Model Risk Management

From Qualitative to Quantitative

Presenters:

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Expectations & Coverage

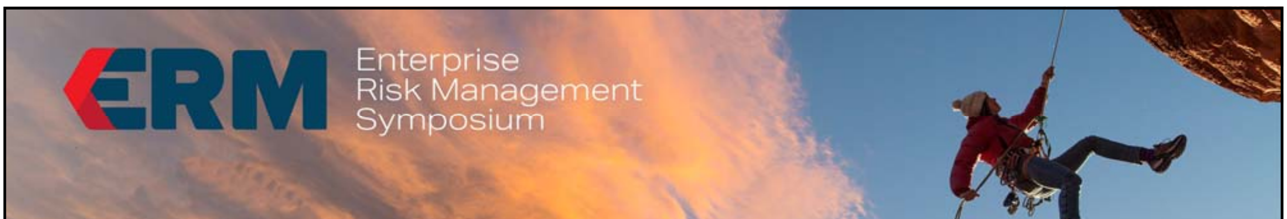
This session is meant to be interactive. Please ask questions and provide insights.

1. **Model Risk Development Life Cycle and Framework**
2. **From Qualitative to Quantitative – Model Risk Measurement and Model Risk Mitigation Controls**
3. **Future Challenges & Opportunities**

Polling Question 1

What industry segment do you represent?

a) Insurance – Life and Annuities
b) Insurance – Property & Casualty
c) Financial Services – Banking – Investment, Institutional, Consumer
d) Investment Management
e) Other (e.g., Advisory, Consulting)



Polling Question 2

What is your role in your organization?

a) 1st line of defense (e.g., Model User, Developer, etc.)
b) 2nd line of defense - Risk Management (e.g., Chief Risk Officer, Model Validator/Reviewer)
c) Other control function (e.g., Internal Audit, Compliance, etc.)

Model Risk Overview (MRM) – Guidance & Principles

Federal Reserve FDIC OCC

BIS PRA

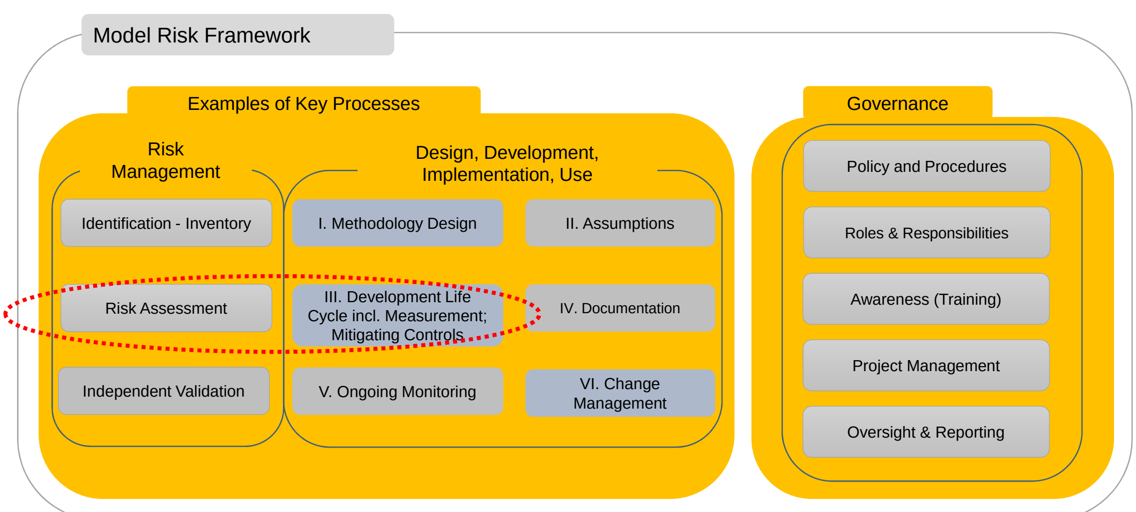
Timeline

- May 2000 – OCC 2000-16 Model Validation guidance
- Feb 2010 – EBA Principles of Risk Management
- April 2011 – SR 11-7 Guidance on Model Risk Management
- January 2013 – BIS risk data aggregation and reporting
- June 2013 – Actuarial Standard Board Modeling Standards
- August 2016 – N.A. CRO Council MRM Principles
- March 2017 – PRA letter – stress testing models guidance

