." These non-linear formulas represent the intra-period optimal transition for key economic variables. They provide the underlying dynamics of the system, connecting endogenous macro and financial variables with the sources of uncertainty: the shocks to economic agents and macroeconomic policies. Within these equations we also obtain the "arbitrage-free" conditions for any financial assets that are priced in the model. In other words, the equilibrium system requires market-consistent pricing for all assets over time.

#### Step 1.B: Build the system of stochastic differential equations that represent solutions to the model

This step is achieved by log-linearization of equilibrium conditions around "steady-state" (the long-term solution for an economic series that is constant over time). The original macro variables get replaced by distances to the long-term values, and the non-linear system gets replaced by its first-order Taylor approximation.[1] This linear system is mapped into a state-space matrix form to facilitate its estimation.

#### Step 1.C: Estimate the linear system of stochastic differential equations

Several techniques are available to estimate (or calibrate) the stochastic system of equations. There is vast and detailed literature on how

**Figure 1** Example of a standard DSGE model set-up

Workhorse example -- Three types of agents: households, firms, government

» Households

$$\max_{c_t, a_{t+1}, b_{t+1}, m_{t+1}, inv_t} E_0 \sum_{t=0}^{\infty} \beta^t u(c_t, l_t)$$

$$\begin{aligned} s.t.\ \ & p_t(1-\tau_t^{vat})c_t + m_{t+1} + p_t^a a_{t+1} + p_t^b b_{t+1} + inv_t = \\ & (1-\tau_t^w)w_t l_t + (p_t^a + p_t r_t^a)a_t + (p_t^b + i_t)b_t + m_t + r_t^k k_t \end{aligned}$$

» Firms

$$\max_{k_t, l_t} \Pi_t = p_t f(z_t, k_t, l_t) - w_t l_t - (1 + r_t^k)k_t$$

» Government

$$\max_{T_t, B_{t+1}} Welfare$$

$$\begin{aligned} s.t.\ \ & \tau_t + B_{t+1} = (1+i_t)B_t + G_t \\ & \tau_t = \tau_t^{vat} c_t + \tau_t^w w_t l_t + \tau_t^{\pi} \Pi_t \end{aligned}$$

Source: Moody's Analytics

**Figure 2** Example of arbitrage-free pricing equations and other optimality conditions

Stochastic dynamic equations: "equilibrum" conditions

- Fixed Income Arbitrage-free

$$p_t^b = \beta E\left[\frac{(p_{t+1}^b + i_{t+1})}{1+\pi_{t,t+1}} \frac{u_c(c_{t+1}, l_{t+1})}{u_c(c_t, l_t)} * \phi(\tau_t^{vat}, \tau_t^w)\right]$$

- Real Assets Arbitrage-free

$$p_t^a = \beta E\left[(p_{t+1}^a + p_{t+1} r_{t+1}^a) \frac{u_c(c_{t+1}, l_{t+1})}{u_c(c_t, l_t)} * \phi(\tau_t^{vat}, \tau_t^w)\right]$$

- Relative Prices

$$w_t = p_t f_l(z_t, k_t, l_t)$$
$$r_t^k = p_t f_k(z_t, k_t, l_t)$$

- Market Clearing (Supply=Demand)

$$f(z_t, k_t, l_t) = c_t + inv_t + G_t$$
$$inv_t = k_{t+1} - (1-\delta)k_t = a_{t+1} + b_{t+1}$$
$$b_{t+1} = B_{t+1}$$
$$a_{t+1} = A_{t+1} = (1+g_a)A_t$$
$$m_{t+1} = M_{t+1} = (1+g_m)M_t$$

Source: Moody's Analytics

to estimate DSGE models using Bayesian techniques. Fernández-Villaverde (2010) provides an overview of existing techniques and illustrates the practical advantages of Bayesian methods in the context of dynamic stochastic differential equations.[2]

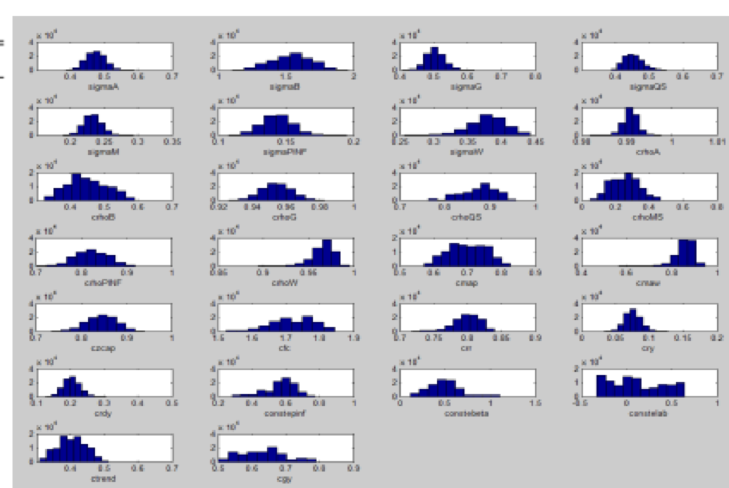
One of the main advantages of using these methods is that after the estimation is completed the modeler has access to (posterior) distributions for all relevant parameters ("betas" that link macro series with each other and key stats for distributional assumptions of the stochastic shocks). These objects provide a very useful and rich platform for robust, forward-looking, dynamic, and consistent simulations of all endogenous variables.

### Step 1.D: Use the estimated system to produce simulations for macro and financial series

This critical step involves shocking the system to produce dynamic simulations out of sample.

**Figure 3** Bayesian estimation: prior assumptions (left) and posterior distributions for key parameters (right)

| | Density | Para (1) | Para (2) | | Density | Para (1) | Para (2) |
|---|---|---|---|---|---|---|---|
| $\psi$ | Beta | 2.00 | 0.50 | $\Phi$ | Normal | 1.25 | 0.12 |
| $\rho$ | Beta | 0.75 | 0.10 | $r_y$ | Normal | 0.12 | 0.05 |
| $r_{\Delta y}$ | Normal | 0.12 | 0.05 | $\bar{\pi}$ | Gamma | 0.62 | 0.10 |
| $100(\beta^{-1}-1)$ | Gamma | 0.25 | 0.10 | $\bar{l}$ | Normal | 875 | 10.0 |
| $\bar{\gamma}$ | Normal | 0.40 | 0.10 | $\sigma_a$ | Invgamma | 0.10 | 2.00 |
| $\sigma_b$ | Invgamma | 0.10 | 2.00 | $\sigma_g$ | Invgamma | 0.10 | 2.00 |
| $\sigma_I$ | Invgamma | 0.10 | 2.00 | $\sigma_r$ | Invgamma | 0.10 | 2.00 |
| $\sigma_p$ | Invgamma | 0.10 | 2.00 | $\sigma_w$ | Invgamma | 0.10 | 2.00 |
| $\rho_a$ | Beta | 0.50 | 0.20 | $\rho_b$ | Beta | 0.50 | 0.20 |
| $\rho_g$ | Beta | 0.50 | 0.20 | $\rho_I$ | Beta | 0.50 | 0.20 |
| $\rho_r$ | Beta | 0.50 | 0.20 | $\rho_p$ | Beta | 0.50 | 0.20 |
| $\rho_w$ | Beta | 0.50 | 0.20 | $\mu_p$ | Beta | 0.50 | 0.20 |
| $\mu_w$ | Beta | 0.50 | 0.20 | $\rho_{ga}$ | Beta | 0.50 | 0.20 |



Source: Moody's Analytics

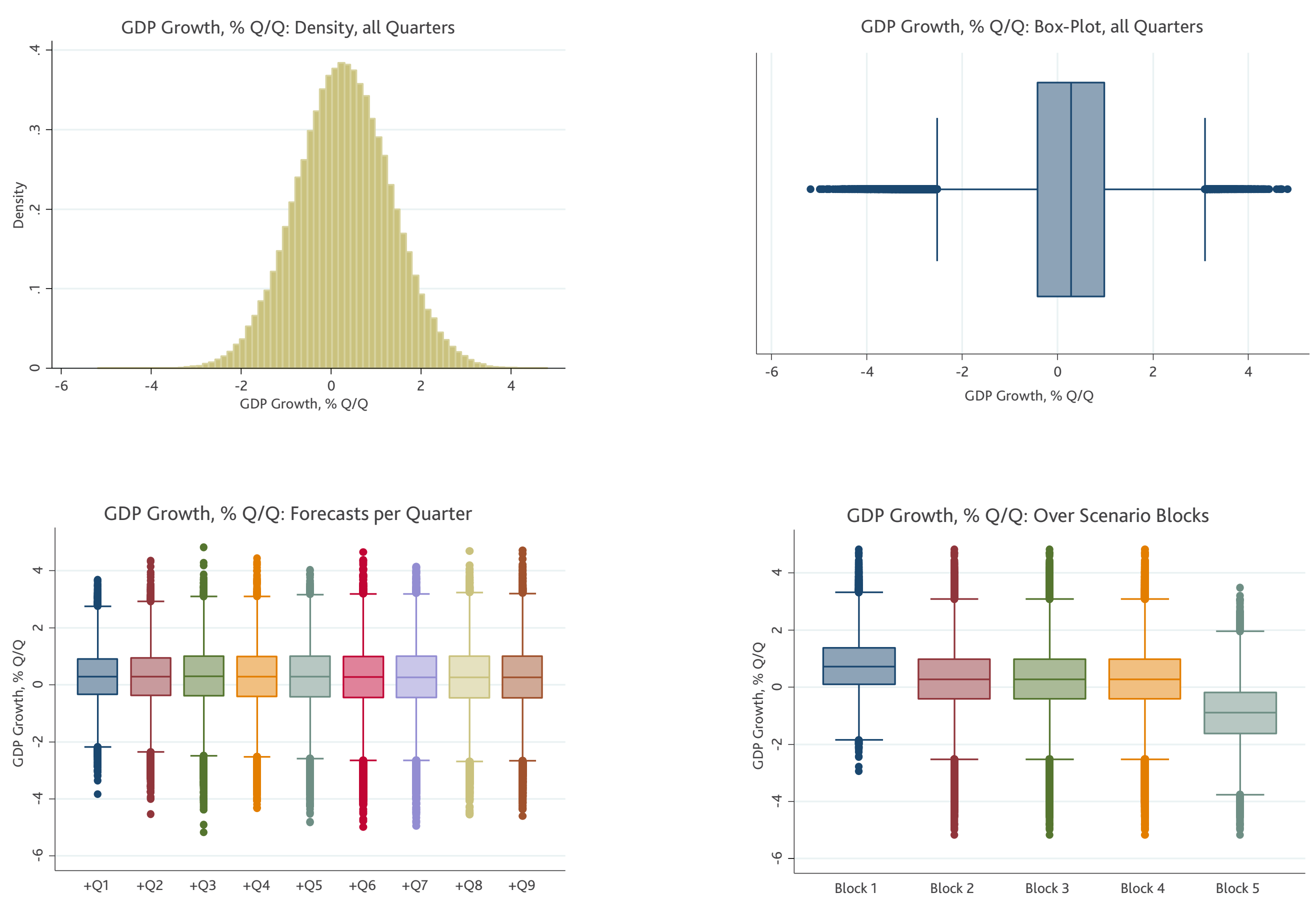
There are two sources of uncertainty that need to be considered: (a) shocks to original random variables in the model (e.g., policy surprises, productivity gains/losses, shocks to consumer preferences, etc.) and (b) the fact that estimated parameters are random variables ("coefficient uncertainty"). Statistical properties of the estimated parameters are derived from their posterior distributions. Here is where Bayesian methods have an advantage. Obtaining the posterior distributions allows a modeler to draw simulated values not only for residuals and shocks, but also for betas and other parameters.

We estimate a workhorse DSGE model for the US economy in line with Smets and Wouters (2007).[3] Throughout this exercise, we focus on nine consecutive quarters out-of-sample for the forecasting period (consistent with stress testing CCAR practices). These periods are labeled +Q1, +Q2, ..., +Q9. (Note that this is simply our choice for this paper and not a preference over an approach that considers longer time-horizons.)

Statistical properties of simulated macro series are illustrated in Figure 4. We include GDP growth, unemployment rate, and home price dynamics as leading indicators. But DSGE models produce between 20 and 30+ economic and financial series, depending on the specifics of the version of the model selected. Histogram (frequency densities) and box-plots help a modeler understand distribution properties of the simulated paths. Some charts contain blocks of simulations as x-axis categories. These blocks represent groups of scenarios according to their severity (see section 2 for a detailed explanation on how the scenarios get rank-ordered). Block 1 groups the most optimistic forecasts while Block

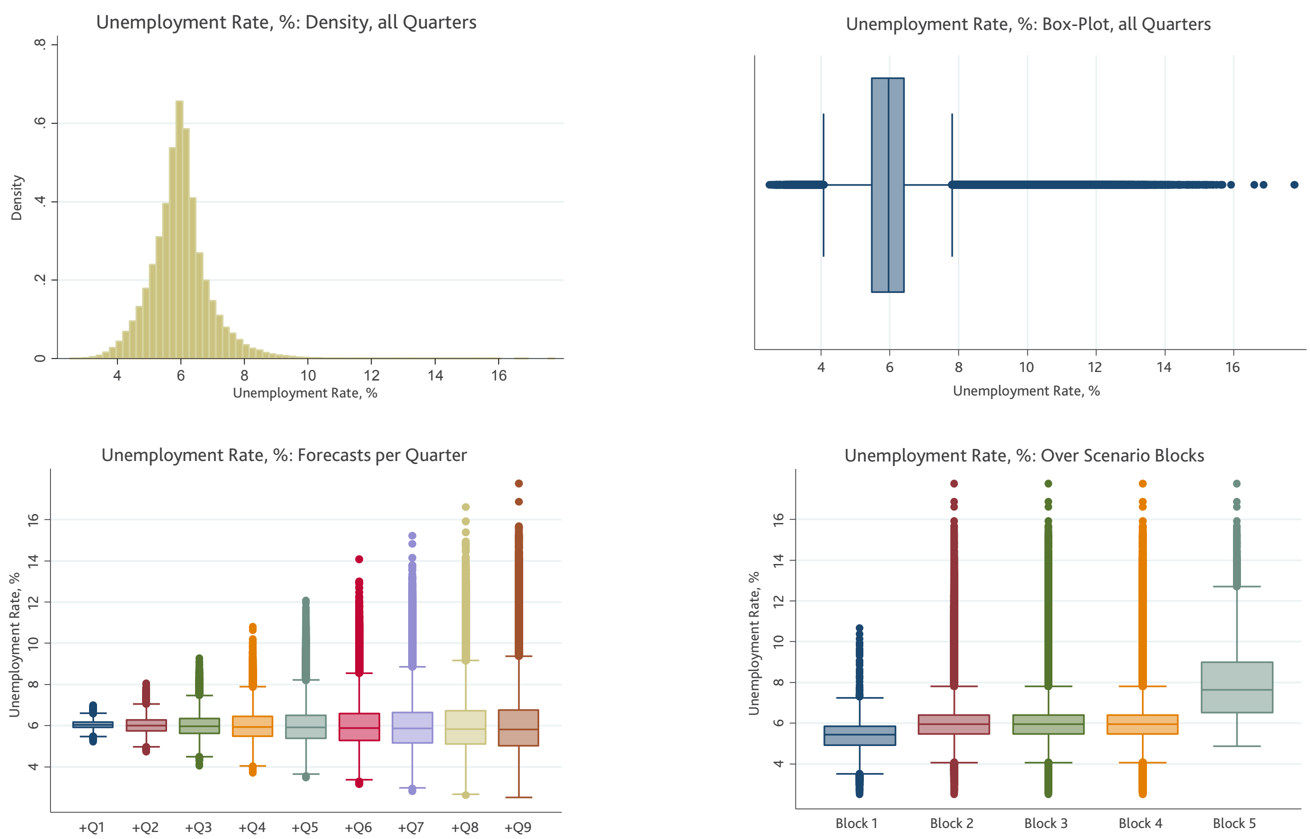
**Figure 4** Statistical properties for key economic factors

**Figure 4.1** GDP growth, % Q/Q




Source: Moody's Analytics

**Figure 4.2** Unemployment rate, %




Source: Moody's Analytics

5 contains stressed scenarios.

