Strategy | Consulting | Digital | Technology | Operations

Credit Risk Model Monitoring

High performance. Delivered.

INTRODUCTION

This scenario might sound familiar:

- A bank uses over 50 analytical models to support its underwriting, pricing and finance functions. There are numerous models in place to generate the probability of default (PD), loss given default (LGD) and exposure at default (EAD) metrics that serve as inputs to the bank's capital computation process.
- Model monitoring and tracking are performed by an understaffed analytics team, using Microsoft Excel® templates and SAS© or other tools that may have been handed down for years.
- Reports for senior management are assembled manually, under pressure, using metrics and formats often not updated for long periods of time.
- A regulatory review of any models used usually triggers a massive manual exercise as reports and documents are created and compiled. There may be multiple rounds of information exchange with the regulator, as internal reports do not address all aspects of model performance.

The above describes the situation at a medium-sized European bank, but is fairly common across the industry.

Model monitoring—the regular analytical review of model performance—may be loosely managed, with its effectiveness dependent on a few key individuals. Processes related to model monitoring may be affected by a number of elements including:

Governance

- A lack of policies around model risk monitoring, or policies in place may not be properly enforced.
- No full model list for audit tracking purposes; or a list not regularly updated.

Organization

- The organization finding itself in reactive mode, often scrambling frantically to meet internal and external deadlines.
- Timelines regularly affected by poor capacity planning and inadequate contingency plans.

Processes and Procedures

- No standards in place surrounding the frequency of model monitoring; similar teams using different standards and procedures for model tracking templates or for performance metrics.

Monitoring Output Analysis

- Poorly performing models remaining in production due to decision making affected by inconsistency in metrics, frequency, lack of analysis of root causes, or by ineffective and poor commentaries on monitoring output.

Operational Risks

- Lack of automation (for example, the manual entry of SAS® outcomes into Microsoft Excel®/Microsoft PowerPoint®), regular controls in code and of tracking logs, leading to a high error rate.
- Lack of contingency plans lead to the risk of losing key historical facts if dedicated personnel leave the firm and adequate logs are not in place.

In today's financial institutions, analytical models are high-value organizational and strategic assets. As models are needed to run the business and comply with regulations, they must be effectively and efficiently managed for optimal performance once in production.

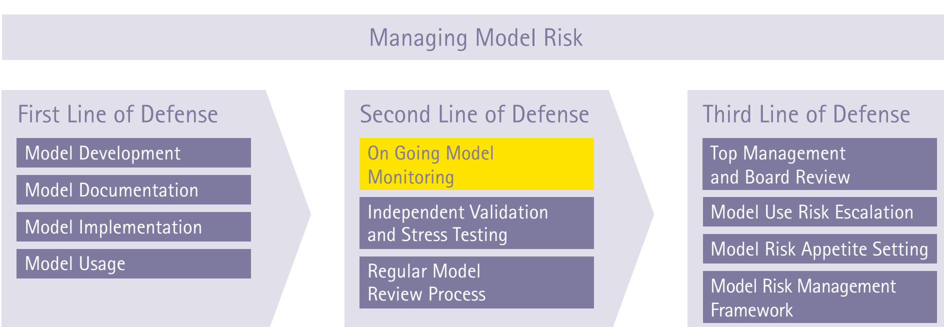
Poor governance and process in the management of these models can expose an organization to the risks of suboptimal business decisions, regulatory fines and reputational damage.

As seen in Figure 1 below, a robust system of ongoing model monitoring is a key component in the management of model risk.