Basic Principles

1. Model Definition and Identification
2. Risk Governance
3. Lifecycle management
4. Effective challenge

End to End Model Risk Management Framework



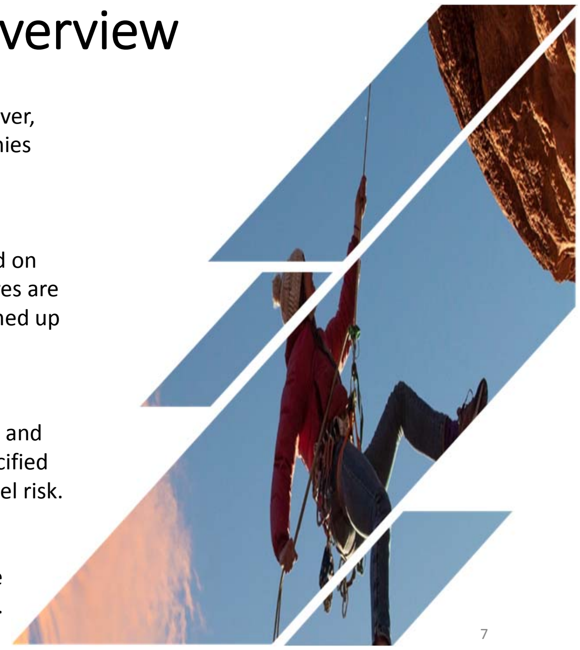
Model Risk Measurement - Overview

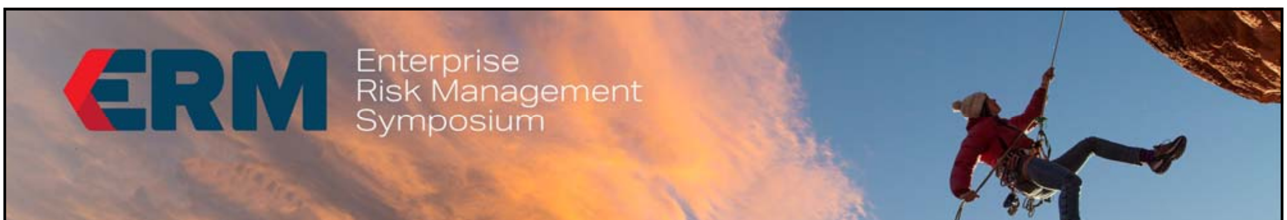
Three approaches are commonly used in measuring model risk, however, none have yet to be considered a standard. In addition, some companies use hybrid approaches by combining two or more approaches.

- **Qualitative scoring method**:
  - ✓ The firm assesses each model within the inventory based on pre-determined risk drivers and expert judgements. Scores are assigned to each risk driver and then multiplied or summed up to get an aggregate score.

- **Modern operational risk management approach**:
  - ✓ The firm views model risk as one type of operational risk and utilizes the event and scenario modeling techniques specified in modern ORM approaches (e.g. AMA) to measure model risk.

- **Bottom up model risk quantification**:
  - ✓ The firm uses a bottom up, sensitivity based quantitative approach to translate model risks into monetary metrics.





Polling Question 3
What model risk measurement is currently being used in your organization?
a) Qualitative scoring method
b) Quantitative using modern ORM
c) Quantitative from bottom-up at model level and then aggregated to a $ amount at Enterprise level
d) Hybrid method by combining subjective inputs with calibrated or empirically tested inputs
e) None of the above

Model Risk Measurement

Qualitative Scoring Method

Qualitative Scoring Method

- Key objectives of this approach are to determine inherent model risk, risk mitigation controls and residual model risk.
- Common inherent risk factors include: model use, frequency, model complexity, uncertainty of inputs and assumptions, and financial impact.
- Risk mitigation factors usually include both first line and second line control activities, such as:
  - ✓ on-going model performance monitoring (first line activity)
  - ✓ independent model validations (second line activity).
- Residual risk is derived from inherent risk and risk mitigation controls.
- Although it is possible that certain factors (e.g. materiality) are quantified, the quantification methods are usually not precise and are not consistently applied on all models. The goal is to put all models on an ordinal scale (e.g. Low, Medium or High materiality), therefore, expert judgements are heavily relied upon.