The result is a full set of dynamic, stochastic, and forward-looking paths for macro and financial series. The equations used to derive these simulations rest on general equilibrium conditions, making the projections consistent across variables and over time. The forward-looking attribute rests on the fact that these scenarios will vary over the business cycle. The DSGE model gets re-estimated with new data and the forecasts are conditional on the starting point of the out-of-sample period.

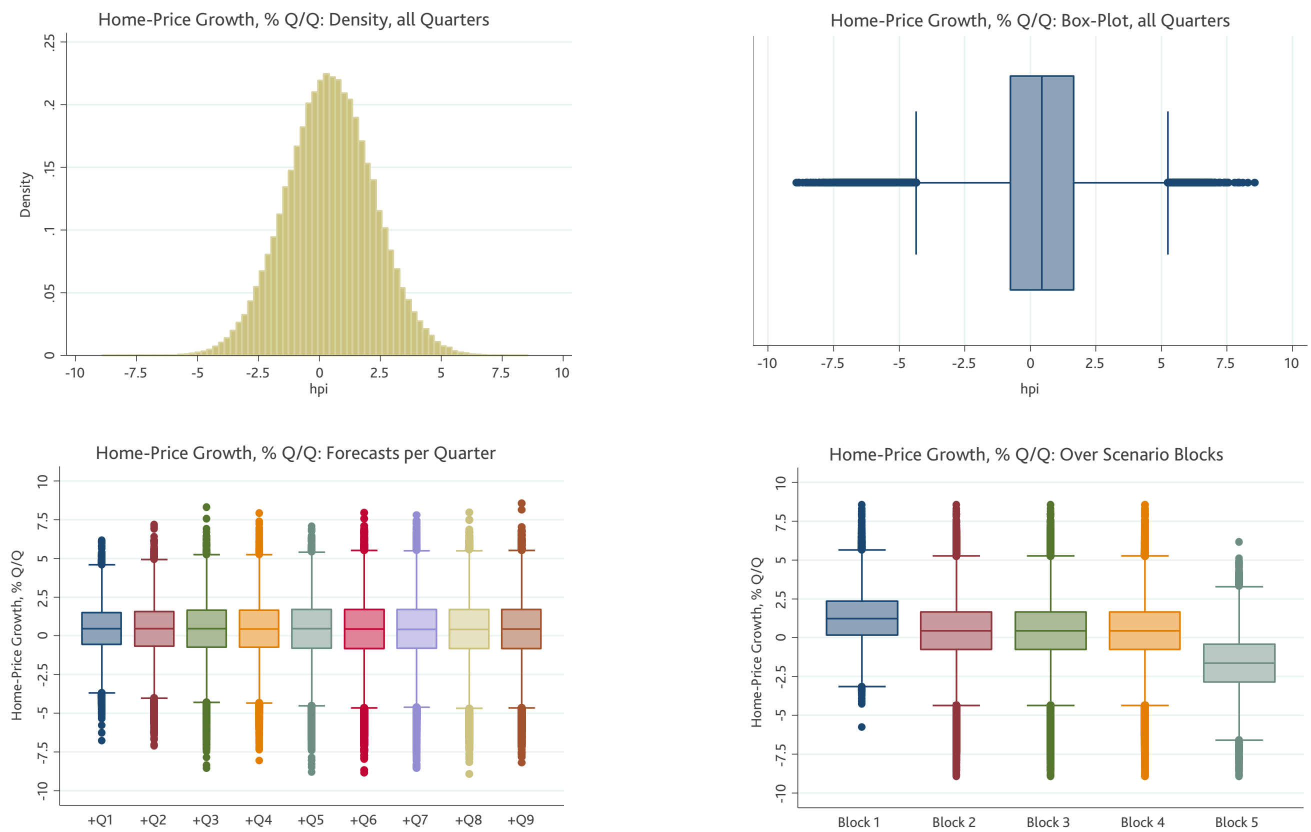
For notation purposes, let's refer to a given scenario as "z," wherein the vector Z contains the whole list of macro and financial series with values at all quarters-out-of-sample (+Q1 to +Q9).

### Step 2: Embedding the stochastic scenarios with a probability structure

A natural next step is to derive probabilities and severities for the simulated scenarios. To achieve this goal, we develop a multi-factor rank-ordering mechanism that attributes severity according to 25+ dimensions of economic severity. The core macro variables that are part of the calculation are: GDP growth, unemployment rate, home price changes, consumption dynamics, investment profiles, interest rate movements, and inflation. For each of these series, we rank the scenarios according to several criteria: average and/or cumulative values over the scenarios, maximum/minimum targets, and volatilities (sigma vs. average).

The algorithm produces a combined score that translates into a ranking for each scenario. The embedded statistical structure can be obtained by (a) calculating the severity of any scenario from the percentage of the simulations that score lower or higher (purely a rank ordering exercise) or (b) grouping scenarios based on fixed intervals for score values. All

**Figure 4.3** Home price growth, % Q/Q




Source: Moody's Analytics

scenarios within a given cluster have the same probability, given by the relative size of the interval (number of scenarios in the cluster divided by the total number of simulations).

We illustrate the rank-ordering process with the properties of three marginal loadings and show the distribution properties of the final, overall score.

Step 2 provides us with a vector "p(z)" that has a single probability value per scenario. Note that it is not time-dependent, as the scoring algorithm has considered information across all relevant macro series observed at all points in time. In other words, our stochastic shocks are represented as dynamic paths for a group of macro and financial series. Each path has an associated probability value p(z).

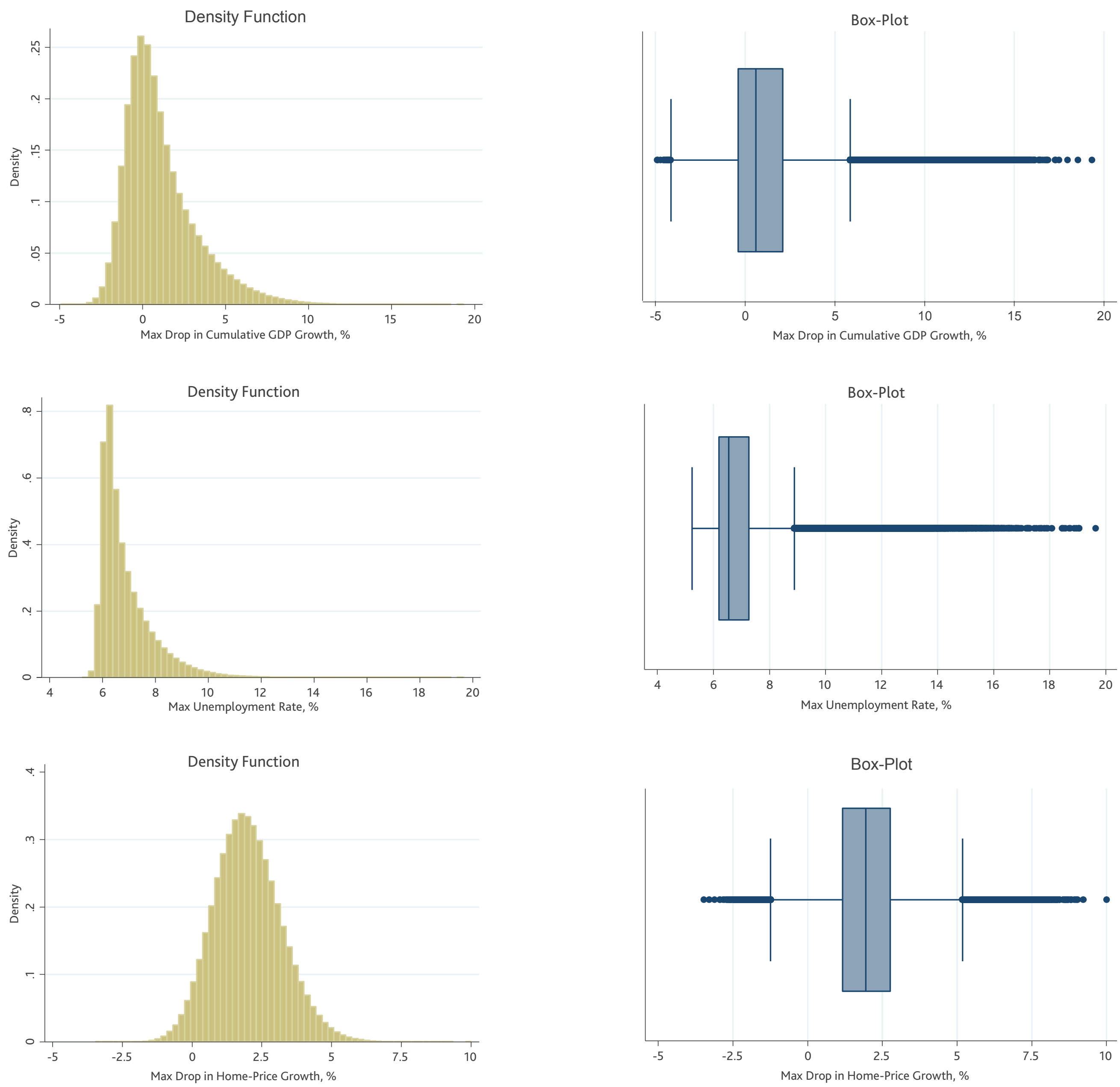
### Step 3: Connecting scenarios to risk parameters using stress testing satellite models

The last step of the process consists of linking scenarios with credit and market risk parameters. The modeler can now leverage recent developments on stress testing methodologies. The financial industry has produced a vast literature on robust models that are able to calculate risk parameters conditional on any given macro scenario. Instead of simply running a handful of multi-period scenarios, we can run thousands of them through stress testing models and obtain conditional realizations for credit metrics.

### Simulations of credit risk parameters: US mortgage portfolio as a leading example

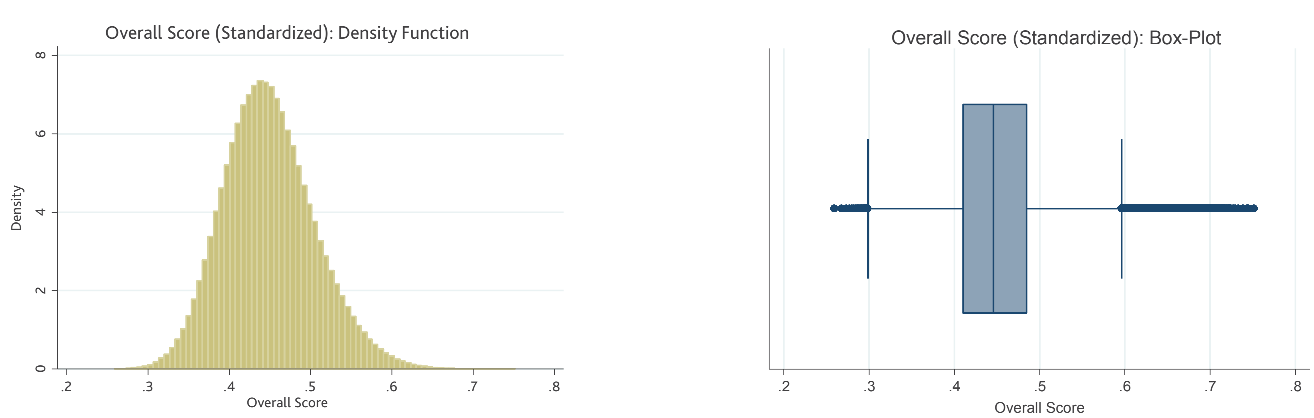
Following the methodology described in Licari and Suárez-Lledó (2013), we leverage a vintage-PD model for US first mortgages to run through the rank-ordered macro simulations.[4] The result is a set of dynamic paths for vintage PDs from +Q1 to +Q9 (results are illustrated in Figures 7 and 8). We need to emphasize that these PDs are not forecasted only for existing vintages, but also

**Figure 5** Leading marginal scores: minimum GDP cumulative growth rates, maximum unemployment rate, maximum drop on home price growth