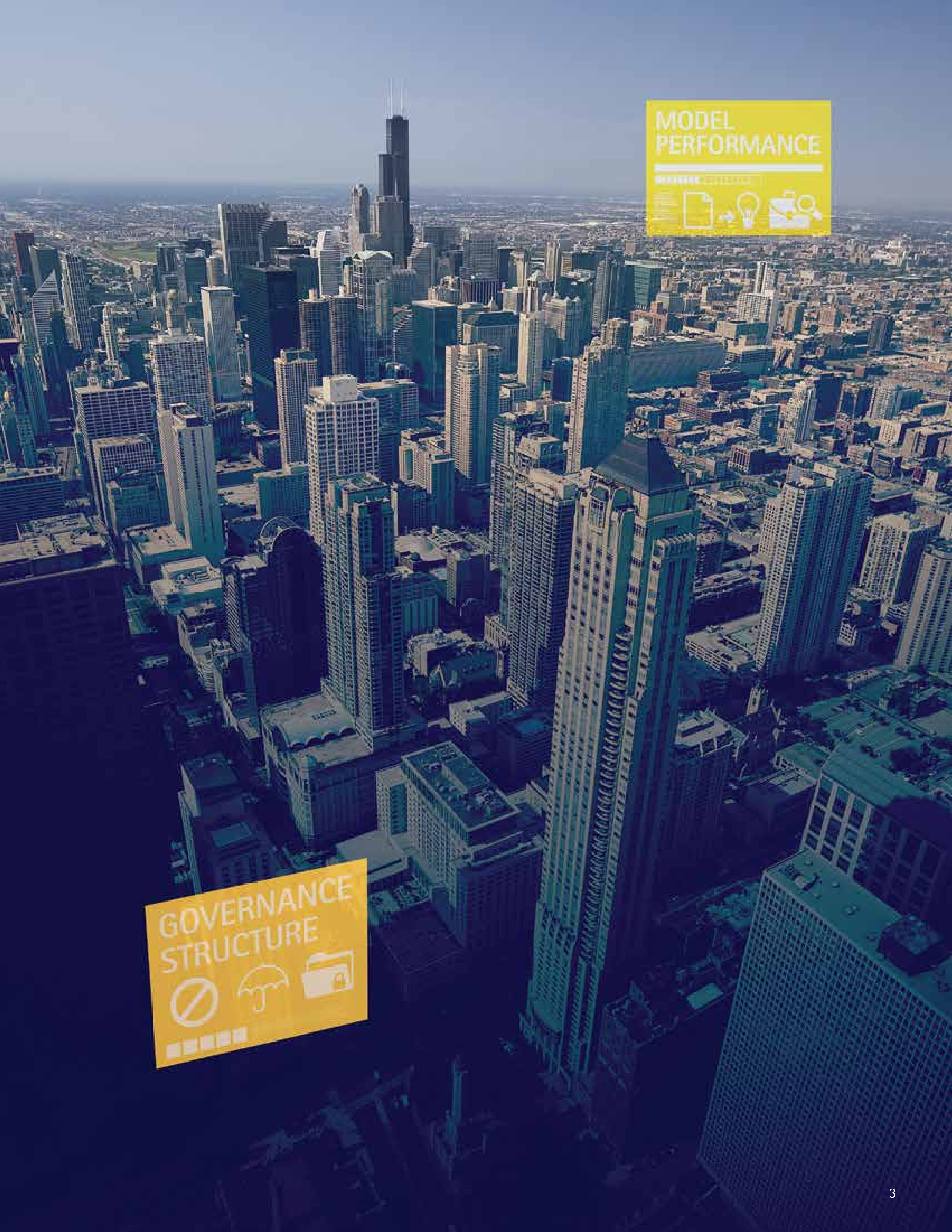
From a broader perspective, the term "model" refers to any approach that processes quantitative data as input, and provides a quantitative output. The definition of a model can prove contentious. Best practice often sees a broader definition of a model, with a sensible model monitoring standards document in place. This should help ensure that all of the models are noted on the master list, but that there are appropriate levels of monitoring put in place.

While we discuss the measurement of credit risk, and therefore refer to scoring or rating PD and LGD models, the best practices to which we refer are applicable to any type of quantitative model.

Figure 1: Managing Model Risk



Source: Accenture, November 2014


MODEL
PERFORMANCE
GOVERNANCE
STRUCTURE

EFFECTIVE MODEL MONITORING: KEY PRINCIPLES

Ongoing monitoring is essential to evaluate whether changes in products, exposures, activities, customers or market conditions call for adjustment, redevelopment, or replacement of the model or to verify that any extension of the model beyond its original scope is valid. Any model limitations or assumptions identified in the development stage should be assessed as part of ongoing monitoring.

In practice, monitoring begins when a model is first implemented in production systems for actual business use. This monitoring process should have a frequency appropriate to the nature of the model, the availability of new data or modeling approaches, and the magnitude of the risks involved. In our view, this should be clearly laid out as part of a monitoring standards document.

ENTERPRISE LEVEL MODEL INVENTORY

A model inventory takes stock of the models used by an institution and establishes clear ownership of the maintenance and usage of the model. Some measure of the materiality of the model or portfolio should be included (common measures include the portfolio balance or exposure at default).

While the existence of a complete listing of models in use and associated materiality may seem like a basic component of risk management, it has been cited as a gap by the Federal Reserve in its 2013 Comprehensive Capital Analysis and Review (CCAR) Guidelines. As the Fed noted, bank holding companies with lagging practices were not able to identify all models used in the capital planning process. They also did not formally review all of the models or assumptions used for capital planning purposes.[1]

Guidelines for establishing a model inventory include:

- Segregate the inventory building exercise by model category; for example segments may include:
  - Underwriting/Application Scoring Models
  - Account/Customer Behavior Scoring Models
  - Risk Decisioning Models
  - Pricing Models
  - Impairment/Provisioning Models
  - Stress Testing Models
  - Collections and Recovery Scoring Models
  - Capital Planning Models such as PD, LGD and EAD.
- Within each category, maintain a complete listing of all models used across the entity or group of entities. One way to do this is to include a measure of portfolio size such as EAD (or portfolio balance where EAD is not available) when building the list and checking that the sum of the sub-portfolio EAD equals the total EAD. This will help ensure that sub-portfolios and models are not missed, and also that the rationale for excluded or untreated segments is noted. This may also be used to track the proportion of portfolio EAD covered by various models, which is often requested by regulators.
- The inventory should be careful to also include any sub-models or 'feeder' models. As the Fed noted banks should keep an inventory of all models used in their capital planning process, including "feeder" models and all input used that produce estimates or projections used by the models to help generate the final loss, revenue or expense projections.[1]
- The inventory should include the following information for each listed model (Table 1).