Model Risk Measurement

Qualitative Scoring Method

Qualitative Scoring Method

- **Pros:**
  - ✓ Easy to understand
  - ✓ Can be implemented quickly
  - ✓ Requires less information
  - ✓ Can leverage model risk assessment (tiering)
- **Cons:**
  - ✓ Scores and weights are highly subjective, might mean different things to different people.
  - ✓ Prone to cognitive bias, such as overconfidence, anchoring and output bias.
  - ✓ Creates imprecision by grouping a range of values under one category in a scale.
  - ✓ Implicitly assumes regular intervals approximate the relative magnitudes being assessed.
  - ✓ Ignores interdependencies between models

Model Risk Measurement

Modern Operational Risk Management approach

Modern ORM Approach

- Views model risk as one type of operational risk and leverages modern operational risk quantification approaches, such as advance measurement approach (AMA).
- This is a quantitative approach that measures model risk by constructing a loss distribution based on frequency and severity of model risk events.
- In order to successfully implement this approach, the firm has to overcome the following obstacles:
  - ✓ Consistently and comprehensively identify loss events due to model risk, taking into consideration the interrelationship between model risk and other risks
  - ✓ Obtain appropriate, accurate and sufficient empirical data (both internal and external)
  - ✓ Select appropriate distribution assumptions
  - ✓ This approach itself, as a model, needs to be risk managed (e.g. validated)

Model Risk Measurement

Modern Operational Risk Management approach

Modern ORM Approach

- **Pros:**
  - ✓ Consistent with how other risks are quantified (i.e. loss distribution)
  - ✓ Provides two-dimension view – severity and likelihood
  - ✓ Can quantify and aggregate model risks coherently
  - ✓ Interdependencies can be added to this approach
- **Cons:**
  - ✓ More complex to implement, especially if the firm does not have existing modern ORM framework.
  - ✓ Subjective scenario-based approaches might be needed to supplement empirical data limitations on risk events.
  - ✓ Hard to distinguish model risk events versus other risks.
  - ✓ When empirical data is not sufficient to pass the credibility test and fit into a parametric distribution, this approach will rely heavily on assumptions/hypothetical events/expert judgement.

Model Risk Measurement

Bottom up model risk quantification:

Bottom-ups Quantitative Approach

- Bottom up approach quantifies model risk for each individual model and applies aggregation assumptions to obtain overall exposure of model risk.
- Four major steps in this approach:
  - ✓ Identify model risk sources – common model risk sources include:
    - ➢ Data deficiency: data error, limited sample size, inaccurate proxies, misinterpretation of outliers, etc.
    - ➢ Flaws in parameter setting and calibration: oversimplifications, omission of critical relationships, inappropriate algorithm and calibration, etc.
    - ➢ Inappropriate model selection: inadequate or incorrect assumptions; model instability; model misspecification, computational difficulties, etc.
    - ➢ Implementation error: IT failures, code errors, etc.
    - ➢ Inappropriate usage: unintended use, lack of re-calibration, limitations are not well understood, etc.
  - ✓ Design quantification approaches for each risk source – common quantification approaches include:
    - ➢ Output sensitivity tests on data (error, absence), parameters and assumptions
    - ➢ Alternative models or market benchmarks
    - ➢ Back-testing
    - ➢ Simulation of decay factors of model predictivity and model misusage

Model Risk Measurement

Bottom up model risk quantification:

Bottom-ups Quantitative Approach

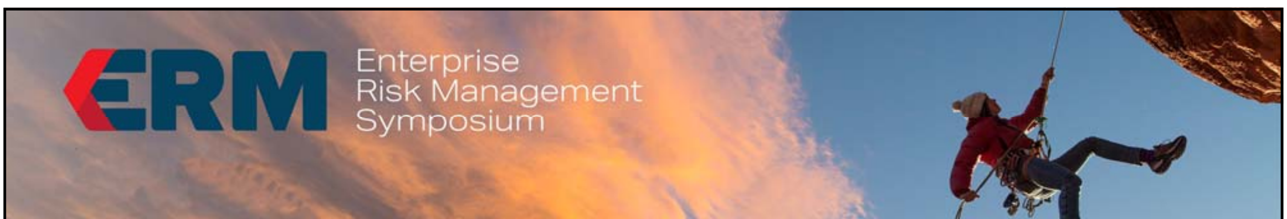
- Four major steps in this approach – continued:
  - ✓ Take into consideration model risk control activities:
    - Certain model risk quantification tests can be run frequently as part of on-going performance monitoring
    - Mitigation factors including expert judgement overlays
    - Other internal review and control functions
  - ✓ Apply aggregation assumptions to individual model risks:
    - Although the quantification methods can be quantitative in nature at individual model level, the aggregation of individual model risks can be qualitative. For example, some companies would use pass/no-pass (0/1) scores to present the model risk for each individual model and then add or apply weighted average to generate overall risk scores.

