Emerging Themes in Model Risk Management

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Model Risk

Risk exists when the outcome of taking a particular decision or course of action is uncertain and could potentially impact whether, or how well, an entity delivers on its objectives.

Models are not right or wrong - they are all wrong because they are by definition imperfect representations of reality. Consequently, the use of models inherently introduces a further "model risk", which may be classified as a consequence of:

- Inappropriate model design for the model's specified purpose, such as: use of inappropriate or incomplete data, incorrect assumptions, inappropriate methodology, over-simplistic or incorrect approximations, errors in calculations, etc.;
- Incorrect implementation of an appropriate model design;
- Inappropriate use of a model where the model is appropriately designed and correctly implemented for a different use. This may be intentionally using the model for unintended use and unintentionally when circumstances change (market conditions, economic conditions, risk appetite, etc.).

Model risk increases with model complexity, higher uncertainty about inputs and assumptions, broader use and larger potential impact.

Box (1987): Essentially all models are wrong, but some are useful.

Model Uncertainty

Broader than model risk.

ECB (2002):

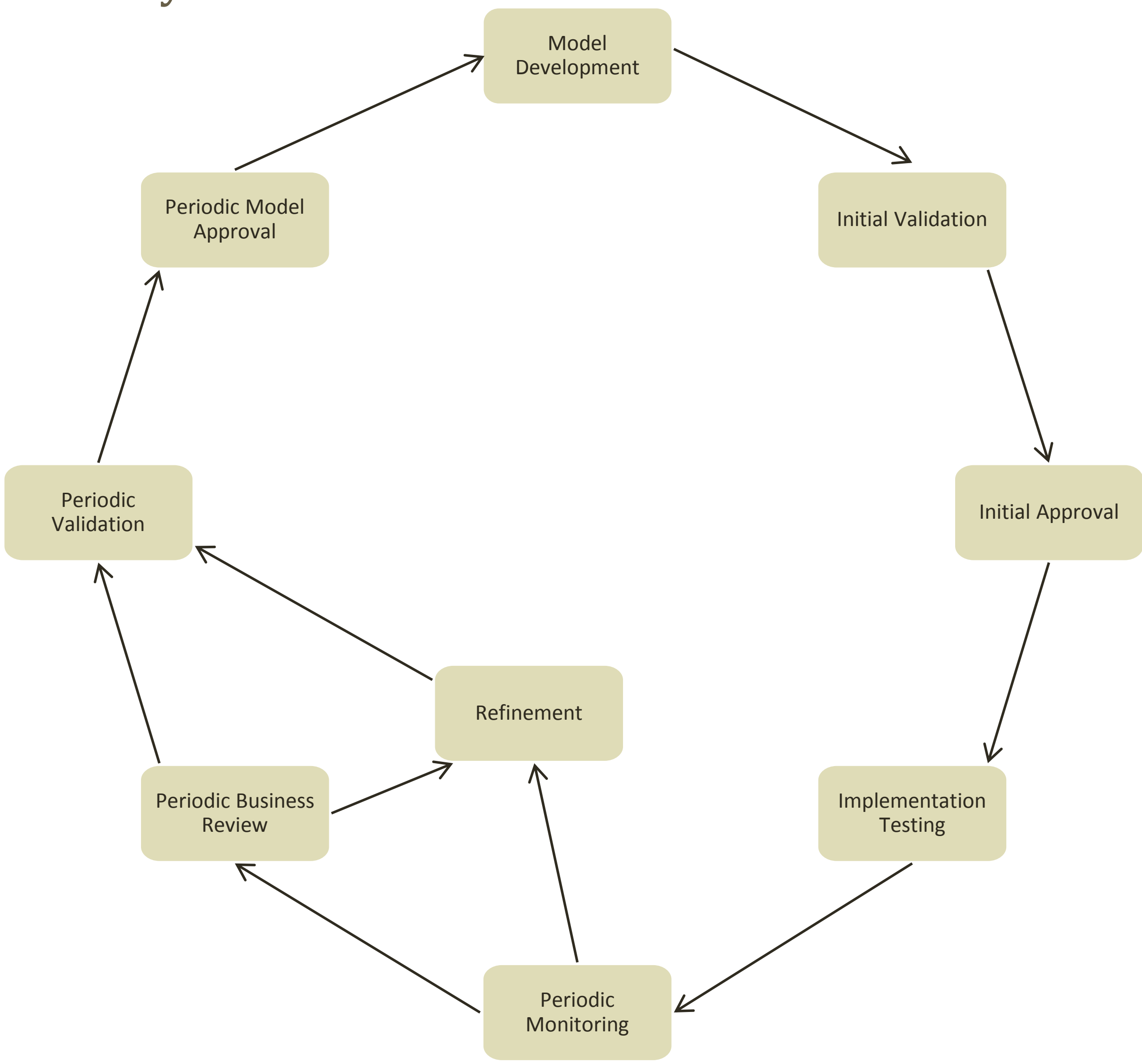
- *first, uncertainty about parameters of a reference model;*
- *second, uncertainty about the spectral characteristics of noise;*
- *third, uncertainty about data quality; and*
- *fourth, uncertainty about the reference model itself.*