Table 1: Enterprise Level Model Inventory

Component	Description
Model Type	Model type to be selected from the list: • Underwriting/Application Models • Account/Customer Behavior Models • Risk Decisioning Models • Pricing Models • Impairment/Provisioning Models • Stress Testing Models • Collections and Recovery Scoring Models • Capital Planning Models
Product Type	Product type to be selected from: • Retail Mortgage • Small and Medium Enterprise (SME) Mortgage • Non-retail Property • Credit Card • Etc...
Portfolio	Use of unique portfolio identifier.
Model Dependencies	Any critical backward or forward linkages in the processes.
Model Usage	What life-cycle process, product and entity does the model impact.
Model Adjustments	What adjustments (if any) are made to the model output before it is fit for purpose.
Materiality	• Portfolio EAD (amount and percentage) covered by each model, and EAD period date and source. If EAD is not available, portfolio balance should be used and noted. • For different model types, alternative materiality measures may be used. For example, application model materiality may be measured by projected pipeline. This should be clearly laid out in the model monitoring standards.
Model Owner	Work contact details for model owner.
Model Developer	Work contact details for employees involved in model creation.
Model Approver	Work contact details for key employees involved in model approval.
Model User	Work contact details for key employees involved in model usage.
Model Maintenance	Work contact details for key employees involved in model maintenance.
Model Approval	Date of model approval.
Last Model Validation	Date of last model validation.
Last Model Monitoring	Date of last model monitoring.
Documentation	• Links to model documentation including development documents as well as any strategy setting/usage documents. • Rationale for model dismissal, approval with exceptions (for example, no change despite poor performance) to policy, and outcomes of validations.
Current Model Status	• Status of model (pending approval, approved, decommissioned). • Should include rationale for model decommission, approval with exceptions. For example, no change despite poor performance to policy, and outcomes of last validation.
Key Technology Aspects	• Implementation platform. • Any issues at implementation or thereafter.
Current Model Risk Rating	The current risk rating of the model (e.g. Red/Amber/Green).

Source: Accenture, November 2014

ROBUST DATA MONITORING PROCESSES

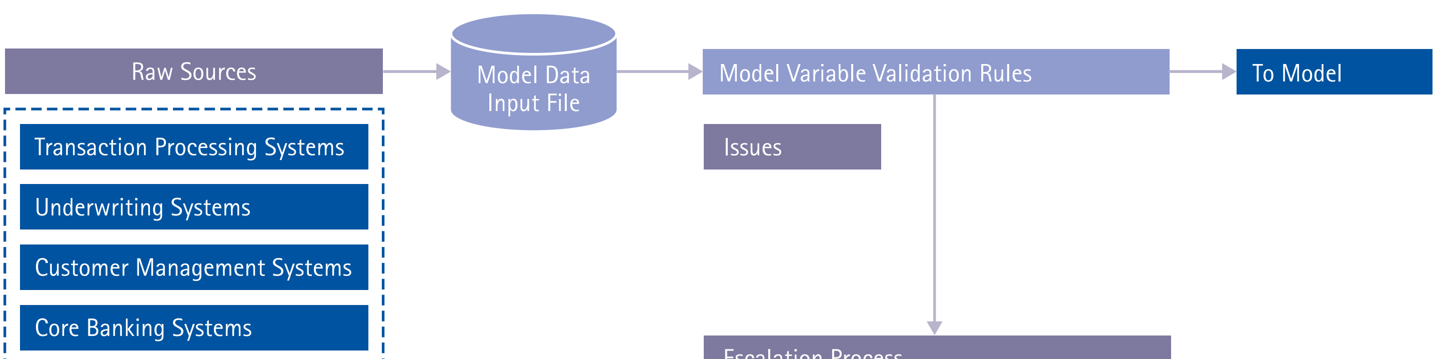
Models are data intensive by their nature and typically are designed to accept inputs from underwriting/origination systems, transaction processing systems, core banking systems and other sources.

Errors in raw data or in model variables may be reflected in model monitoring reports, but often happens too late to prevent negative effects on the business. To avoid such problems, data quality and consistency rules should be considered and created for each raw data field to help ensure the integrity of the data dimensions feeding the model.

A best practice common to a number of large banking institutions is to establish a data monitoring process that precedes model monitoring, as seen in Figure 2 below.

A large European bank has a monthly process to help run all model input data through a validation engine with approximately 8,000 rules. The engine analyzes the model input file and generates a monthly model data quality report, indicating the variable(s) affected and models affected, if any. This is combined with data on portfolio materiality to define an escalation process for data issues.

Figure 2: Data Monitoring Process



Likelihood level

Consequence level	Unlikely	Unlikely	Possible	Likely	Very likely
Catastrophic	High	High	Extreme	Extreme	Extreme
Major	Medium	High	High	Extreme	Extreme
Moderate	Low	Medium	High	High	High
Minor	Low	Low	Medium	Medium	Medium
Insignificant	Low	Low	Low	Low	Medium

Source: Accenture, November 2014

GOVERNANCE STRUCTURE

Critical components of a robust governance structure around credit risk model monitoring include:

- Independence of the model monitoring team from the model development team;
- Effective model audit processes and procedures; and
- Engagement and involvement from senior management.

While the necessity for an independent model monitoring team may seem obvious, in practice, modeling functions are often loosely structured, and independence may exist only in theory.