Model Risk Measurement

Bottom-up Approach

Bottom up model risk quantification:

- Pros:
  - ✓ Less subjective than scoring method as risk sources, quantification approaches and outcomes are traceable at model level
  - ✓ Once quantification approaches/tests are set up, they can be run repeatedly (as on-going performance monitoring activity) and/or delegated to an independent third party
  - ✓ Interdependencies can be captured if model inventory contains risk taxonomies such as upstream/downstream models, shared inputs, etc.
- Cons:
  - ✓ Costly to develop model-specific quantification approaches
  - ✓ Subjective assumptions have to be made on aggregation approach



Polling Question 4

Does your organization currently consider mitigation controls when assessing model's risk profile?

a) Yes

b) No

c) N/A; Do not know

Model Risk Mitigation - Overview

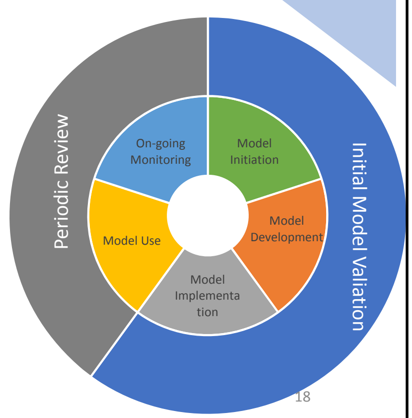
- Model risk mitigation controls are direct inputs to Model Risk Measurement (quantification) and are critical in closing the loop of model risk management cycle.
- Mitigation controls should happen at:
  - ✓ Both first line and second line
  - ✓ During every stage of model life cycle
- The effectiveness of certain types of model risk mitigation controls is quantifiable while others can only be assessed qualitatively:
  - ✓ Quantifiable controls, e.g.:
    - Technological
    - Mathematical-Numerical
    - Adjustment and Override
  - ✓ Not quantifiable controls, e.g.:
    - Expert judgement overlays
    - Other internal review/control functions

Model Risk Mitigation

Mitigation controls during model life cycle – First Line

Mitigation Controls – First Line

- Model Initiation Stage:
  - ✓ Define business purpose and intended use of the model
  - ✓ Assess current model inventory to determine if any existing model can be leveraged
  - ✓ If a new model needs to be created, model owner is responsible for drafting the model requirements
- Model Development Stage:
  - ✓ Define acceptable criteria (i.e. expectations of model performance)
  - ✓ Design testing procedures that reflect all parts of the model specification and requirement (e.g. out of sample testing)
  - ✓ Leverage expertise from control functions (including MRM) to ensure compliance with internal standards (e.g. MRM, IT) and avoid expensive failures
- Model Implementation Stage:
  - ✓ IT implementation testing
  - ✓ UAT test
  - ✓ Model back-up and version controls

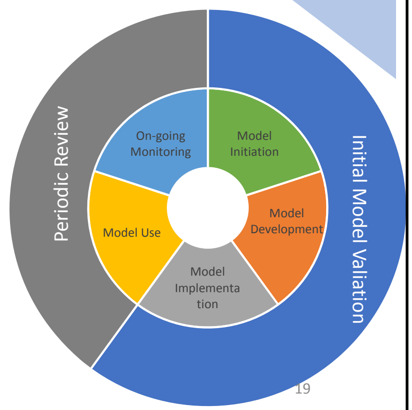


Model Risk Mitigation

Mitigation controls during model life cycle – First Line

Mitigation Controls – First Line

- Model Use Stage:
  - ✓ Data integrity review/testing
  - ✓ Peer review
  - ✓ Management sign-offs
  - ✓ Change management process
- Model On-going Monitoring:
  - ✓ Back-testing (e.g. Chi-square, Lilliefors test, KS test, Jarque-Bera(JB) test, Kuiper test)
  - ✓ Sensitivity test on key assumptions
  - ✓ Benchmarking against alternative models (e.g. calculate QPS function to rank model against its alternatives)