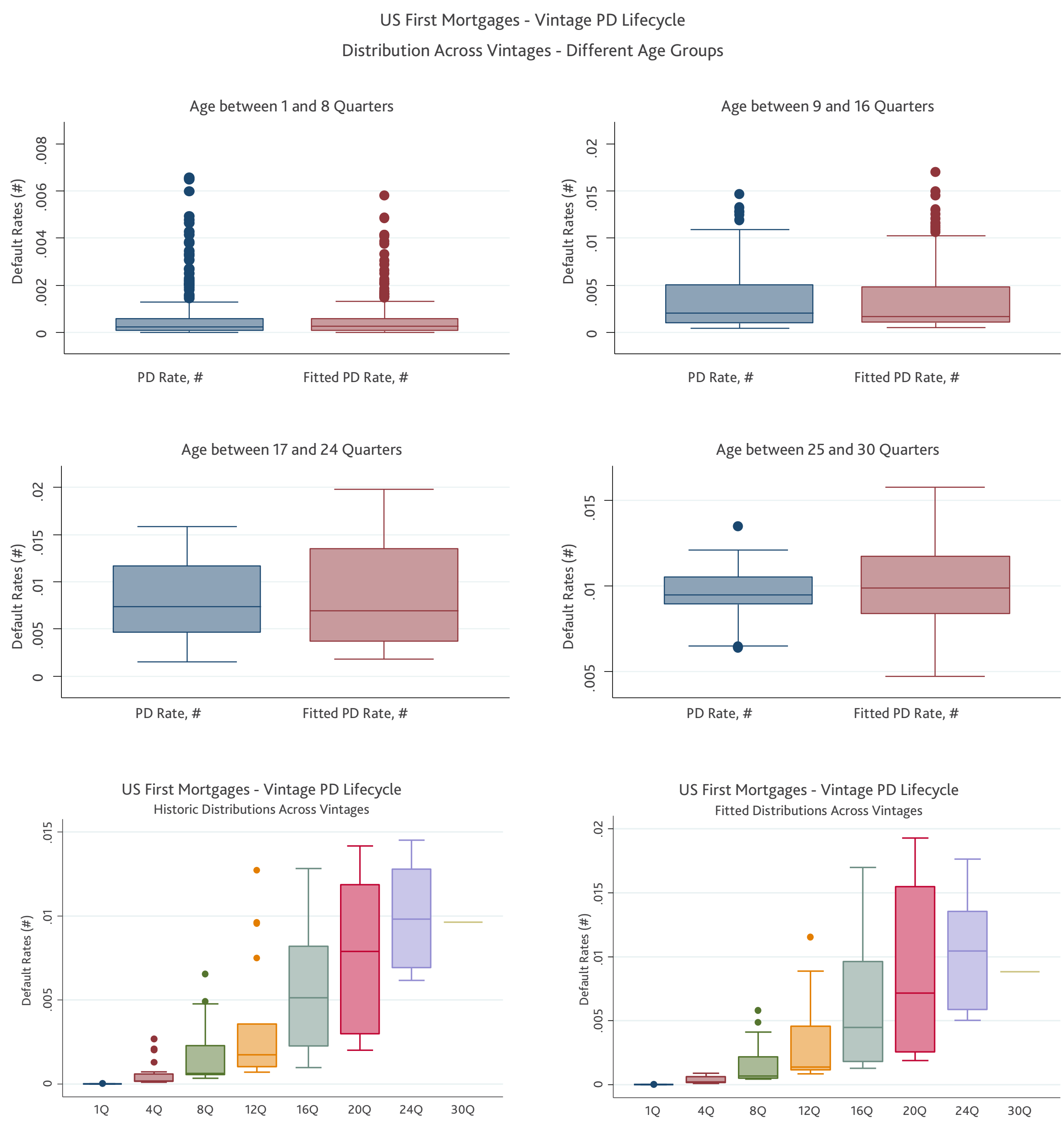

Source: Moody's Analytics

**Figure 6** Statistical properties of the standardized overall score




Source: Moody's Analytics

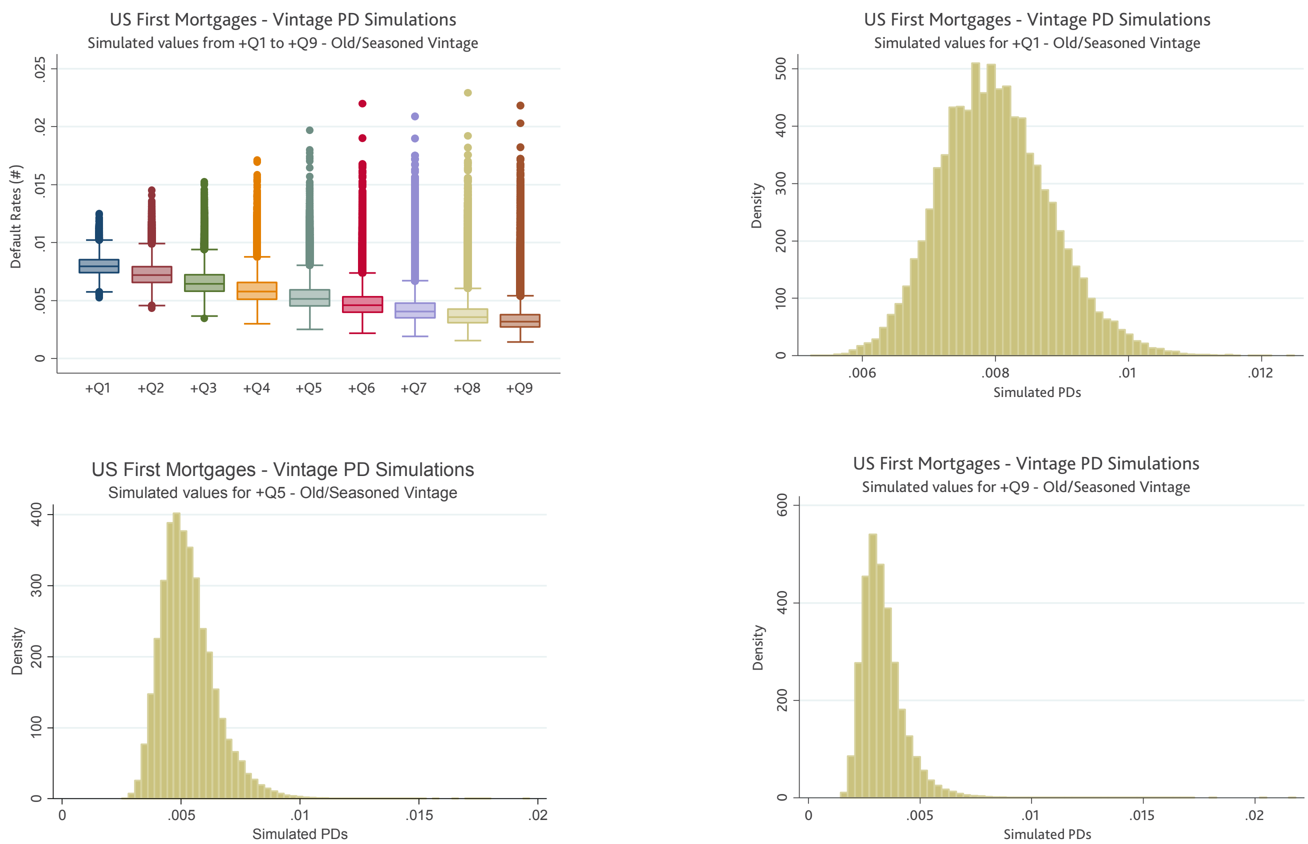
**Figure 7** Historic vs. fitted PDs over age intervals – PD lifecycle (term-structure)




Source: Moody's Analytics

**Figure 8** Simulated PDs across quarters-out-of-sample (+Q1 to +Q9)

**Figure 8.1** Old/seasoned vintage




Source: Moody's Analytics

**Figure 8.2** Future vintage (booked in the out-of-sample period – dynamic projection)


Source: Moody's Analytics

for loans in vintages that will be originated in the future, together with the level of forecasted volumes for these new originations. This is of particular importance when performing dynamic stress testing and multi-period portfolio credit analysis. Figure 8.2 presents the simulated PD values for a vintage of mortgages that gets originated in the first out-of-sample period (+Q1).

The outputs of this exercise consist of simulated paths of conditional PDs (for each vintage in the mortgage portfolio and across all out-of-sample periods). These conditional PDs – combined with the probability vector p(z) – become the necessary inputs for running multi-period credit portfolio analysis.

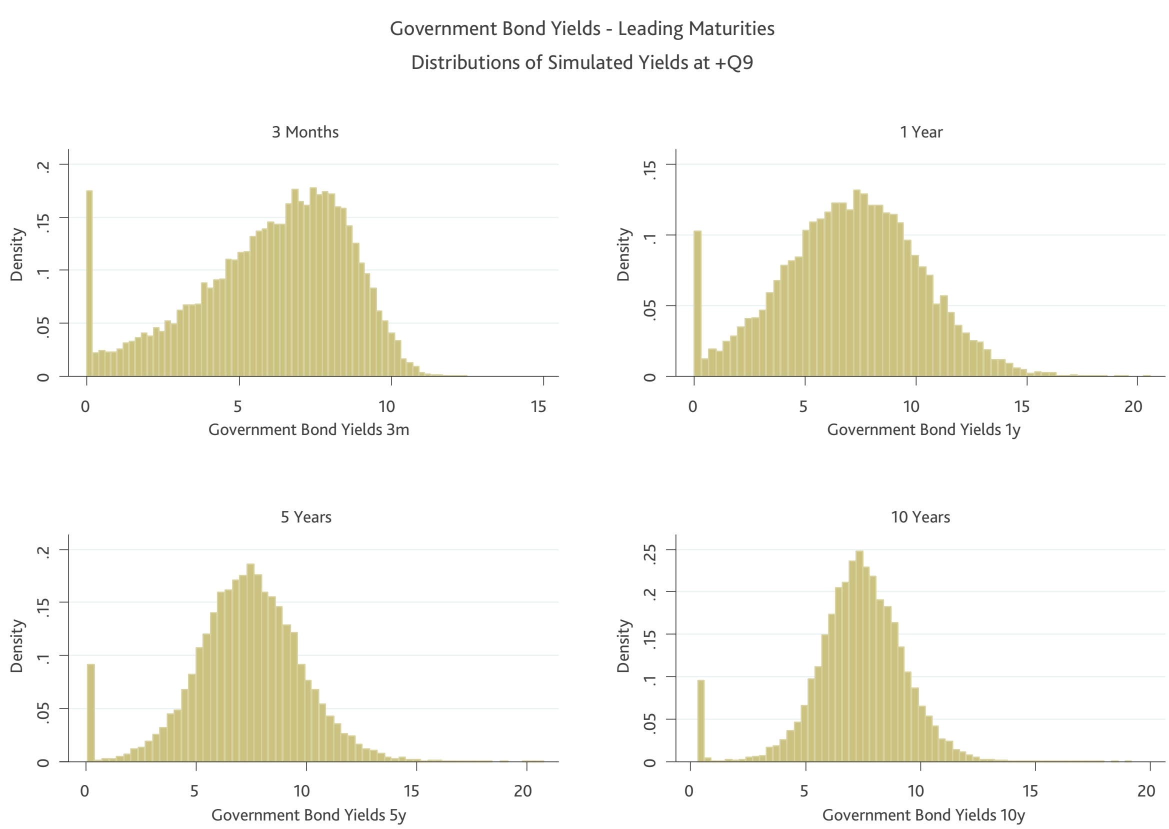
**Simulations of market risk parameters: interest rates and credit spreads as leading example**

We now study the translation of the stochastic scenarios into relevant mark-to-market metrics. Government bond yields and corporate credit spreads are presented as leading examples, following econometric techniques developed in Licari, Loiseau-Aslanidi, and Suárez-Lledó (2013).[5] The modeling methods rest on a combination of principal component analysis and time-series estimation techniques.

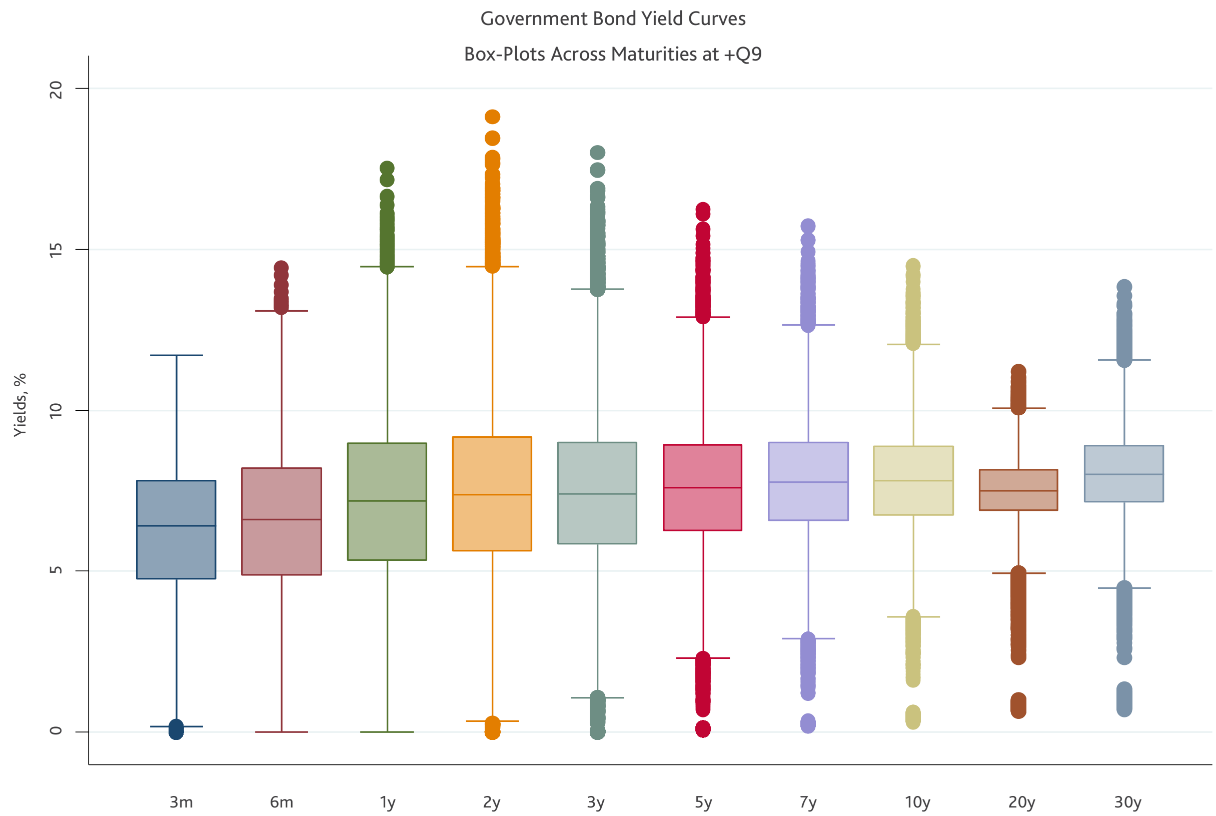
It is worth highlighting the dynamic behavior of simulated term-premiums (as a proxy for the yield curve slope), as illustrated in Figure 9.3. The simulations produce different shapes,