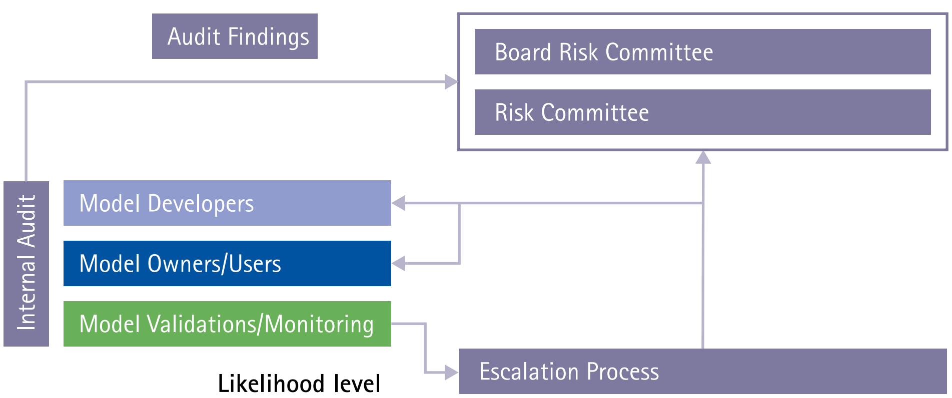
Ideally the organization should have a clear separation among model developers/users and validation functions. Incentive structures should not discourage the escalation of model issues as appropriate, with a clearly defined escalation matrix.

A robust internal audit process is a key element of any model monitoring program. The audit function would typically audit all stakeholders—including developers, users, and monitoring/validation teams—and would also examine all processes involved. This is a critical element; in an anecdotal case, the model monitoring Microsoft Excel® spreadsheets used by a large Asian regional bank were found to have several formula errors. The spreadsheets had been used for several years and were assumed to be correct.

Senior management and board involvement in model governance may be the most important element of all. This is essential to help ensure awareness and ownership of models and related issues, appropriate decision making in relation to potential business and regulatory impacts, and existence of appropriate incentive structures. The communication lines of a good governance framework may be found in Figure 3.

It is important in our view to have communication across all three lines of defense. Figure 3 outlines these lines of communications for the functions previously identified in Figure 1. This can help ensure that low level model issues can be actioned quickly, without senior management involvement. However, having an escalation channel to senior management can help raise major issues should action be required. Internal audit also has a very clear role to play in helping to provide assurance that all processes have been carried out effectively.

Figure 3: Governance for Model Monitoring



Likelihood level

Consequence level	Unlikely	Unlikely	Possible	Likely	Very likely
Catastrophic	High	High	Extreme	Extreme	Extreme
Major	Medium	High	High	Extreme	Extreme
Moderate	Low	Medium	High	High	High
Minor	Low	Low	Medium	Medium	Medium
Insignificant	Low	Low	Low	Low	Medium

Source: Accenture, November 2014


POPULATION
STABILITY
INDEX
MODEL
DISCRIMINATION

COMPREHENSIVE INDICATORS FOR MODEL PERFORMANCE

There are several aspects related to the performance of a credit risk model (as seen in Table 2) that should be represented in a good monitoring system. In practice, it is often observed that organizations adhere to a few simple metrics (notably the Kolmogorov-Smirnov (KS) Statistic, and the Gini Coefficient) for regular monitoring purposes, leaving the more comprehensive checks and related metrics for periodic (often annual, if not bi-annual) validation exercises.

Infrequency in measuring comprehensive checks can have adverse consequences. For example, a major UK lender had poorly calibrated PD models across several portfolios, leading to negative regulatory comments.

A key best practice employed in conjunction with various performance criteria is the definition of performance thresholds (often called 'Traffic Lights') for various metrics. While industry standards are available for certain metrics, most banks would determine acceptable thresholds internally, subject to regulatory supervision.

Table 2: Evaluating Credit Risk Model Performance

Component	Description
Model Discrimination	• The ability of the model to differentiate between events and non-events based on its input values, such as defaults and non-defaults. • For models that do not have a binary outcome, this can be measured similarly as a 'High'/'Low' indicator.
System or Population Stability	• How different is the current data being scored by the model, compared to the data from the model development; is the model stable over time?
Characteristic Stability	• How different is the distribution of the current population in each explanatory variable in the model compared to the population used for model development? • What impact does this have on model performance?
'Actual versus Expected' or Calibration	• Does the model deliver accurate point predictions? • This is particularly significant for Regulatory Capital models where systematic under or over-prediction may have capital implications.
Score Distribution Analysis	• Does the model generate large concentrations at particular deciles or credit grades? • Has there been a large migration over time in scores that needs to be investigated?
Override Analysis	• To what extent and why are there judgmental overrides over and above the raw model output?

Source: Accenture, November 2014

MODEL DISCRIMINATION

Many credit risk models feature a binary classification structure, as they have to assess an obligor's future status using their present characteristics (application models) or recent behavior (behavioral models). The measurement of a classification tool's ability to assess an obligor for the future status is commonly called discrimination.

The concept is also applicable to models that predict continuous variables (such as loss given default) in terms of the model's ability to differentiate between high and low values. Table 3 illustrates some measures of discrimination observed in industry literature.