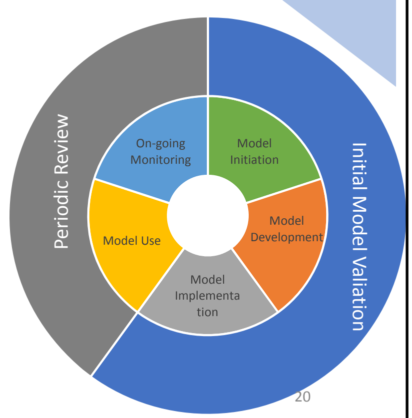


Model Risk Mitigation

Mitigation controls during model life cycle – Second Line

Mitigation Controls – Second Line

- Initial Model Validation:
  - ✓ Proactively provide non-binding suggestions during model initiation and development stage
  - ✓ Initial model validation should be comprehensive:
    - o It should cover all aspects of model risks (including conceptual soundness, input accuracy and appropriateness, implementation, validity and reporting of output)
    - o It should provide an assessment of the compliance with model risk framework and the sufficiency of first line mitigation controls
    - o Testing approaches should be tailored based on the uncertainty, complexity, materiality as well as the intended use of the model
- Periodic Review:
  - ✓ Periodic review does not have to be comprehensive, it can be light-touch compared to initial model validation
  - ✓ Periodic review should be performed with agility based on “need”
  - ✓ Periodic review can leverage tests/challenger models developed during initial model validation and/or first line on-going monitoring exercise



Model Risk Mitigation

Quantifiable Risk Mitigation Controls

Quantifiable Risk Mitigation Controls

Model risk mitigating control that are quantifiable – can be associated to numerical values:

- Technological – depend mainly on the platform and interconnectivity; e.g. Excel-based optimizer is not suitable for no-linear optimization problems, algorithmic trading required speed in the order of nanosecond to be effective, comparable technology (benchmarking), etc.

- Mathematical-Numerical - for example, in a MC simulation one can translate/associate model performance to measure such as accuracy, precision, confidence interval, etc. *Implementation*: select optimal value or values and measure. Optimal values can be hypothetical, selected from other measures such as average, lowest, highest, or historical like back-testing, etc.

- Adjustment and Override: can be used address technological or numerical limitation of known errors. Modeler must have a clear understanding about what caused the error.

- Observed that mitigating controls should be monitor to assess effectiveness though time – they may change base on the life cycle status of the model.

Model Risk Mitigation

Qualitative Risk Mitigation Controls

Qualitative Risk Mitigation Controls

Model risk mitigating control that are difficult to measure (due to non-quantifiable nature of the control):

- This type of mitigation control relies usually on subjective expert knowledge.

- Governance: require testing for: implementation and development, specific testing requirements (pricing, valuation, etc.)

- Preventative: usually implemented during certification and prior to launch
  - Enforce review by second line of material changes - what is a material change?
  - Other control functions can serve as risk mitigating controls
    - Control for Financial Reporting (GAAP)
    - Control for Pricing
    - Control for Forecasting
    - Control for Capital / Liquidity

- Detective:
  - Data Validation: limiting cases, parameter space,
  - Benchmarking (check for indication of recalibration or redesign)