**Figure 9** Simulated government bond yield curves

**Figure 9.1** Distributions of yields at +Q9 for different maturity points

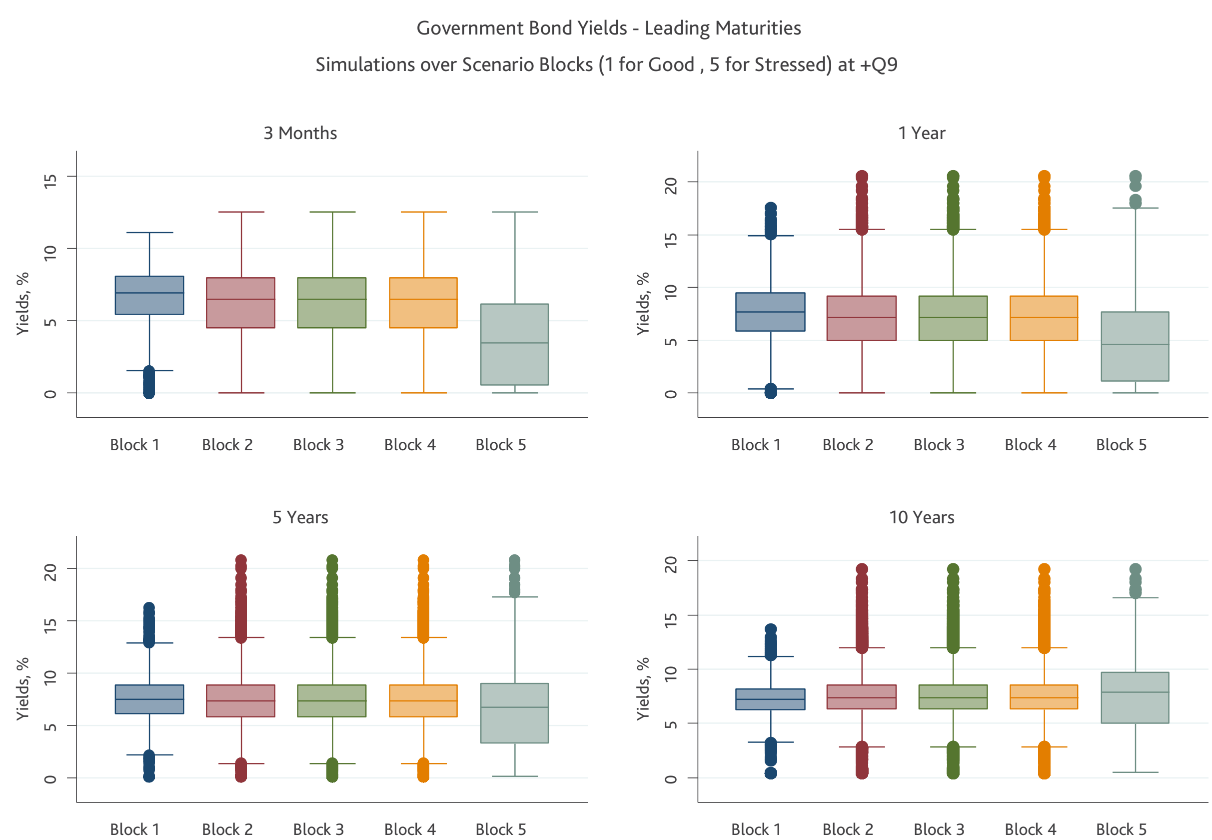



Source: Moody's Analytics




Source: Moody's Analytics

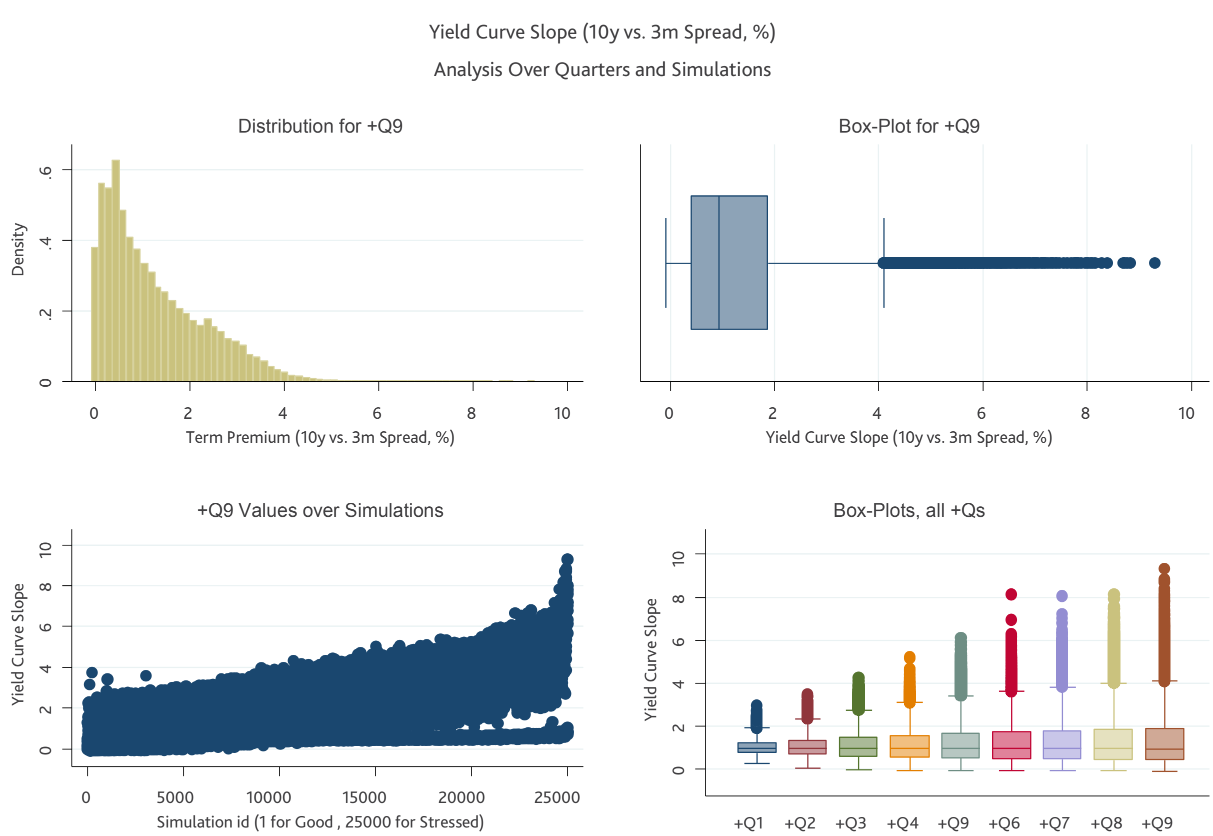
**Figure 9.2** Yields over blocks of scenarios at +Q9 and over quarters-out-of-sample (+Q1 to +Q9)




Source: Moody's Analytics


Source: Moody's Analytics

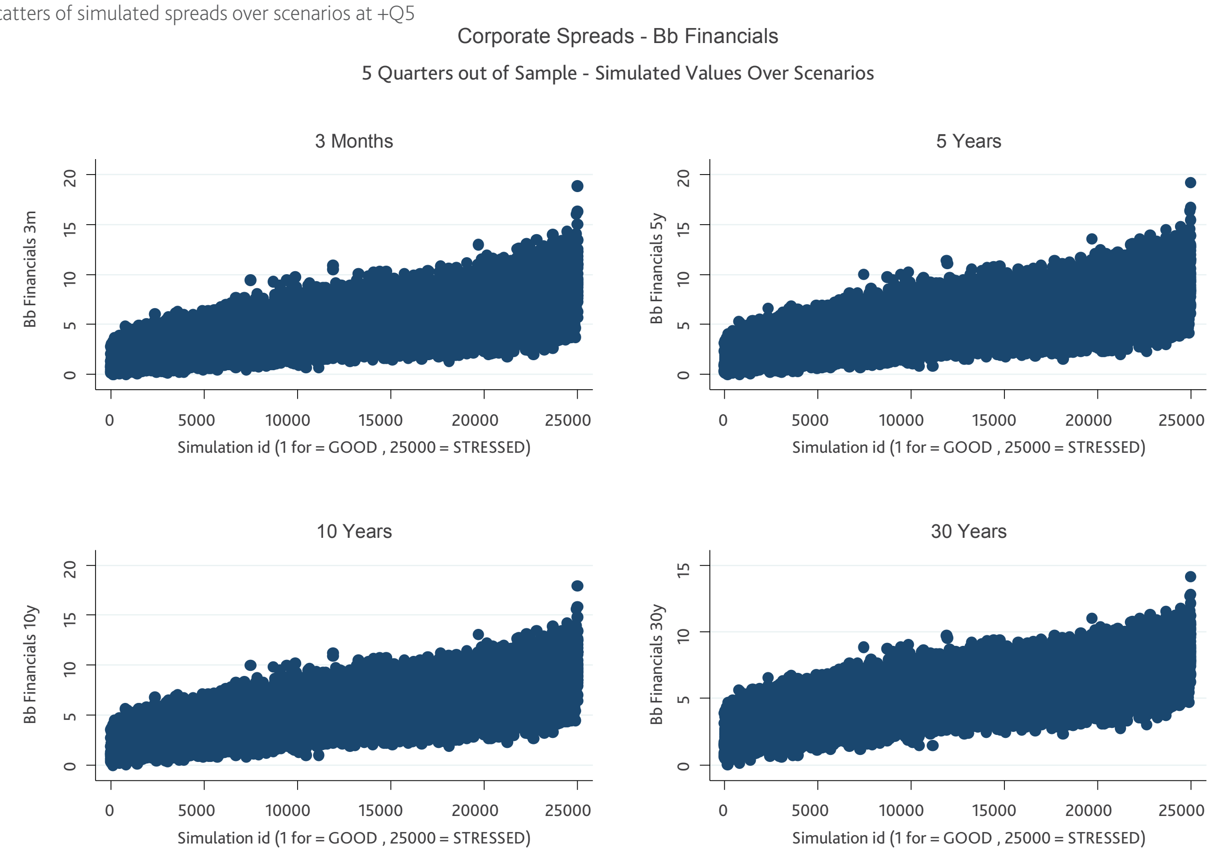
**Figure 9.3** Term-premium spreads (yield curve slope) at +Q9

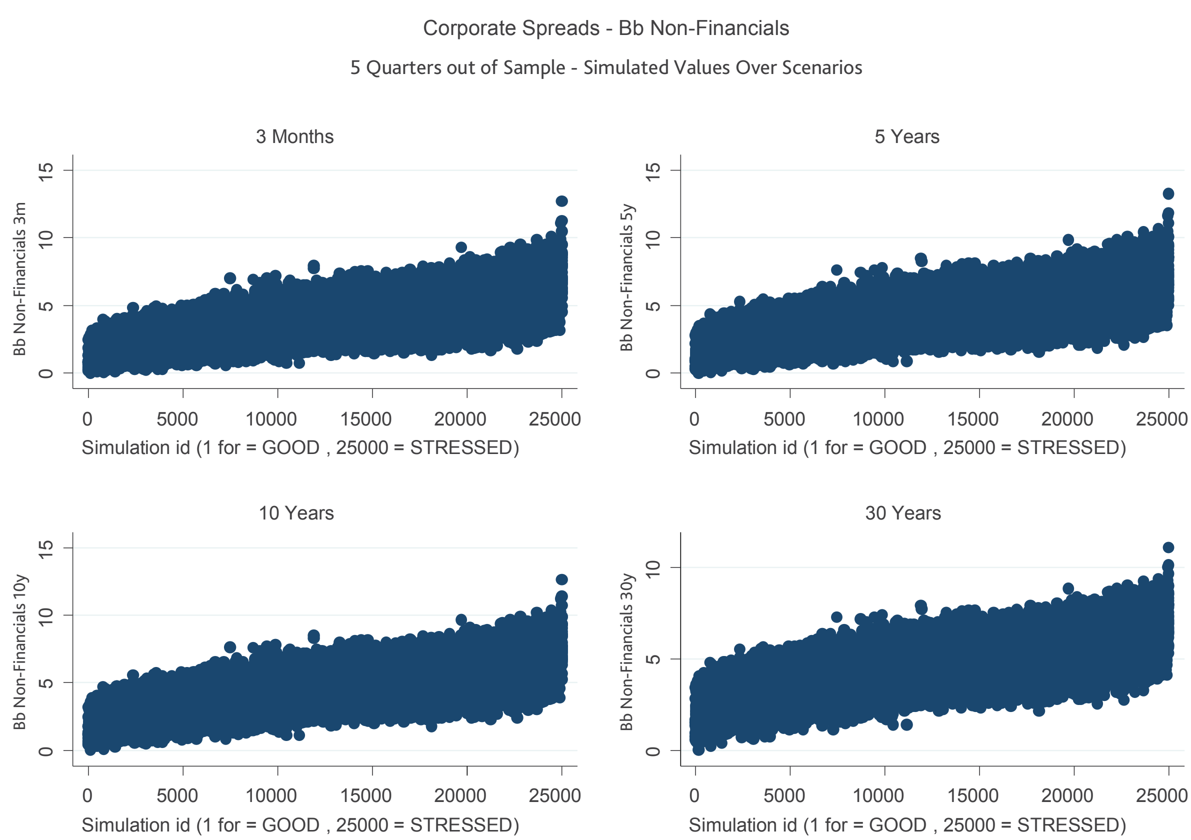



Source: Moody's Analytics

**Figure 10** Simulated corporate credit spreads – financials and non-financials – over rating classes and maturities

**Figure 10.1** Scatters of simulated spreads over scenarios at +Q5




Source: Moody's Analytics

**Figure 10.2** Box plots of simulated spread curves at +Q5


Source: Moody's Analytics

**Figure 10.3** Box plots of simulated spreads, 5-year maturity, +Q1 to +Q9


Source: Moody's Analytics

including inverted curves (negative premiums) and severe scenarios with high values for the yield-curve slope.

Corporate credit spreads are observed across financial and non-financial sectors. Within each sector, there is further segmentation across rating classes (Aaa, Aa, A, Bbb, Bb, and B) and maturities (3m, 1y, 3y, 5y, 7y, 10y, 20y, and 30y). Statistical properties for simulated spreads are illustrated in Figure 10.