The KS Statistic and Gini Coefficient are the two most frequently used metrics in an industry context; in banking, the Basel Committee recommends the Gini Coefficient or accuracy ratio (AR) and the area under curve (AUC) measures.[2]

Table 3: Measures of Model Discrimination

Component	Description
Gini Coefficient or Accuracy Ratio (AR)	• Area under Gini Curve/Lorenz Curve of model as compared to the 'perfect' model, or one that would capture 100% of events in the first score bucket/decile. • Values ranging from 0-1. • This measure enables a direct comparison across models.
Kolmogorov–Smirnov (KS) Statistic	• The maximum separation between the percentage of events captured and percentage of non-events captured by the model in cumulative distributions of events and non-events. • Values ranging from 0-1. • This measure enables a direct comparison across models.
Receiver Operating Characteristic Curve/ Area Under Receiver Operating Characteristic (ROC) Curve	• Enables a comparison of two models on their ability to identify a true positive (that is, an event) as opposed to a false positive. • The area under the ROC curve (AUC) is a measure of the probability that the model will rank a randomly chosen event higher than a randomly chosen non-event and is related to the Gini Coefficient (G) by the formula $G = 2(AUC) - 1$.
Pietra Index	• The maximum vertical distance between the model Lorenz Curve and the line representing a random decision rule. This distance may be interpreted as the maximum 'lift' over random provided by the model.
Change in Gini Coefficient	• A comparison of the model's most recent Gini calculation with that observed for the previous tracking period. A large decrease or increase would indicate a need for further investigation.

Source: Accenture, November 2014

SYSTEM STABILITY

System stability or population stability compares the data sample the model was developed on with a more recent data sample on which the model has been used. The discriminatory power of a model is based on information contained in the development dataset, and hence large variances from this may cause model performance to deteriorate, or make the model unfit for purpose. Table 4 shows some standard measures of stability.

The Population Stability Index (PSI) is the standard measure for system stability and is also recommended by most regulatory bodies. The PSI is also applicable to models that predict continuous outcomes.

The transition matrix is critical to PD models and is in most cases a required submission to regulators. Thresholds for the degree of transition that is deemed acceptable are usually set internally by the institution.

Table 4: Evaluating System Stability

Component	Description
Population Stability Index (PSI)	• Measure of the relative change in distribution of the development and recent data samples by score deciles/ranges (to be defined on the development sample).
PSI: Events	• Measure of the relative change in distribution of events (such as defaults) between the development and recent data samples by score deciles/ranges (to be defined on the development sample).
PSI: Non-Events	• Measure of the relative change in distribution of non-events (e.g. non-defaults) between the development and recent data samples by score deciles/ranges (to be defined on the development sample).
Transition Matrix (Migration Matrix)	• This compares two time periods—usually the previous and current periods for model monitoring—and examines what proportion of the portfolio migrated to a higher or lower score category or decile. This measure is typically used for PD models.

Source: Accenture, November 2014

CHARACTERISTIC STABILITY

The system stability measures examine a model as a whole but do not examine how individual model characteristics or variables may have changed in distribution during two time periods. While the overall system stability (as seen in the PSI value) may be acceptable, when analyzed in detail it may conceal large variations in individual model characteristics. Table 5 examines some measures of characteristic stability.

Characteristic stability measures are increasingly requested by regulators and external auditors as evidence of the thoroughness of a model monitoring system, in addition to the PSI measures.

Table 5: Characteristic Stability Metrics

Component	Description
Characteristic Stability Index (CSI)	• Measure of the change in the distribution of a variable between the development and recent data. • This uses the categories generated for the concerned variable on the development data as a basis for comparison.
Change in Characteristic Information Value (IV)	• A large change in the IV for a particular characteristic indicates a change in its distribution – or possibly over fitting to the model development data initially. • The IV is a measure of the discriminatory power of a given variable.

Source: Accenture, November 2014

'ACTUAL VERSUS EXPECTED' OR CALIBRATION

The calibration or actual versus expected performance of a model refers to its ability to yield an accurate point prediction for the output variable. This is particularly relevant for Regulatory Capital models where systematic over or under prediction may be subject to regulatory scrutiny and overrides. Table 6 discusses some measures of calibration observed in the industry and within vendor tools.

The Basel III norms explicitly cite "appropriate calibration of the risk functions, which convert loss estimates into regulatory capital requirements."[3] This level of scrutiny can be expected to increase within this important aspect of model performance.

Table 6: Evaluating Model Calibration

Component	Description
Hosmer-Lemeshow (HL) or Chi-Square Test	• The HL test quantifies if the model is a good fit given the current data. It compares observed versus predicted counts of outcome defaults in each rating grade or score decile. • Quality of fit is thus summarized into a single statistic.
Brier Score	• The Brier score measures the accuracy of probabilistic predictions, measuring the mean squared differences between predicted and actual outcomes. • The score is only suitable for models predicting a binary outcome.
Calibration Curve Shape Test	• This is a technique based on a confidence interval created around the model prediction. • Depending on the number of instances where the actual outcome lies outside this confidence interval, the test is classified as a Red, Amber or Green outcome. • The calibration curve plot accompanying the test provides a useful visual view of model calibration.