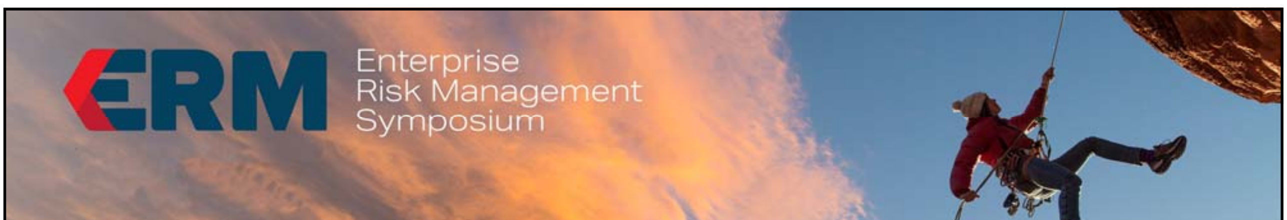
Model Risk Mitigation

Risk Mitigation Controls

For Quantitative and Qualitative Risk Mitigation Controls

Recommendations

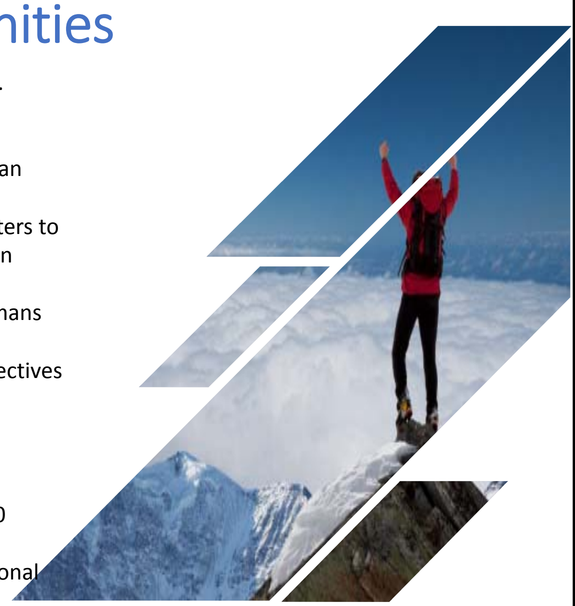
- Mitigating controls should be directly associated with performance of the model
- Continuous assessment on how to determine the effectiveness of model risk mitigation controls.
- Mitigating control should be measurable in order to monitor and close the model risk management cycle



Polling Question 5
Does your organization currently utilize advanced model technologies (AI, ML, Cognitive Computing) to drive business decision making?
a) Yes
b) No
c) N/A; Do not know

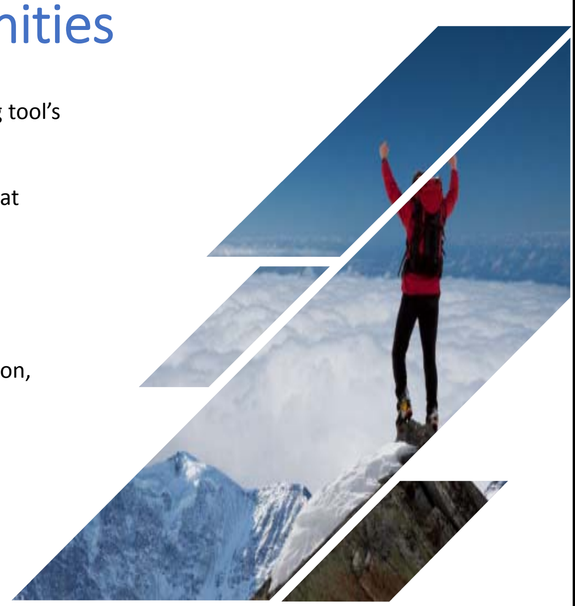
Future Challenges & Opportunities

- Disruptive technologies will change company's model risk profile.
  - ✓ Disruptive technologies that create the new "Gold Rush":
    - ➢ AI: Allow computers to perform tasks that require human intelligence
    - ➢ Machine Learning (ML): Subset of AI. Empower computers to learn, interpret, analyze, and make predictions based on data.
    - ➢ Cognitive Computing: Make computers "think" like humans
- Novel model risk management methods might create new perspectives and solutions for the company.
  - ✓ There has been research on quantifying model risk using differential geometry (e.g. Riemannian Geometry) and information theory (e.g. Relative Entropy) during the past 10 years.
  - ✓ There have been recent discussions on how to adjust traditional model risk frameworks to adapt to AI/ML models.



Future Challenges & Opportunities

- Assessment of a company's model risk profile will entail the understanding of the interconnectedness between the modelling tool's platform, intended use, and modeling capabilities / limitations.
- Platform lens: Are your applications outsourced or in-house? What platform does it sit in (Excel vs. IT application)?
- Capabilities lens: What types of analytics are performed? What advanced methodologies are used?
- Modeling / intended use lens: What is the data used for – valuation, pricing, risk management, operations, customers?