The methods described in this section provide a modeler with forward-looking, dynamic simulations for risk-free rates and credit spreads. These consistent projections together with their probabilities, p(z), represent the building blocks for mark-to-market risk assessments for traded credit portfolios.

## Concluding remarks

In this article, we develop a dynamic framework for stochastic scenario generation. The proposed methodology sets the necessary inputs for dynamic stress testing and multi-period credit portfolio analysis.

Of particular relevance is the ability to build (simultaneously) consistent projections for standard credit risk metrics and mark-to-market parameters within a single, unified environment. In other words, using stochastic dynamic macro models as the scenario foundation allows us to integrate conditional credit and market risk modeling.

1 Other techniques consider higher-order approximations in order to understand the effects of non-linear relationships. See Schmitt-Grohé and Uribe (2004) for quadratic approximation methods: Schmitt-Grohé S. and Uribe M., ***Solving Dynamic General Equilibrium Models Using a Second-Order Approximation to the Policy Function***, Journal of Economic Dynamics & Control 28, 755–775, 2004.

2 Fernández-Villaverde, J., ***The Econometrics of DSGE Models***, SERIEs,1:3–49, 2010.

3 Smets, F. and Wouters R., ***Shocks and Frictions in US Business Cycles***, European Central Bank Working Paper Series N 722, 2007.

4 Licari, J. and Suárez-Lledó, J., ***Stress Testing of Retail Credit Portfolios***, Risk Perspectives Magazine, 2013.

5 Licari, J., Loiseau-Aslanidi, O. and Suárez-Lledó, J., ***Modeling and Stressing the Interest Rates Swap Curve***, Moody's Analytics Working Paper, 2013.

# STRESS TESTING SOLUTION PROCESS FLOW: FIVE KEY AREAS

By Greg Clemens and Mark McKenna

**Greg Clemens**
*Director,*
*Stress Testing Solutions*

As a member of the Stress Testing Task Force at Moody's Analytics, Greg helps clients automate their stress testing processes – providing insight about architectures, data management, and software solutions for risk management.

**Mark McKenna**
*Senior Director,*
*Stress Testing Solutions*

Mark is responsible for business and relationship management for Moody's Analytics Stress Testing Solutions. Prior to his current role, he was with the Structured Analytics & Valuations Group, leading valuations and cash flow analytics projects. He has worked with many US financial institutions, providing risk management tools and loss estimation models for their retail portfolios.

Most banks are able to stand up to quantitative stress testing and even prove their capital adequacy. But what many organizations lack is a streamlined process that allows them to run stress tests with ease, efficiency, and control. This article outlines a five-step process that will help banks maximize their stress testing investment, making compliance easier while improving their interior management.

## Current stress testing challenges

The Federal Reserve (Fed) has required banks to run the Dodd-Frank Act Stress Test (DFAST) and the Comprehensive Capital Analysis and Review (CCAR) for a number of years. While they are the Fed's primary supervisory mechanism for assessing the capital adequacy of large banks, these exercises remain extremely complicated. CCAR and DFAST continue to cause banks to spend extensive resources – both time and money – to run the exercises, prepare the results, and respond to the findings of regulators.

DFAST tests whether banks have sufficient capital to absorb losses and support operations during adverse economic conditions (e.g., housing crash, unemployment increase, severe GDP drop, or stock market crash) while using a standardized set of capital action assumptions. (The assumptions keep each bank's current dividend and do not include share repurchase plans.) CCAR tests banks under similar adverse economic scenarios, but in this case regulators consider the capital action plans submitted by each bank. Under CCAR, a bank submits its proposed capital plan for the next four quarters (dividend hikes, share buybacks, etc.), and the Fed assesses whether that bank would be able to meet required capital ratios under shaky economic conditions. Put simply, can a bank afford to give dividends to shareholders if the economy starts to falter? If the answer is yes, banks then announce their capital plans to the public.

Over the years, there have been fewer and fewer "quantitative" stress test failures. This may be because banks are in better condition, because they have become familiar with the test, or perhaps a bit of both. Meanwhile the "qualitative" assessment has become an exceedingly important component of the regulatory program. In any case, the pressure is still on banks to demonstrate that they can manage their risks while running their businesses.

> The true aim of the stress testing exercises, however, is not that banks demonstrate that they can pass tests like the severely adverse scenario per se, as no one actually expects such a scenario to come to pass, but that banks demonstrate that they have the ability to weather a storm, whatever it may be.

The DFAST and CCAR exercises are a part of the Fed's effort to ensure that banks have robust processes for determining how much capital they need to maintain access to funding and continue to serve as credit intermediaries, even under stressed conditions. The most onerous test the banks must pass is called the severely adverse scenario, which features a severe recession with rising unemployment and steep declines in the stock market, housing prices, commercial real estate, and GDP.

The true aim of the stress testing exercises, however, is not that banks demonstrate that they can pass tests like the severely adverse scenario per se, as no one actually expects such a scenario to come to pass, but that banks demonstrate that they have the ability to weather a storm, whatever it may be.

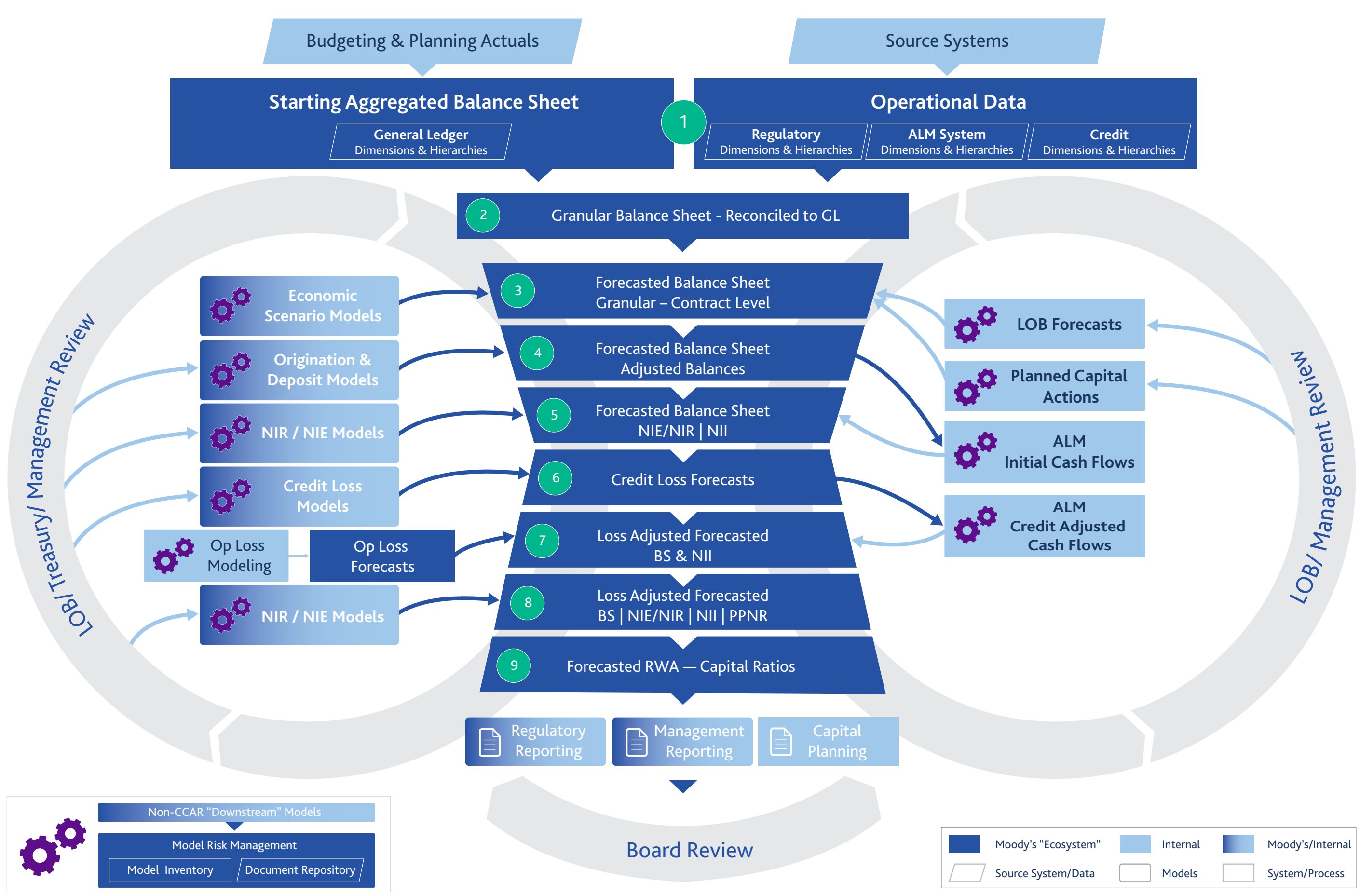
The challenge for banks is to institute a process for running stress tests faster and with more control, to meet the changing demands of regulators while also improving both the process itself and the way they run the bank. CCAR applies only to the largest Bank Holding Companies (BHCs), but the challenge also applies to the next-tier banks that only need to run the DFAST exercise. While the CCAR and DFAST are US exercises, the issue is no less relevant for the banks in Europe and around the globe.

## A solution to managing the stress testing process flow

There are five major areas, or components, of the stress testing process.

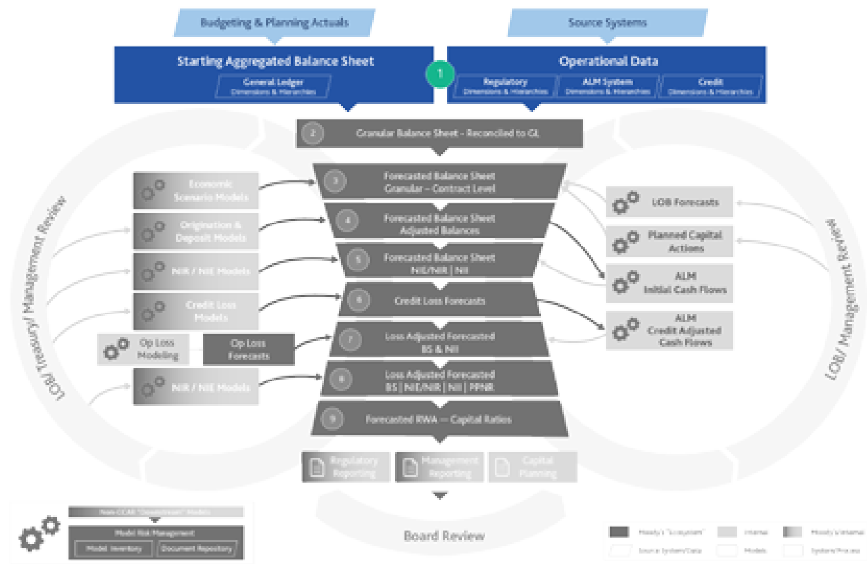
1. Bringing all the data together
2. Preparing the preliminary balance sheet forecast
3. Conditioning the forecast with credit losses
4. Completing the remaining calculations, capital ratios, and RWA forecasts to prepare the required reports and capital plan
5. Overlaying a common framework for model risk management

**Figure 1** Stress testing process workflow




Source: Moody's Analytics

**Figure 2** Stress testing process workflow: Central data definitions




Source: Moody's Analytics

## 1. Central data definitions

In the first step, all the necessary data from the various areas and business units involved in the process are brought together. The data model should support forecasting throughout the process at the most granular level, supported by multiple hierarchies and dimensions across all areas.

**The data model for the process should be thought of as the single source of truth for stress testing.** Organizations should take three main points into account when creating this model:

- » A central risk, finance, and treasury datamart is needed to support a large range of models and reporting requirements
- » They should leverage investment in current systems, infrastructures, and data warehouses
- » Data quality and reconciliation against production systems are important considerations

The ongoing, complex, and ever-changing regulations are pushing IT budgets at most financial institutions, requiring systems that can handle an increasing amount of data at a granular level.

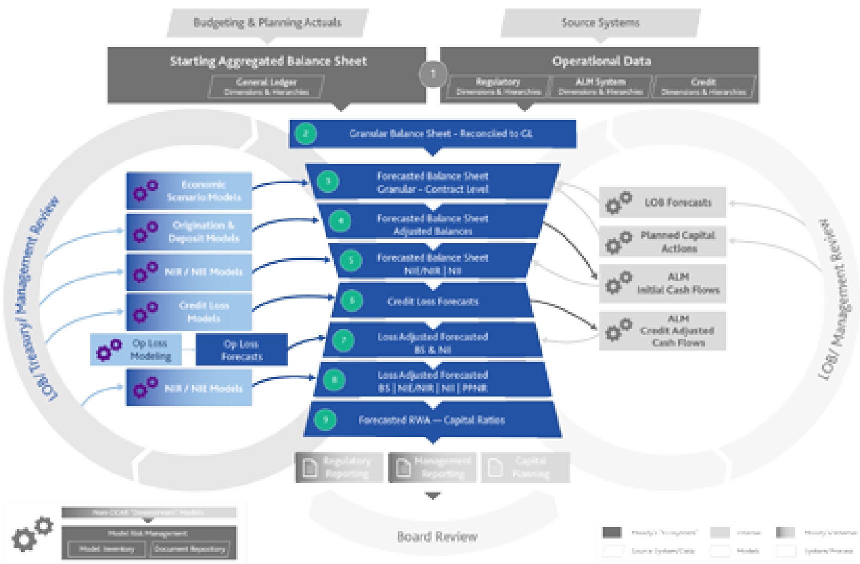
Organizations must access, validate, and reconcile data across the enterprise. **On top of the data aggregation challenges, banks need to improve the scope, accuracy, and governance of their ballooning data.**

Organizations must access, validate, and reconcile data from across the enterprise, including all geographies, portfolios, and instruments, irrespective of the origin of the data. A few points to bear in mind:

- » The data model should support a repeatable, transparent, and auditable process
- » Data is not complete in each source system
- » Data is stored at different levels of granularity in different systems

These challenges are straining firm resources even further. Institutions are looking for ways to improve data quality, streamline and standardize data flows, improve the efficiency and accuracy of regulatory reporting, support validation requirements, improve auditing capabilities, and supplement management reporting. They must satisfy both the regulators and their boards about the accuracy, scalability, and sustainability of the data structure and the processes used for data management.

**Figure 3** Stress testing process workflow: Preliminary balance sheet forecast




Source: Moody's Analytics

## 2. Preliminary balance sheet forecast

The second step involves preparing the initial balance sheet forecast. With increased regulatory expectations for scenario design, banks need a process that is user friendly, as well as auditable, transparent, and repeatable.