Source: Accenture, November 2014

SCORING ANALYSIS DISTRIBUTION

Models which produce large concentrations in particular credit grades or scores can be problematic, and undesirable from a regulatory perspective. A large bank was asked to redevelop several rating models that assigned more than 20 percent of the concerned portfolio to one credit grade. The concentration of the score can be measured by the Herfindahl-Hirschman Index, which is outlined in Table 7.

Table 7: Evaluating Score Distribution

Component	Description
Herfindahl-Hirschman Index (HHI)	• The HHI has long been used as a measure of market concentration, with a value of 0 indicating near-perfect competition and a value of 1 indicating a monopoly. • The same measure may be computed for concentrations by score/credit grade – in practice, values of the HHI in excess of 0.25 may indicate a need for further action.

Source: Accenture, November 2014

OVERRIDE ANALYSIS

This measure addresses what level of managerial or other overlays are in place over and above the raw model results. An override is defined as having occurred whenever the model output has been ignored or amended. This measure may vary significantly by the nature of the portfolio or business. For instance, unsecured retail lending models may generate a low number of model overrides, while significant model overrides are more the norm for secured retail or wholesale lending models.

Table 8: Evaluating Override Occurrence

Component	Description
Distance Analysis for Overrides	• Distance analysis compares the raw quantitative score or credit grade assigned by a model with the final grade assigned after any overrides. • The metric analyzed is the proportion of portfolio EAD that has a 'distance' of two or more credit grades. • This measure must be used with care for secured retail lending and wholesale/commercial lending models where overrides are frequently used.

Source: Accenture, November 2014

EFFECTIVE MANAGEMENT INFORMATION SYSTEMS (MIS)

There are numerous metrics that may be used to set up a comprehensive model monitoring system, these should be incorporated into a robust and timely MIS program. Some industry best practices observed for model risk monitoring MIS are:

Be Comprehensive: Often model monitoring systems within institutions present only the KS and Gini statistics, which may mask serious issues with model calibration or other areas.

Be Timely: Model monitoring should ideally be performed on a monthly basis, especially for models involved in real-time decision making. While this may seem obvious, cases have been observed where such models are monitored only in an ad hoc manner; this is especially true of models in areas not subject to a high degree of regulatory scrutiny.

Coverage: Using the model inventory discussed earlier, we suggest that all of the models which are used for credit risk rating be monitored on a regular basis. This will help the organization be aware of the portfolio coverage of its various models.

Data/Formula Integrity and Validation: Model monitoring tools should be subject to independent validation for data aggregation processes and formulae prior to the reporting cycle (for example, on a monthly cycle for data and quarterly for formulae). Formula errors have been observed in the model monitoring tools of at least one large European bank, leading to a regulatory reprimand.

Use of Thresholds: The absolute values of most computed metrics are difficult to interpret without the use of visual signals. 'Traffic Lights' for computed metrics are now increasingly common in most vendor offerings and can be easily interpreted. These should be defined in the model monitoring standards.

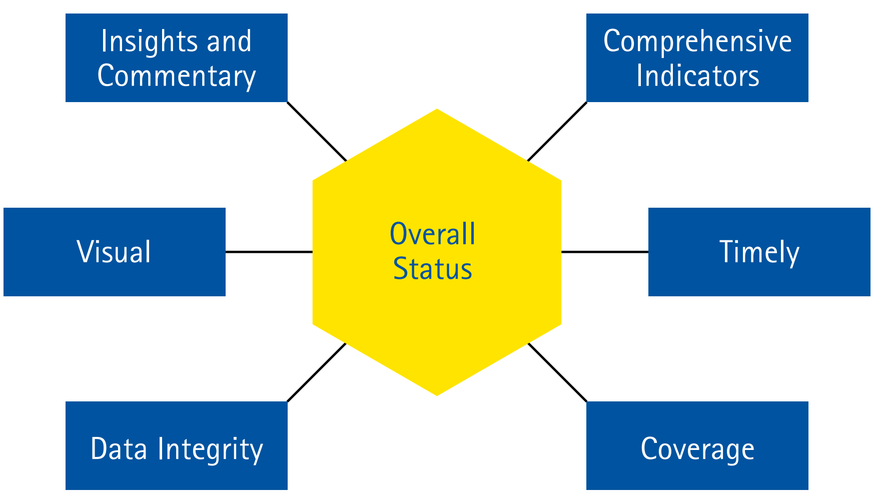
Provide an Overall Assessment: Depending on performance outcome, model monitoring is usually performed to lead to one of three possible decisions:

Performance	Action
Model still fits for purpose.	No change
Model still provides satisfactory discriminatory performance but does not yield accurate point prediction.	Recalibration
Fall in discriminatory power, possibly due to a large change in population.	In-depth analysis of root causes and optional solutions.
Model still provides satisfactory discriminatory performance and is accurate, but it is yielding poor results in some of the other metrics.	Decision to be taken as to whether or not this requires further analysis/ remediation action.

Include Clear and Relevant Insights and Commentary: Quantitative outcomes are not self-explanatory; they require interpretation and explanation, and skills and time are not always sufficient to do a thorough job. This is probably one of the most time-consuming tasks for the monitoring unit, but it can also be the most valuable for the organization if the regular analysis process provides key findings to senior management.