Future Challenges & Opportunities

Disruptive Technologies

Disruptive Technologies

- Why are the advantages and challenges in adopting AI/ML models?
  - ✓ Efficiency: faster response to market and customers' needs
  - ✓ Cost-reduction: engaging system 2 in human decision-making process can be costly
  - ✓ Better decision making: avoid human cognitive bias
  - ✓ High implementation / sustainability cost
  - ✓ Lack of internal knowledge to build or even maintain these models
  - ✓ Complex model risk profiles and new challenges to model risk management framework

- What are the nuances to traditional model risk management?
  - ✓ Conceptual soundness is hard to assess in a "black box" tool
  - ✓ Overreliance on data integrity, especially the quality of unstructured data
  - ✓ Bias - human cognitive bias is transferred through the preparation of data; data-generation process itself can be biased
  - ✓ Prone to errors in parameter selection since parameters are defined before the training process
  - ✓ Significant increase in model complexity and might be overfitting
  - ✓ Documentation difficulty
  - ✓ Dynamic calibration and automatic redevelopment create difficulty in model validation and on-going monitoring

Future Challenges & Opportunities

Novel model risk management methods

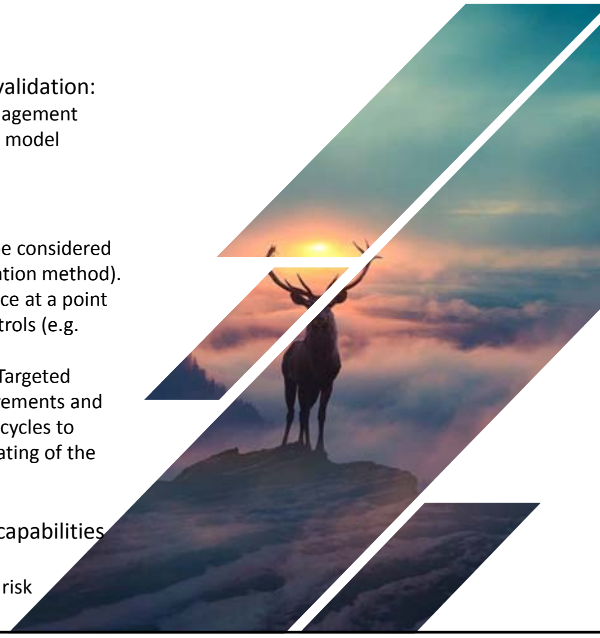
Novel MRM Methods

- What are the novel model risk quantification approaches discussed in the industry?
  - ✓ Measuring the plausibility of an alternative model using relative entropy theory in paper "Robust risk measurement and model risk"
  - ✓ Using Banach spaces over weighted Riemannian manifolds to represent model risk in paper "A Novel Approach to Quantification of Model Risk for Practitioners"

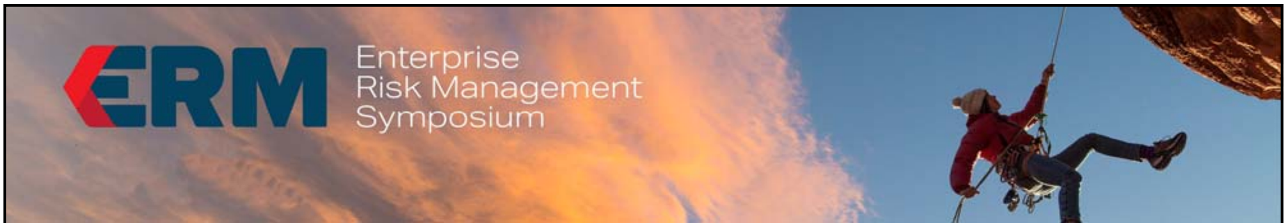
- What enhancements should be considered to add to the traditional model risk management framework?
  - ✓ Pay extra focus on bias in data: assessing the soundness (fairness) of data development and holdout process
  - ✓ Include bias – variance analysis when assessing model accuracy and stability: due to the complexity of the feature engineering for ML models, the models are prone to overfitting and underfitting
  - ✓ Include validation of hyper-parameters in model development: hyper-parameters are defined prior to the training process in ML, as a result, the conceptual soundness of these parameters is critical to the performance of ML models.
  - ✓ Take consideration of the readiness of product system: a good model without a good supportive production system is useless.
  - ✓ Develop on-going monitoring process for ML with auto-redevelopment capabilities: model validators have to understand and validate the business logic behind the auto-redevelopment of ML models.