This requires:

» Clear understanding of the key forecast drivers and their relation to the current state
» Granular balance sheet with all jump-off data
» A common, central source of data that allows different areas to view data in the way they are accustomed (hierarchy and dimensions)

**Stress testing forces institutions to complement traditionally expert judgment-driven planning processes with quantitative approaches to produce forecasted cash flows.**

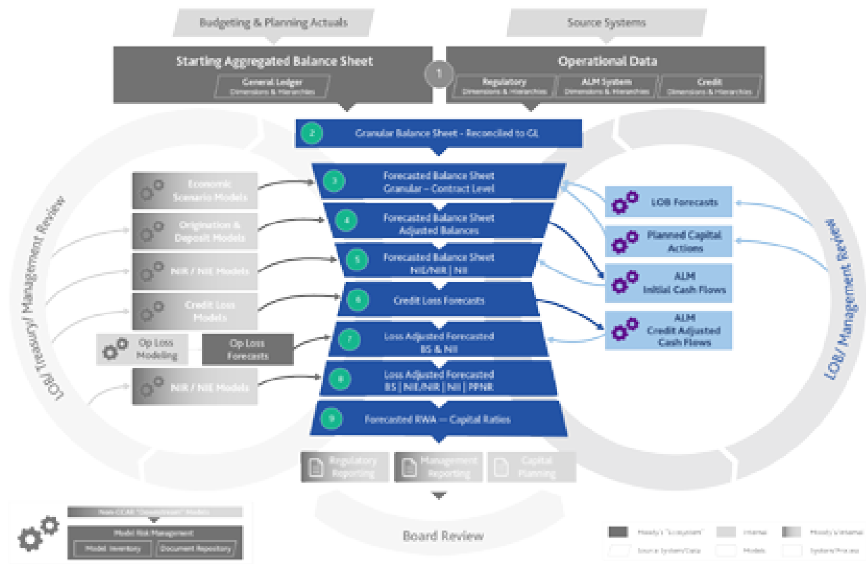
The approach needs to incorporate:

» A material risk identification process
» An effective challenge process for management and the board
» Policies that lay out expectations for all functions involved in the capital adequacy process

Data infrastructure and system integration is a fundamental problem at most banks. Banks have been going from one short-term fix to another using SharePoint and Excel as go-betweens for multiple systems. Instead, they need a longer-term vision for how to build an infrastructure that enables effective stress testing, featuring:

» Integration of multiple systems
» Auditability of the results
» Coordination across finance, treasury, and risk groups

**Figure 4** Stress testing process workflow: Credit loss adjusted balance sheet forecast




Source: Moody's Analytics

### 3. Credit loss adjusted balance sheet forecast

The third component of the process takes the preliminary balance sheet forecast and adjusts it for credit losses and other forecast considerations, including Pre-Provision Net Revenue (PPNR), risk-weighted assets (RWA) for market risk, and operational risk losses.

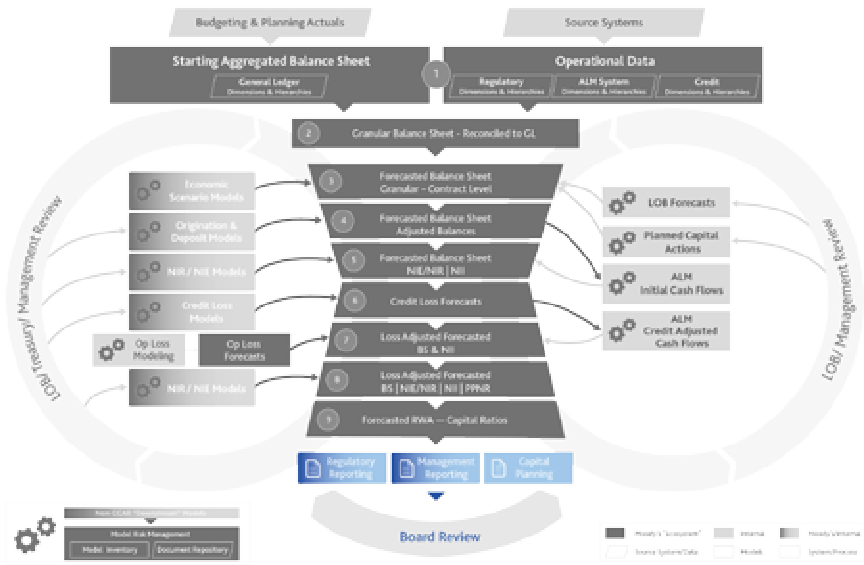
Methodologies to project loss estimation, PPNR, and RWA are in various degrees of development. Most are housed in a range of formats (SAS, R, Matlab, and Excel, etc.), making documentation, validation, and the challenge process more difficult.

To facilitate loss-adjusted forecasting, the process needs to incorporate customizable workflow and reporting functions, including data management, auditability, and regulatory reporting. Steps in this process include:

- Implementing a workflow that connects with banking systems to determine the role and functionality of each component in the process
- Determining methodologies to project loss estimation, PPNR, and RWA, including documentation, validation, and the challenge process
- Projecting losses through the bank's asset and liability management (ALM) system for forecasted cash flows

Leveraging the bank's current models and systems and managing the process through the workflow streamlines the stress testing and capital planning processes.

**Figure 5** Stress testing process workflow: Capital planning and reporting




Source: Moody's Analytics

## 4. Capital planning and reporting

The fourth component takes the adjusted balance sheet and prepares the results to be used for the various regulatory reports, management reports, and capital plans.

Existing reporting solutions are not well suited for the complexities of data aggregation, edit checks, and management reviews needed for both CCAR and DFAST regulatory and management reporting requirements.

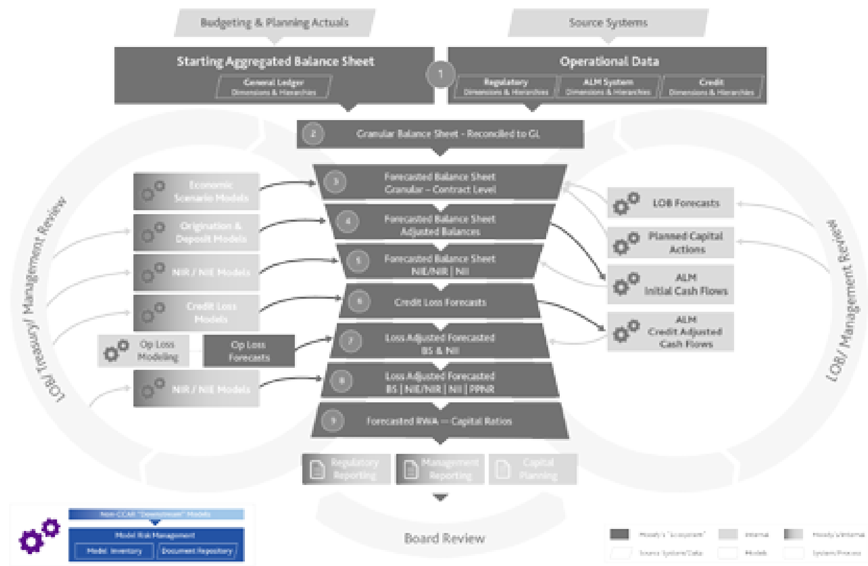
A comprehensive solution must be capable of:

» Handling many issues around connection points and hand-offs
» Managing regulatory edit checks, changes, and report linkages (e.g., between 14A and 9C)
» Supporting management reporting needs, including board and effective challenge documents

Banks need the ability to perform "what-if" and sensitivity analyses and make comparisons across forecasts to facilitate capital planning. They need to ensure the efficient alignment of financial plans, models, and forecasts across lines of business (LOBs), departments, and the board.

The process needs to facilitate capital planning and reporting by reconciling multiple sets of regulatory reports and including internal dashboards tailored to each group of end users.

**Figure 6** Stress testing process workflow: Model risk management




Source: Moody's Analytics

## 5. Model risk management

Finally, the entire process should include an overlay framework for model risk management.

**A common framework for managing a model throughout its life cycle is critically important as banks strive to meet deadlines from external agencies.** The framework should streamline the process of creating, managing, deploying, and monitoring the bank's analytical models, while facilitating sensitivity analysis around key assumptions and making it easier to identify sources of uncertainty.

The Fed's 2015 CCAR Summary Instructions and Guidance document states: "BHCs are required to provide the Federal Reserve with an inventory of all models and methodologies used to estimate losses, revenues, expenses, balances, and RWAs in CCAR 2015. The inventory should start with the FR Y-14A line items and provide the list of models or methodologies used for each item under each scenario and note the status of the validation or independent review of each model or methodology (e.g., completed, in progress)."[1]

This suggests that the process needs to include a model risk management framework covering stress loss, revenue, and expense estimation models, which all in turn should be tailored to the task. Banks need a model risk management framework tailored to the task of stress testing at their own specific bank, not just a standardized database/document repository.

The model management framework should be repeatable and make it easy to register, validate, deploy, monitor, and retrain analytic models. As such, it should include the following capabilities:

> Stress testing forces institutions to complement traditionally expert judgment-driven planning processes with quantitative approaches to produce forecasted cash flows.

- Perform common model management tasks such as importing, viewing, and attaching supporting documentation
- Facilitate the creation of a model and document repository (including model ownership, validation issue tracking,

upstream/downstream models, and status of each model in the inventory)

- Serve as a document repository with all relevant model documentation and comments
- Track and flag issues arising in non-CCAR/DFAST models that impact the submission
- Indicates model risk management ownership, roles, and responsibilities (e.g., validate, approve, etc.) as prescribed by regulatory guidance

A model management framework enables banks to meet the objectives set forth by the FRB, OCC, and FDIC in the same system as the process automation, thereby reducing the burden of multiple systems and allowing for consistent and tractable expert judgment overlay capture.

### Building a better stress testing process

Banks need a better and faster stress testing process that can be governed with more control. The stress testing process flow outlined in this article supports the intersections between risk, finance, treasury, and regulatory compliance, while leveraging existing investments in current systems and models used for stress testing.

An effective flow:

- Provides the governance of a process that is repeatable, transparent, and auditable
- Is a part of managing the bank
- Allows increased frequency of stress testing
- Leverages investment in current data warehouse, systems infrastructure, and existing models

If banks implement a similar process, their stress testing program will become more business-as-usual, freeing up valuable resources and making the entire program more accurate and efficient.

1 The Federal Reserve, *Comprehensive Capital Analysis and Review 2015: Summary Instructions and Guidance*, 2015.

# SUBJECT MATTER EXPERTS

## Greg Clemens

*Director, Stress Testing Solutions*

Greg is a member of the Stress Testing Task Force at Moody's Analytics. He helps clients automate their stress testing processes, providing insight about architectures, data management, and software solutions for risk management. Greg has in-depth knowledge of the risk management business, coupled with a strong technology development background, and has extensive experience developing innovative and strategic technology solutions.

Prior to joining Moody's Analytics, Greg had senior roles in Oracle Financial Services and Citigroup, where he ran a large risk technology development group.

greg.clemens@moodys.com
MoodysAnalytics.com/GregClemens

## Cayetano Gea-Carrasco

*Head of Stress Testing Services and Advisory*

Cayetano is the Head of Stress Testing Services and Advisory at Moody's Analytics. He has extensive experience working with financial institutions on credit portfolio management across different asset classes, analysis of structured credit portfolios, derivatives pricing, counterparty credit risk analytics, stress testing (CCAR, CLAR), liquidity management, and enterprise risk management.

Cayetano holds a BSc and MSc in Telecommunication Engineering, a Master in Economics and Finance, and a MSc in Financial Mathematics, with distinction, from King's College London.

cayetano.gea-carrasco@moodys.com
MoodysAnalytics.com/CayetanoGea-Carrasco

## Pierre Gaudin

*Senior Director, Enterprise Risk Solutions*

Pierre is in charge of strategic initiatives in Asia-Pacific for risk appetite management, stress testing, and origination at Moody's Analytics, assisting with subject matter expertise, client requirement analysis, and use case illustrations. He joined Moody's Analytics via Fermat in 2004, and he has lead several Basel RWA implementations in Europe and Asia.
He also developed Fermat Education services, designing and delivering regulatory compliance and ALM training to clients and system integrators worldwide.

Pierre has 15 years of experience delivering software implementation services for capital markets and risk management solutions at major commercial banks in Paris, Bruxelles, London, Hong Kong, and Singapore. Pierre has a Master's Degree in Systems and Networks Engineering from Supélec, France.

pierre.gaudin@moodys.com
MoodysAnalytics.com/PierreGaudin

## Kevin Hadlock

*Senior Director*

Kevin is a Global eLearning Solution Specialist and supports all training-related activities throughout the Asia-Pacific region. He has designed numerous distance-learning and web-based training programs, developed and taught many seminars, webinars, and full, blended training programs, and has authored a substantial body of content used globally by thousands of credit trainees.

Prior to his current role, Kevin headed up elearning and blended training development for the organization globally, and was the architect for the company's wholesale credit elearning solutions. Kevin had 13 years of experience in the banking industry before joining Moody's Analytics in January 1990. Kevin holds a BA degree from the University of Utah in Business Management.

kevin.hadlock@moodys.com
MoodysAnalytics.com/KevinHadlock

## Dr. David T. Hamilton

*Managing Director, Head of Stress Testing and Credit Risk Analytics, APAC*

Based in Singapore, David has two decades of experience in credit risk modeling, credit ratings, and economic research. He helps provide insight into the practical challenges of credit risk measurement, management, and stress testing.

He has lectured on credit risk topics at Columbia Business School, the Stern School of business at New York University, and the City College of New York (among others). He is on the editorial board of the Journal of Credit Risk and holds a BA in economics and classical studies from Texas A&M University and a PhD in financial economics from the City University of New York.

david.hamilton@moodys.com
MoodysAnalytics.com/DavidHamilton

## Brian Heale

*Senior Director, Business Development Officer (Global Insurance)*

Brian is an insurance market and Solvency II specialist who has significant experience in the technology solutions and issues for the global insurance industry. He has an in-depth knowledge of the practical aspects of the insurance business, coupled with a comprehensive understanding of enterprise technology in relation to the development and implementation of core administration, actuarial/risk, data, and Solvency II reporting systems.