The ideal model monitoring process should provide such a recommendation, together with next steps and an assessment from the model owner, rather than merely listing various indicators (Figure 4).

Figure 4: Elements of a Robust Model Monitoring MIS



Source: Accenture, November 2014


MODEL INVENTORY
MANAGEMENT INFORMATION SYSTEM

CONCLUSION

Model monitoring is an area of increasing importance and regulatory scrutiny as models are treated as critical organizational assets.

The Federal Reserve, for example, has issued guidelines on model monitoring in its SR 11-7 guidance note as well as annual guides on the CCAR process;[4] similar documents have been issued by the Basel Committee and the Bank of England.[5]

A strong credit risk model monitoring process is not only required by regulations, but it has proven to be a potent competitive advantage for those organizations that take extra steps to help ensure the effectiveness of their model monitoring. These steps include diligently tracking model performance, escalating and resolving model issues, involving senior management in decision making, fine-tuning models on a timely basis, and maintaining well-documented logs and rationales of changes. Effective monitoring allows institutions to closely control and better empower the strategic risk management tools for day-to-day operational management as well as for purposes of calculating capital requirements.

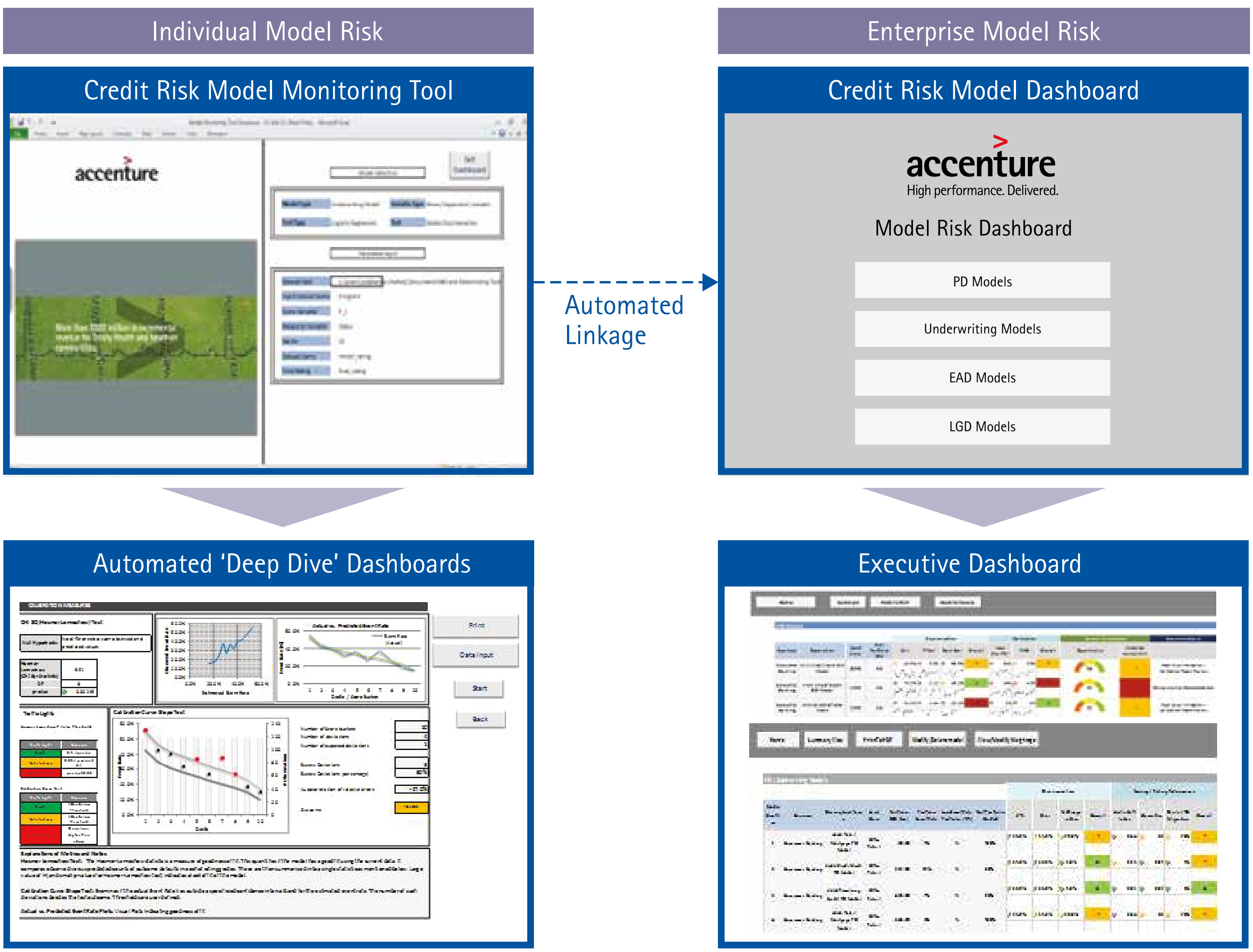
HOW ACCENTURE CAN HELP

Accenture has extensive experience in all aspects of model validation and monitoring, including a team that has delivered more than 500 risk analytics solutions.