Final Thoughts

- The scope of model risk management is bigger than model validation:
  - ✓ Model validation is one element of the overall model risk management framework and can be viewed as mitigation control. However, model validation is not equal to model risk management.
- Model risk management should be pro-active and agile:
  - ✓ Model risk mitigation controls and risk measurement should be considered during developing phase (e.g. bottom up model risk quantification method). Validation should not only test the model's current performance at a point in time, but also check the effectiveness of risk mitigation controls (e.g. back testing, benchmarking…)
  - ✓ As our industries encounter significant model changes (CECL, Targeted Improvements), take the opportunity to challenge the measurements and mitigation controls during the design and implementation life cycles to capture a quantitative model risk score rather than rely on a rating of the model inventory.
- Model risk management should start before new modeling capabilities being introduced to the company:
  - ✓ Before company jumps on AI/ML models, check if your model risk management is ready.



Questions or comments?

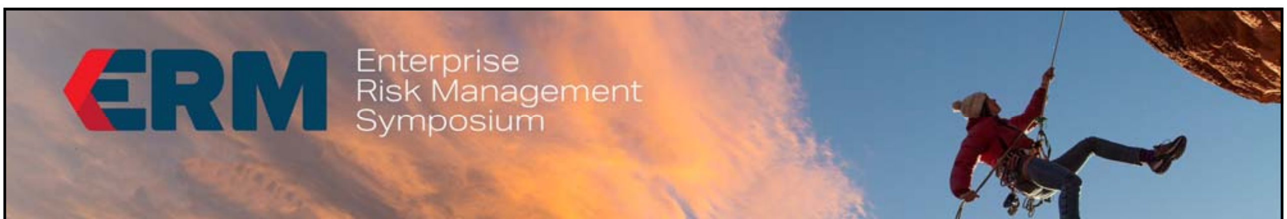


Presenter Biography – Emily Li

Emily Li, FRM, CERA, MAAA

Emily Li is an audit manager specialized in model risk at Prudential Financial, Inc. Her current work focuses primarily on assessing the design and implementation of model risk framework and evaluating the quality and effectiveness in model validation for actuarial, risk and capital models.

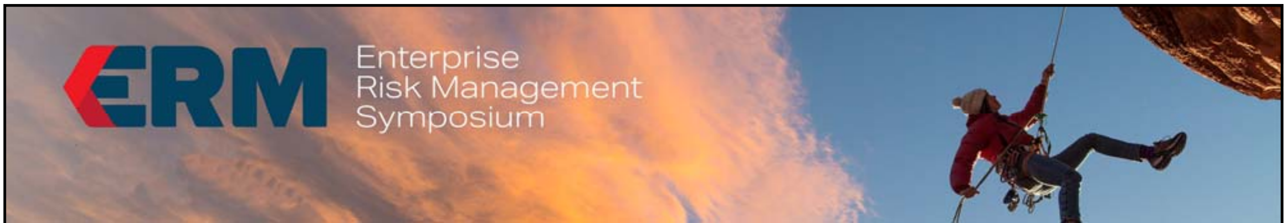
Emily has a total of 8 years risk management experience in asset management and insurance industry. She attained her FRM certification in 2015, ASA designation in 2018 and CERA designation in 2019.



Presenter Biography – George Alvites

George Alvites, MBA, CPA, CISA

George Alvites is an audit and advisory Vice President in Prudential, Inc. specialized in model risk management, optimization, and simplification. His current work focuses leading global audit and advisory coverage of model life cycle framework and risks, including the quality and effectiveness in model validation, end user computing solutions



Presenter Biography – Luis Ortega

Luis F. Ortega, Ph.D.

Mr. Ortega serves as a lead advisor and Subject Matter Expert (SME) in Prudential Financial. He is responsible for the examination of corporate level audits covering all aspects of model risk management of firm-wide high-profile quantitative models. As a contributor, Mr. Ortega has assisted in the shaping of Prudential's Model Risk Framework, and, in an advisory role, supported the undertaking before the Federal Reserve Bank. At Goldman Sachs, Mr. Ortega reviewed, assessed, and provided effective challenge to financial/investment models involving all phases of the model life-cycle. Mr. Ortega experience in the public sector includes the Securities and Exchange Commission (SEC) where he performed statistical analysis and reporting for SEC examinations.

Mr. Ortega previous professional experience incorporates 12+ years in the telecommunication sector, working for companies such as: the World Bank, Verizon Wireless, NYNEX in USA, and for government of Ecuador. His academic credentials include: Ph.D. in Financial Engineering, M.B.A., M.S. Computer Sc., and B.E. Electrical Eng. from Stevens Institute of Technology, USA.