Actuarial perspective (Cairns, 2000):

- *uncertainty due to the stochastic nature of a given model (that is, a stochastic model produces randomness in its output);*
- *uncertainty in the values of the parameters in a given model (if we have a finite set of data then we cannot estimate parameter values exactly);*
- *uncertainty in the model underlying what we are able to observe and which determines the quantity of interest; and*
- *the possibility of measurement errors in the data.*

Model risk and model uncertainty can be mitigated through robust controls. Quantifying model uncertainty is not easy and a conservative approach is not always appropriate.

Model Control Lifecycle



Insurance View of Model Risk

Yoost (2013): An argument can be made that models are more critical for insurers than banks. Insurers require models to accurately prepare their liabilities which are subject to external audit and regulatory review. This will result in increasing scrutiny by these third parties. Stress testing of the capital requirements of insurers and meeting regulatory requirements also use models. Banks, on the other hand, do not heavily rely on models in preparing the financial statements. Banks use models almost exclusively as tools in stress testing capital requirements and valuing certain assets.

There are three areas in which insurers' model risk management programs merit increased attention:

- Actuarial models –These models have unique aspects and often are used to develop values (particularly for reserves) in accordance with prescribed professional standards. Often the developed values are recognized as conceptually inadequate representations of real economic values. Managing this dichotomy requires care.
- Assumption setting – Assumption setting plays a very significant role in insurance models. The process and governance of assumption management merit a clearly defined pillar in an insurer's model risk management framework. Recognizing that assumptions also come from other models or professional judgment may be the best way to put them into this framework.
- Ongoing monitoring and benchmarking – In terms of the core elements of a validation framework, outcomes analysis is limited due to long time horison required for outcomes; in fact, for many models, conceptual soundness is less important that compliance to a standard. Insurers' validation efforts will need to place more emphasis on ongoing monitoring and benchmarking.

Changes in Banking Modelling Landscape

Exponential growth in data quantity from multiple sources (e.g. social media)

Machine learning and artificial intelligence algorithms

Automated decisioning enhancing customer experience

Increasing complexity of models/algorithms

Increasing scope of use

Used in aggregate strategic decisioning

Competitive advantage

Competition with FinTech disruptors

Cost and regulatory pressures

Challenges

Machine learning and analytics replacing traditional customer relationships and human decision making.

Analytics playing a central role in multiple relationship of trust between board, shareholders, staff, customers and regulators. Prove that you know your customers and understand their needs and you can quickly build trust relationships.

Analytics are typically treated as a “black box”. In reality, organisations need to start thinking about analytics as independent decision-making entities onto themselves, the understanding of which is essential.

Increasing amount of data and data sources require investment in cyber security and data protection. Organisations will need to ensure the quality, trustworthiness and applicability of data, particularly from third party sources.

Just as banks need their employees to act with integrity, they need their models/algorithms to act with integrity. Banks will need to ensure that the models/algorithms are used in the best interest of the consumer.

Ethical use of data from multiple sources. Compliance with data privacy laws.

Does the historical data inherently contain biases that will self-perpetuate through its use in analytics? Avoidance of the pernicious feedback loop.

Challenges (continued)

Machine learning and AI – causality versus correlation.

Micro-targeting of models/algorithms and extreme granularity of data may mean that the models/algorithms only perform under certain conditions and over short periods of time, requiring frequent redevelopment.

Abstraction of observed experience being influences by the developer’s biases.

Algorithm lag, where over time the analytics may lag behind best current practice in human decision making.

Opacity of methodology and objective/purpose.

Cost-effective corrective feedback mechanism allowing for refinement of models/algorithms.

Discussion