In addition to skills related to model development, validation and monitoring and an understanding of the regulatory implications of Basel II and III, Dodd-Frank, Federal Reserve and UK Prudential Regulation Authority (PRA) requirements (among others), Accenture has developed proprietary assets that can help accelerate and simplify the setting up of a robust model monitoring process with pre-written modules in SAS® and automated dashboards. Figure 5 below illustrates one such offering, Accenture's Credit Risk Model Monitoring.

For more information on the topics covered in this document, as well as any general queries on model risk monitoring, please contact the authors.

Figure 5: Accenture Credit Risk Model Monitoring Suite



Source: Accenture, November 2014

NOTES

1."Capital Planning at Large Bank Holding Companies: Supervisory Expectations and Range of Current Practice," August 2013, Board of Governors of the Federal Reserve System. Accessed at: http://www.federalreserve.gov/bankinforeg/bcreg20130819a1.pdf.

2."BCBS Working Paper No. 14: Studies on the Validation of Internal Rating Systems, Revised," May 2005, Bank for International Settlements. Accessed at: http://www.bis.org/publ/bcbs_wp14.htm

3. "Basel III: A global regulatory framework for more resilient banks and banking systems," December 2010 (rev June 2011), Bank for International Settlements. Accessed at: http://www.bis.org/publ/bcbs189_dec2010.htm

4. "SR 11-7 Guidance on Model Risk Management," April 4, 2011, Board of Governors of the Federal Reserve System. Accessed at: http://www.federalreserve.gov/bankinforeg/srletters/sr1107.htm

5. "Documentation in the Internal Model Approval Process," December 2013, Bank of England Prudential Regulation Authority. Accessed at: http://www.bankofengland.co.uk/pra/Pages/solvency2/internalmodel.aspx

ABOUT THE AUTHORS

Larry Lerner is a managing director, Accenture Digital. Based in Washington, he leads Accenture Analytics and is a member of the group's leadership team. He has extensive consultancy and enterprise experience in Financial Services and Analytics and has built industrialized underwriting, marketing and credit risk management capabilities. Over the years he has held several leadership roles in business intelligence, analytics, banking payment and capital markets enterprises and now guides clients on their journey to high performance.

Parvez Shaikh is a managing director, Accenture Digital. Based in Bangalore, Parvez leads the Risk Analytics practice in India serving global Financial Services clients. His areas of experience include risk modeling and quantification, stress testing, pricing, valuation, economic capital, provisioning/loss forecasting and development/validation of risk rating scorecards, frameworks and methodologies. Parvez also has broad exposure to global Financial Services regulation with a particular focus on North America and is a featured speaker at industry risk conferences. Prior to joining Accenture, he held leadership roles in Risk Management at a number of global financial institutions.

Tadhg O'Suilleabhain is a senior manager, Accenture Digital. Based in Dublin, Tadhg has over 13 years of enterprise and consultancy experience in Risk Management and Analytics across global retail banking and capital markets sectors. His experience extends to risk model building and developing and validating Basel risk models (PD, EaD, LGD), impairment models and Risk/Reward models in both retail and non-retail settings. He also has extensive policy writing experience in both Basel and impairment model risk management settings.

Siddhartha Chatterji is a senior manager Accenture Digital. Based in Gurgaon, India, Siddhartha has 12 years of global risk and marketing analytics experience. He has worked in the areas of Basel II analytics, risk scorecard development and lifecycle management covering retail and commercial risk, as well as core risk management roles in retail and commercial risk. He holds a B.A. (H) in Economics from St Stephens College Delhi, a Master's Degree in Economics from the Delhi School of Economics and an MBA in Finance & Marketing from ISB Hyderabad.

AKNOWLEDGEMENTS

The authors would like to thank the following Accenture employees for their contribution to this document:
Medb Corcoran
Alessandro Quadrelli

ABOUT ACCENTURE

Accenture is a global management consulting, technology services and outsourcing company, with more than 305,000 people serving clients in more than 120 countries. Combining unparalleled experience, comprehensive capabilities across all industries and business functions, and extensive research on the world's most successful companies, Accenture collaborates with clients to help them become high-performance businesses and governments. The company generated net revenues of US$30.0 billion for the fiscal year ended Aug. 31, 2014. Its home page is www.accenture.com.

DISCLAIMER: This document is intended for general informational purposes only and does not take into account the reader's specific circumstances, and may not reflect the most current developments. Accenture disclaims, to the fullest extent permitted by applicable law, any and all liability for the accuracy and completeness of the information in this document and for any acts or omissions made based on such information. Accenture does not provide legal, regulatory, audit, or tax advice. Readers are responsible for obtaining such advice from their own legal counsel or other licensed professionals.

STAY CONNECTED

Accenture Finance & Risk Services:
http://www.accenture.com/microsites/financeandrisk/Pages/index.aspx

Connect With Us
https://www.linkedin.com/groups?gid=3753715

Join Us
https://www.facebook.com/accenturestrategy

http://www.facebook.com/accenture

Follow Us
http://twitter.com/accenture

Watch Us
www.youtube.com/accenture

Copyright © 2014 Accenture
All rights reserved.

Accenture, its logo, and High Performance Delivered are trademarks of Accenture.

Rights to trademarks referenced herein, other than Accenture trademarks, belong to their respective owners. We disclaim proprietary interest in the marks and names of others.

14-6082_lc

12460054