Brian has previously worked with a number of major insurers and technology and consulting companies across the world. He has run administration, product development, and sales divisions, and also has considerable experience in strategic planning.

brian.heale@moodys.com
MoodysAnalytics.com/BrianHeale

## Dr. Tony Hughes

*Managing Director of Credit Analytics*

Tony oversees the Moody's Analytics credit analysis consulting projects for global lending institutions. An expert applied econometrician, he has helped develop approaches to stress testing and loss forecasting in retail, C&I, and CRE portfolios and recently introduced a methodology for stress testing a bank's deposit book.

Tony was formerly the lead Asia-Pacific economist for Moody's Analytics. Prior to that, he held academic positions at the University of Adelaide, the University of New South Wales, and Vanderbilt University. He received his PhD in Econometrics from Monash University in Melbourne, Australia.

tony.hughes@moodys.com
MoodysAnalytics.com/TonyHughes

## Nicolas Kunghehian

*Director, Business Development*

Nicolas is responsible for providing thought leadership on ALM, liquidity, and market risks for the EMEA region to help financial institutions define a sound risk management framework. Nicolas worked as an ALM and risk manager in two French banks for more than six years before joining Fermat in 2005, which was acquired by Moody's Analytics in late 2008.

Nicolas holds a degree in Mathematics and Economics from the Ecole Polytechnique and a degree in Finance and Statistics from the Ecole Nationale de la Statistique et de l'Administration Economique.

nicolas.kunghehian@moodys.com
MoodysAnalytics.com/NicolasKunghehian

## Eric Leman

*Director, Solutions Specialist*

Eric has served as a Solutions Specialist of banking compliance and risk management since 2009, helping organizations make more informed risk management decisions – specifically Basel III capital adequacy (credit risk, market risk), asset and liability management, stress testing, and credit risk monitoring.

He joined Fermat in 2006 (acquired by Moody's Analytics in 2008), working as an Implementation Consultant for three years in Europe, Middle East, and the US. Before joining Fermat, Eric worked for over four years on implementation services at CSC and internally at Danone. Eric holds an engineering degree from Ecole des Mines de Saint Etienne, a prestigious French Grande Ecole.

eric.leman@moodys.com
MoodysAnalytics.com/EricLeman

## Dr. Juan M. Licari

*Senior Director, Head of Economic and Consumer Credit Analytics*

Juan and his team are responsible for generating alternative macroeconomic forecasts for Europe and for building econometric tools to model credit risk phenomena. His team develops and implements risk solutions that explicitly connect credit data to the underlying economic cycle, allowing portfolio managers to plan for alternative macroeconomic scenarios. These solutions are leveraged into stress testing and reverse stress testing practices.

Juan communicates the team's research and methodologies to the market and often speaks at credit events and economic conferences worldwide. He holds a PhD and an MA in Economics from the University of Pennsylvania and graduated summa cum laude from the National University of Cordoba in Argentina.

juan.licari@moodys.com
MoodysAnalytics.com/JuanLicari

## Dr. Samuel W. Malone

*Director of Economic Research*

Sam primarily develops systemic risk solutions that are actionable by individual financial institutions and also actively contributes to consulting projects, such as model validations and bespoke research, taken on by the Specialized Modeling Group (SMG).

Sam has taught and consulted at top institutions in Europe and South America, including Oxford, the University of Navarra, and the Central Banks of Venezuela and Peru. He is a coauthor of the book *Macrofinancial Risk Analysis*, published in the Wiley Finance series with a foreword by Nobel Laureate Robert Merton, as well as the author of multiple academic journal articles in economics and applied math published in outlets such as the *Journal of Applied Econometrics*, the *International Journal of Forecasting*, and the *Annual Review of Financial Economics*. He holds undergraduate degrees in mathematics and economics from Duke University, where he studied as an A.B. Duke scholar and graduated with summa cum laude Latin honors, and MPhil and doctoral degrees in economics from the University of Oxford, where he studied as a Rhodes Scholar.

samuel.malone@moodys.com
MoodysAnalytics.com/SamMalone

## Mark McKenna

*Senior Director, Stress Testing Solutions*

Mark is responsible for business and relationship management for Moody's Analytics stress testing solutions. Prior to his current role, he was with the Structured Analytics & Valuations Group as a solutions specialist leading valuations and cash flow analytics projects with structured finance participants. Additionally, he worked with numerous US financial institutions providing risk management tools and loss estimation models for their retail portfolios.

Mark has been with Moody's for more than 23 years, always in client-facing roles. His past responsibilities have included relationship management for the largest and most strategically important money managers in the US. Early in his career, he managed a team of relationship managers and product specialists for the research, data, and analytics group. He holds a BA degree in economics and political science from Fairfield University.

mark.mcKenna@moodys.com

## Yuji Mizuno

*Director, Business Development Officer*

Yuji leads the product and consulting areas of Moody's Analytics Japan and has extensive knowledge of regulations and risk management practices among financial institutions. He provides clients with insight on regulatory compliance, ALM, liquidity, and ERM frameworks. He also functions as a main contact for Japanese regulators and financial institutions.

Before joining Moody's Analytics in 2009, he worked for ex-Sanwa Bank, Bank of America Securities, Aozora Bank, and JP Morgan securities. He holds a Bachelor of Law from Tokyo University.

yuji.mizuno@moodys.com
MoodysAnalytics.com/YujiMizuno

## Dr. Gustavo Ordonez-Sanz

*Director, Stress Testing Specialist Team*

Based in London, Gustavo advises financial organizations on the different aspects of stress testing scenario analysis at the firm-wide level. This includes: scenario generation; risk, revenue, and capital modeling and forecasting; embedding scenario analysis in the firm's decision-making processes (risk appetite, portfolio management, pricing, etc.); and governance, infrastructure, and reporting.

Gustavo also has experience in credit portfolio and counterparty credit risk modeling and management. Gustavo holds a degree in Theoretical Physics from the University Autonoma of Madrid and a PhD in Physics from Radboud University Nijmegen.

gustavo.ordonez-sanz@moodys.com

## Dr. Brian Poi

*Director, Economic Research*

Brian develops a variety of credit loss, credit origination, and deposit account models for use in both strategic planning and CCAR/DFAST environments. He is equally adept at developing primary models and validating models developed elsewhere. He also provides thought leadership and guidance on the use of advanced statistical and econometric methods in economic forecasting applications.

Before joining Moody's Analytics, Brian was an econometric developer and director of professional services at StataCorp LP, a leading provider of statistical analysis software. He received his PhD and MA in Economics from the University of Michigan after graduating magna cum laude from Indiana University.

brian.poi@moodys.com

## Buck Rumely

*Senior Director, Client Management*

Buck leads the Americas team of credit and technology specialists at Moody's Analytics. He has helped design credit and risk management systems for a variety of financial, governmental, and energy firms throughout North and South America.

Prior to joining Moody's Analytics, Buck was a partner in a leading technology consulting firm. He began his career in software systems development with a national consulting firm, and is a graduate of Indiana University's Kelly School of Business. He has published papers on credit risk in *Risk Magazine*, the *Journal of the International Energy*

*Credit Association*, and the *Journal of National Petroleum and Energy Credit Association.*

buck.rumely@moodys.com

## Peter Sallerson

*Senior Director, Structured Analytics and Valuation*

Peter focuses on the CLO market at Moody's Analytics via the further development of our Structured Finance Portal's CLO section and related research. During his long career, he has worked in the Corporate Finance department at Nomura Securities, was a Managing Director and one of the founders of the CLO effort at Bear Stearns, and ran CLO origination at Mitsubishi UFJ Securities (USA).

Peter graduated Phi Beta Kappa and magna cum laude with a BA in Economics from Middlebury College and his MBA is with honors from the University of Chicago Graduate School of Business.

peter.sallerson@moodys.com
MoodysAnalytics.com/PeterSallerson

## Vivek Thadani

*Director, Structured Finance Valuations & Consulting Group*

Vivek is primarily responsible for developing and maintaining analytical models for various asset classes across the structured security space. Prior to his current role, Vivek supported investor and asset manager clients at Wall Street Analytics across CLO & RMBS asset classes.

Vivek holds a BE in Computer Science from Mumbai University and a MEM from Dartmouth College.

vivek.thadani@moodys.com

## Dr. Christian Thun

*Senior Director, Strategic Business Development*

Christian is responsible for providing thought leadership on credit risk management and strategic business development in the EMEA region and functions as a main contact for regulators and senior management of financial institutions.

With almost 20 years of experience, Christian has worked with numerous financial institutions in the EMEA region on Basel II implementation, risk management, stress testing, and portfolio advisory projects, and in the process has become an internationally-known expert on credit risk management.

christian.thun@moodys.com
MoodysAnalytics.com/ChristianThun

## Michael van Steen

*Senior Director, Enterprise Risk Solutions*

Michael helps deliver advanced portfolio credit risk, stress testing, correlation, and valuation solutions to global financial institutions and regulatory organizations. He is the practice lead for origination services in the Americas, developing and managing services around stress testing, lending workflows, pricing, and limit setting. Previously, Michael worked in the portfolio credit risk area of Moody's Analytics, delivering over 40 portfolio analysis projects that covered economic capital, stress testing, portfolio optimization, correlation estimation, retail pooling, and portfolio valuation.

Michael has BS and MS degrees in Engineering from the University of California, Berkeley, and credit-related coursework at the Stanford Graduate School of Business and at the Kellogg School of Management.

michael.vansteen@moodys.com
MoodysAnalytics.com/MichaelvanSteen

# MOODY'S ANALYTICS RISK MANAGEMENT SOLUTIONS

LEVERAGE POWERFUL SOLUTIONS FOR ENTERPRISE-WIDE RISK MANAGEMENT

Moody's Analytics offers deep domain expertise, advisory and implementation services, in-house economists, best-in-breed modeling capabilities, extensive data sets, and regulatory and enterprise risk management software. Our risk management solutions:

» Improve strategic business planning and facilitate meeting regulatory requirements

» Assist with defining both macroeconomic and business-specific scenarios

» Offer a comprehensive and granular credit risk, economic, and financial data set

» Help model the impact that macroeconomic cycles, regulatory directives, and/or outlier events may have on an institution's risk profile

» Deliver an integrated stress testing software solution to calculate stressed performance indicators across the risk and finance functions

For more information, contact our integrated risk management experts at RiskPerspectives@moodys.com.

## INFRASTRUCTURE

### Scenario Analyzer™

Coordinates the stress testing process across the enterprise, centralizing a wide range of Moody's Analytics, third-party, and proprietary models.

### RiskAuthority™

Delivers comprehensive regulatory capital calculation and management for Basel I, II, and III, including the risk-weighted asset (RWA) calculations required for CCAR reporting.

### RiskAnalyst™

Provides comprehensive and consistent view of your firm's counter-party risk by combining financial spreading, credit analysis and robust data storage using one flexible, secure enterprise platform.

### RiskOrigins™

Risk-focused, workflow-driven software platform that allows commercial lenders to streamline and standardize the commercial credit underwriting process, incorporating Moody's Analytics industry-leading risk assessment capabilities which help lenders demonstrate compliance to regulators.

### Regulatory Reporting Module

Create, validate, and deliver monthly, quarterly and annual CCAR (FR Y-14) and DFAST reporting requirements. Fully integrated with our enterprise risk platform, this module creates and delivers reports in the required formats.

### RiskIntegrity™

Provides a comprehensive and modular solution to manage all aspects of Solvency II compliance, ranging from centralized data management, internal model development, solvency capital requirement calculations, risk type aggregation, and integrated regulatory and business reporting.

### Regulatory Reporting for Solvency II

Integrated with our end-to-end insurance regulatory capital solution, the easy-to-use and cost effective Regulatory Reporting module produces accurate management and regulatory reports in local supervisors' commonly used formats and languages.

### B&H Capital Modeling Framework

Comprised of three products: B&H Economic Capital Calculator, B&H Proxy Generator, and B&H Risk Scenario Generator. Together, they provide a rapid and highly flexible approach to calculating economic capital for complex liabilities in the life insurance industry, and establish the processes required by Solvency II and ORSA for assessing insurance capital solvency.

### B&H Proxy Generator

Creates proxy functions that can be used to meet a range of business needs, such as interim valuation, capital calculations, and hedge effectiveness.

### B&H Property & Casualty ESG

Provides automated Economic Scenario Generation solutions for P&C insurers with modeling capability and calibration content. It is specifically developed to meet the needs of P&C insurers, as part of an internal capital model or for asset portfolio risk management.

### B&H Defined Benefit ALM

Is a sophisticated ALM solution underpinned by the B&H Economic Scenario Generator and calibration content. Provides a comprehensive risk modeling framework that allows advisors, asset managers, and in-house pensions teams to measure and manage the risks facing defined benefit pension funds.

### B&H PensionsLite

Differs from B&H Defined Benefit ALM in that it has a simpler, more accessible user experience that enables interactive meetings with trustees or corporate sponsors, and a slightly less sophisticated modeling engine.

### RiskFrontier™

Produces a comprehensive measure of risk, expressed as Credit VaR or Economic Capital, which comprises the basis for deep insight into portfolio dynamics for active risk and performance management.

## SCENARIOS

### Global and Regional Macroeconomic Scenarios

Delivered by a team of over 80 experienced economists, who offer standardized alternative economic scenarios, supervisory scenarios, and bespoke scenarios customized to your specific needs for 49 countries, as well as US states and metro areas.

### B&H Economic Scenario Generator

Provides Monte Carlo simulation paths for the joint behavior of financial market risk factors and economic variables. The automated, market-leading Economic Scenario Generation for life insurance offers modeling capabilities and calibration content for many levels of user sophistication.

### B&H Market-Consistent Economic Scenario Generator

Addresses the challenges of market-consistent liability valuation required in Solvency II. It includes the award-winning B&H Scenario Generator (ESG).

### B&H Scenario Service

Is an alternative to ESG software and provides insurers with scenario sets on an annual, semi-annual, or quarterly basis. Insurers and reinsurers can decide between the control and flexibility of a software installation or the simplicity and ease-of-use offered by the scenario service.

## DATA

### RiskFoundation™

Integrates your enterprise financial and risk data to calculate regulatory capital, economic capital, ALM, liquidity, counterparty risk, and for a global view of your exposures.

### Moody's Content Licensing Services

Provides a suite of comprehensive data covering all current Moody's Investors Service issuer and issue-related ratings.

### Global and Regional Macroeconomic Scenarios

Delivered by a team of over 80 experienced economists, who offer standardized alternative economic scenarios, supervisory scenarios, and bespoke scenarios customized to your specific needs for 49 countries, as well as US states and metro areas.

### Global Economic, Financial, and Demographic Data

Provides a comprehensive view of global economic conditions and trends. Our database covers more than 180 countries with more than 260 million time series from the best national and private sources, as well as key multinational data sets.

### Moody's Analytics Credit Research Database (CRD)

Is the world's largest and cleanest database of private firm financial statements and defaults, built in partnership with over 45 leading financial institutions around the world.

### Exposure at Default (EAD)

Data is derived from a subset of the CRD Database and is compiled of 10+ years of usage data for estimating and calculating EAD. The EAD database contains quarterly usage and Loan Equivalency Ratio data for both defaulted and non-defaulted private firms since 2000.

### PD Time Series Information

Offers time series of observed default rates and calculated PDs, covering more than two economic cycles. This data is collected and calculated for both public and private firms.

### Credit Migration Data

Enables users to construct detailed credit migration (transition) matrices. This detailed private firm data allows users to be more granular with segmentations across industry, region, and asset size using several different PD rating calculation methodologies.

### Credit Cycle Adjustment Data

Combines financial statement ratio information of private firms with credit cycle factors in the public equity markets to derive a dynamic, through-the-cycle PD measure.

### Structured Finance (SF) Data

Offers loan, pool and bond level performance data for RMBS, CMBS, ABS and CDOs. SF Data can be used for bottom-up mortgage stress testing model creation and calibration. SSFA data and calculations are also available.

### Default and Recovery Database

Allows users to look at how default experience varies at different points in the economic cycle, and which factors made default experience in each economic cycle unique. The data includes detailed rating histories, 30-day post default pricing, and three views into ultimate recovery.

## INVESTMENT ANALYSIS/SURVEILLANCE

### Moody's CreditView

Research and data to assist risk practitioners with investment analysis, creation of internal risk scores and meeting due diligence requirements.

## MODELS

### CreditCycle™

Provides retail credit portfolio insights into the expected and stressed performance of existing and future vintages, enabling loss forecasting and stress testing.

### CreditEdge Plus™
Bridges the equity, bond, and credit derivative markets, enabling an in-depth understanding of their impact on credit risk.

### Stressed EDFs™
Estimate PDs for public firms using a range of macroeconomic scenarios, including EBA and user-defined scenarios.

### Commercial Mortgage Metrics (CMM®)
Is the leading analytical model for assessing default and recovery risk for commercial real estate (CRE) loans. CMM's stress testing capabilities leverage Moody's Analytics Economic and Consumer Credit Analytics, Federal Reserve's CCAR, and custom scenarios.

### GCorr®
Moody's Analytics Global Correlation Model (GCorr) is an industry-leading granular correlation model used to calculate each exposure's contribution to portfolio risk and return for improved portfolio performance.

### GCorr® Macro
Macro Stress testing with GCorr Macro produces instrument-level stress expected losses across multiple asset classes to help manage credit risk.

### LossCalc™
Calculates the Loss Given Default (LGD) for loans, bonds, sovereigns, municipals and preferred stock using a range of Asset Classes and a Comprehensive Database of Defaulted Instruments.

### Portfolio Analyzer (PA)
Is a loan level capital allocation and risk management tool providing stressed PDs, LGDs, and prepayments for RMBS, auto ABS, mortgage and auto loans under the Fed's CCAR scenarios and custom scenarios.

### RiskCalc™ Plus
Enables clients to calculate forward-looking PDs for private firms across different regions and industries and measure how borrowers would be affected by stressed scenarios versus a baseline scenario.

### RiskFrontier™
Produces a comprehensive measure of risk, expressed as Credit VaR or Economic Capital, which comprises the basis for deep insight into portfolio dynamics for active risk and performance management.

### WSA Platform
Is a risk and portfolio management tool used for stress testing structured finance transactions. Moody's Analytics maintains a global structured finance deal library. WSA integrates macroeconomic, credit models, pool, and loan level performance data to forecast cash flows, PDs, LGDs, and prepayments.

## SERVICES

### Enterprise Risk Solutions Services
Provide stress testing, model validation, and implementation services.

### Valuation and Advisory Services
Provide stress testing, model validation, and implementation services for all structured finance assets.

### B&H Calibration Service
Is a market-leading calibration service that provides prompt quarterly updates for Moody's Analytics models, reflecting the latest market conditions and economic outlook. Also provides a range of calibration types for specific applications.

### Outsourcing Services
Our Copal Partners unit is one of the world's leading providers of outsourced high quality research and analytics services to institutional customers. Copal's workflow processes are designed to ensure the highest possible level of data integrity and auditability while delivering rigorously verified research and analysis.

## TRAINING & CERTIFICATION
Moody's Analytics designs, develops and facilitates training programs and solutions for financial services institutions and individuals interested in banking, finance, and personal and organizational development.

Company Learning Solutions

### Instructor-led Training
Our subject-matter expertise and course selection can be tailored to the needs of multiple levels of an organization – from new hires that need basic training – to experienced professionals seeking an update on current thinking or insights into new markets.

### eLearning and Blended Solutions
Offer a suite of training solutions for financial institutions that enable companies to minimize people risk, with customized learning solutions using practical learning methodologies and the Moody's Analytics expertise in credit and finance.

Individual Learning Solutions

### Public Seminars
Moody's Analytics offers over 200 open-enrollment courses throughout the year, in major financial centers around the world, on fundamental through advanced topics in finance and risk.

### eLearning Programs
Provide the industry's most comprehensive eLearning curricula for corporates, commercial and investment banks, as well as asset managers and regulators. Our programs are accessible online and on-demand from any web-enabled computer.

# CONNECT WITH US

## Get More Insight from Moody's Analytics

There are many ways to view our content online. Register just once and you'll gain free access to all of our valuable insight, including *Risk Perspectives* articles, webinars, white papers, and more.

» View previous editions of *Risk Perspectives* at MoodysAnalytics.com/RiskPerspectives

» Sign up for our newsletters at MoodysAnalytics.com/Register

» Learn about our events at MoodysAnalytics.com/Events

» Stay in touch with our Subject Matter Experts at MoodysAnalytics.com/SME

» Follow our social channels for the latest insight at MoodysAnalytics.com/Connect

## About Risk Perspectives

Each edition of *Risk Perspectives* magazine explores an industry or regulatory topic in depth, presenting a wide range of views, best practices, techniques, and approaches, all with one larger goal in mind – to deliver essential insight to the global financial markets.

# ABOUT US

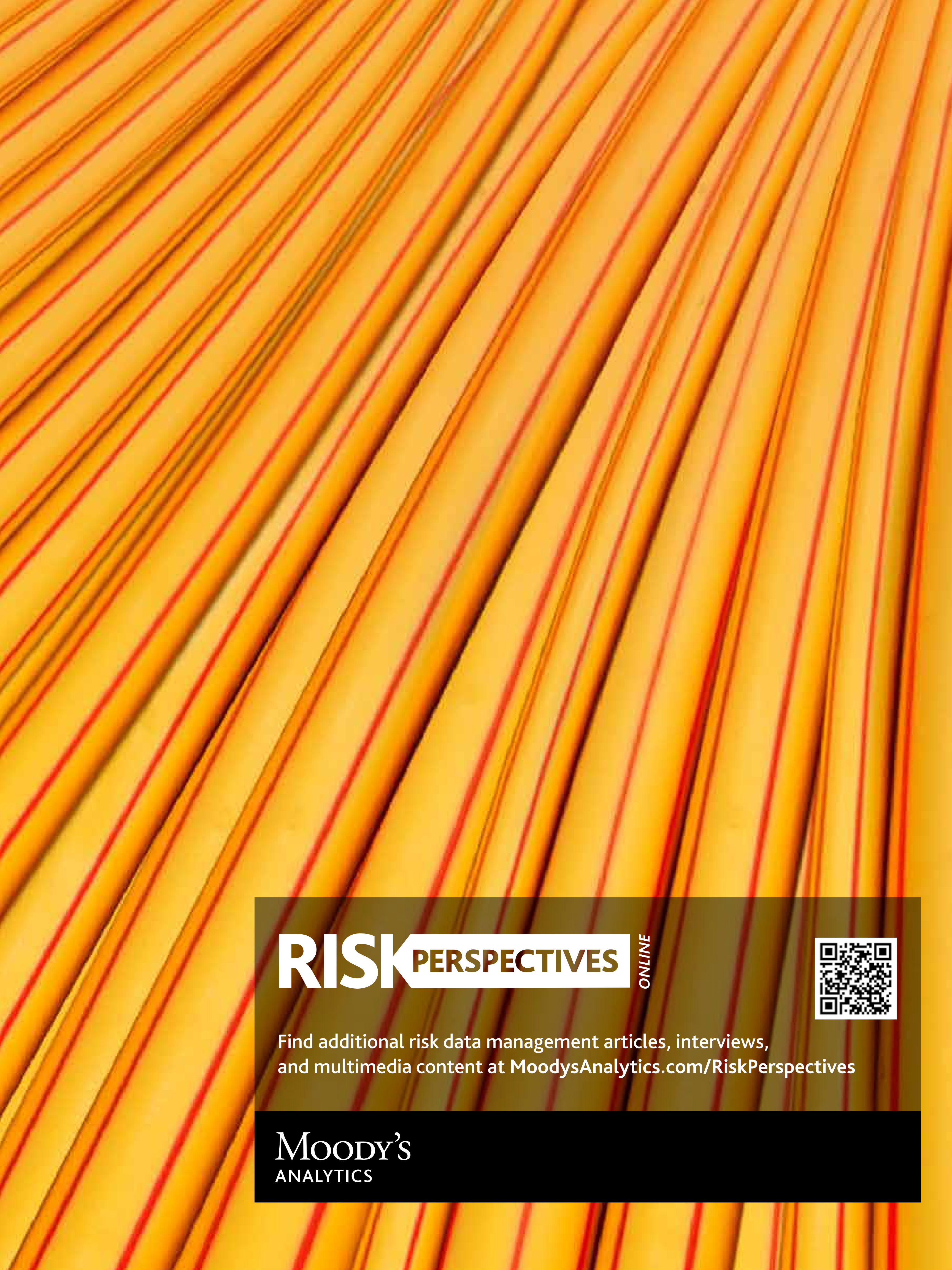
Moody's Analytics offers award-winning solutions and best practices for measuring and managing risk through expertise and experience in credit analysis, economic research, and financial risk management. By providing leading-edge software, advisory services, data, and research, we deliver comprehensive investment, risk management, and workforce solutions. As the exclusive distributor of all Moody's Investors service content, we offer investment research, analytics, and tools to help debt capital markets and risk management professionals worldwide respond to an evolving marketplace with confidence.

We help organizations answer critical risk-related questions, combining best-in-class software, analytics, data and services, and models – empowering banks, insurers, asset managers, corporate entities, and governments to make informed decisions for allocating capital and maximizing opportunities. Through training, education, and certifications, we help organizations maximize the capabilities of their professional staff so they can make a positive, measurable impact on their business. More information is available at moodysanalytics.com.

# GLOSSARY OF TERMS

| | |
|---|---|
| ALM | Asset and Liability Management |
| BCBS | Basel Committee on Banking Supervision |
| BHC | Bank Holding Companies |
| BIS | Bank for International Settlements |
| BoE | Bank of England |
| CCAR | Comprehensive Capital Analysis and Review |
| CCP | Central Counterparty |
| CCR | Central Credit Register |
| CDS | Credit Default Swap |
| CECL | Current Expected Credit Loss |
| CLO | Commercial Loan Origination |
| CRE | Commercial Real Estate |
| CRM | Customer Relationship Management |
| CRO | Chief Risk Officer |
| DFAST | Dodd-Frank Act Stress Test |
| DGC | Degree of Granger Causality |
| DGI | Data Gaps Initiative |
| DSGE | Dynamic Stochastic General Equilibrium |
| D-SIB | Domestically Systematically Important Banks |
| EAD | Exposure at Default |
| EBA | European Banking Authority |
| ECB | European Central Bank |
| EDF | Expected Default Frequency |
| EL | Expected Loss |
| ELR | Expected Loss Ratio |
| ERM | Enterprise Risk Management |
| FASB | Financial Accounting Standards Board |
| FDSF | Firm Data Submission Framework |
| FFELP | Federal Family Education Loan Program |
| FRB | Federal Reserve Board |
| FSAP | Financial Sector Assessment Program |
| FSB | Financial Stability Board |
| FTP | Funds Transfer Pricing |
| GAAP | Generally Accepted Accounting Principles |
| GFC | Global Financial crisis |
| GFMA | Global Financial Markets Association |
| G-SIB | Globally Systematically Important Banks |
| HQLA | High-Quality Liquid Asset |
| IAP | Insurance Analytics Platform |
| IASB | International Accounting Standards Board |
| IFRS | International Financial Reporting Standards |
| IRB | Internal Ratings-Based |
| LCR | Liquidity Coverage Ratio |
| LEI | Legal Entity Identifier |
| LGD | Loss Given Default |
| LTV | Loan-to-Value |
| MRA | Matters Requiring Attention |
| NSFR | Net Stable Funding Ratio |
| ORSA | Own Risk Solvency Assessment |
| P&L | Profit and Loss |
| PD | Probability of Default |
| PPNR | Pre-Provision Net Revenue |
| PRA | Prudential Regulation Authority (UK) |
| REO | Real Estate Owned |
| RMBS | Residential Mortgage-Backed Security |
| RMSE | Root Mean Squared Prediction Error |
| RWA | Risk-Weighted Asset |
| SIFI | Systemically Important Financial Institutions |
| SLABS | Student loan Asset Backed Security |
| SSFA | Simplified Supervisory Formula Approach |
| UCA | Uniform Credit Analysis |
| VaR | Value-at-Risk |

AnaCredit Solvency II Datamart
Basel Risk Systems LGD AnaCredit
FTP Framework Forecasting P&L
Data Integration Risk Appetite
IAS 39 Expected Loss The Fed
Stress Testing
Data Governance
Credit Risk IFRS 9
Basel III LGD FR Y-14Q
DFAST Expected Default Frequency
Stochastic Scenario Generation
CCAR Granular Data PD
IFRS 4 Monte Carlo Study Data Quality
Portfolio Indicators FR Y-14Q
BCBS 239 Forecasting P&L
Data Management
RWA
FR Y-14M
Regulatory Big Data
Human Data
IFRS 4


RISK PERSPECTIVES ONLINE
Find additional risk data management articles, interviews, and multimedia content at MoodysAnalytics.com/RiskPerspectives
MOODY'S ANALYTICS