Applied Model Risk Management for Financial Institutions

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Disclaimer

The information, opinions, and recommendations contained in this presentation are my own and do not necessarily reflect the policies, procedures, or opinions of AIG.

Managing a firm's analytic infrastructure and overall analytic capability is important because:

1. Profitability and market share (and ultimately firm survival) will depend critically on it
2. It's fun and interesting
3. Regulatory expectations (requirements) in this area continue to grow*

> *"Model risk should be managed like other types of risk. Banks should identify the sources of risk and assess the magnitude… Banks should consider risk from individual models and in the aggregate.",*
> *SR Letter 11-7 Model Risk, page 4.*

*In rare but actual cases, failure to meet regulatory expectations and survival can become intertwined.

What do Financial Institutions use models for?

- Assess and price property & liability risk
  - Natural catastrophe risk
  - Man made catastrophe risk
  - Corporate liability risk
  - Consumer liability risk
- Assess macroeconomic risk including
  - Stressed scenario analysis
  - Mortality, morbidity, and catastrophe risk
  - Interest rate, currency, & commodity price risk
- Assess market dynamics and price market risk
- Hedge economically hedgable risks including
  - Purchasing swaps, forwards, options and other derivatives
  - Entering into reinsurance treaties
  - Pooling, tranching, and redistributing risk through securitizations
- Design & structure products including
  - Securities
  - Commercial loans
  - Insurance policies
- Assess diversification (correlation) effects and manage and allocate capital
- Etc.

Costly Model Risk Episodes

Examples of costly model errors

- Model-related errors
  - Bank of America (2014) – data/process error causes $4B reduction in reported capital
  - London Whale (2012) – models error caused $5.8B of trading losses
  - Banamex (2002) Modeling teams destroy approximately 5 years worth of default data due to faulty data processing. Computer literature suggests that the value of 100 megabytes of data is valued at approximately $1 million,
  - Between 2001 and 2012 SEC public registrants announced over 12,000 financial restatements, most due to data processing and/or model errors

Other costly model errors with Model tie-ins

- Operational errors
  - S&P and Moody's (2008) – errors in models for rating complex debt products. Huge reputational damage
  - Knight Capital Group (2012) – trading software malfunction led to more than $450M losses
  - Goldman Sachs (2013) – software glitch caused erroneous flood of stock option orders, creating significant trading losses
- Basic model errors
  - Long Term Capital Management (1998) – over reliance on short term history to calibrate models, use of VaR. Resulted in bankruptcy
  - 2008-2009 financial crisis – CDO default models ignored dependence on rising national housing prices

The revenue loss from other undiscovered and unreported models deficiencies cannot be estimated, but must be huge

We can envision three phases to the evolution of model management within an institution

Model Governance

- Accurate inventory
- Detailed documentation
- Conceptual soundness assessment
- Performance testing
- Controlled use
- Change control

Model Risk Management

- Model risks measured at the model level
- Model network fully diagrammed, “circuit board”
- Model risk aggregation capability in place
- Model Risk infrastructure in place

Analytics Asset Management

- Model *returns* measured
- Model risk/return calculated
- Strategic analytic resource allocation based on efficient frontier

Why is model risk measurement hard?

- All risk measurement is hard
- Model “failure” criteria hard to fully define
- Apples & oranges problems
- Direct and indirect effects

But we can take inspiration from some (unlikely) heros:

- Simon Kuznets – inventor of GNP
- Frank Knight – “If you can’t measure it, measure it anyway”, Economic Freedom; Toward a Theory of Measurement, Walter Block, 1991

Practitioners need to maintain an inventor/entrepreneurial attitude. Read Frank Knight’s “Risk, Uncertainty, & Profit”.

Quantification of risk - basic principles apply to model risk too

- Risk is a psychic concept, i.e. it is “perceived”
- Technical risk analytics requires assumptions about underlying preferences – typically expressed through a utility function. Such analysis is usually used to:
  - Rationalize behavior we observe
  - Provide guidance/control over our own behavior
- The theoretical foundation for the existence of utility functions is the ability of the agent to rank order preferences over a choice set

Thus, we do not necessarily need utility functions to create an institutional model risk framework – but we *do* need preference ordering

To have a framework that senior leaders will accept, we need to be explicit about what model risk means

To do that we need to:

1. Enumerate bad outcomes
2. Identify preference rank ordering (poll leaders)
3. Associate models with bad outcome potential
4. Enumerate modes of failure for model types
5. Associate failure modes with bad outcome likelihood

Risk must be based on somebody's preferences

In one type of framework, requirements 1, 2, 3, & 5 could be organized around a single model risk concept

1. Enumerate bad outcomes
   - Any model failure that could impact stock price
2. Identify preference rank ordering
   - No ranking is necessary, the only bad outcome is a negative impact on stock price
3. Associate models with bad outcome potential
   - For different model classes, how likely are failures to affect stock prices?

5. Associate failure modes with bad outcome likelihood
   - For each model class, how likely are different failure modes to affect stock prices?

With enough data such a framework may be feasible, but it still must reflect somebody’s preferences

More practically, we may need to manage a clunkier model risk measurement framework

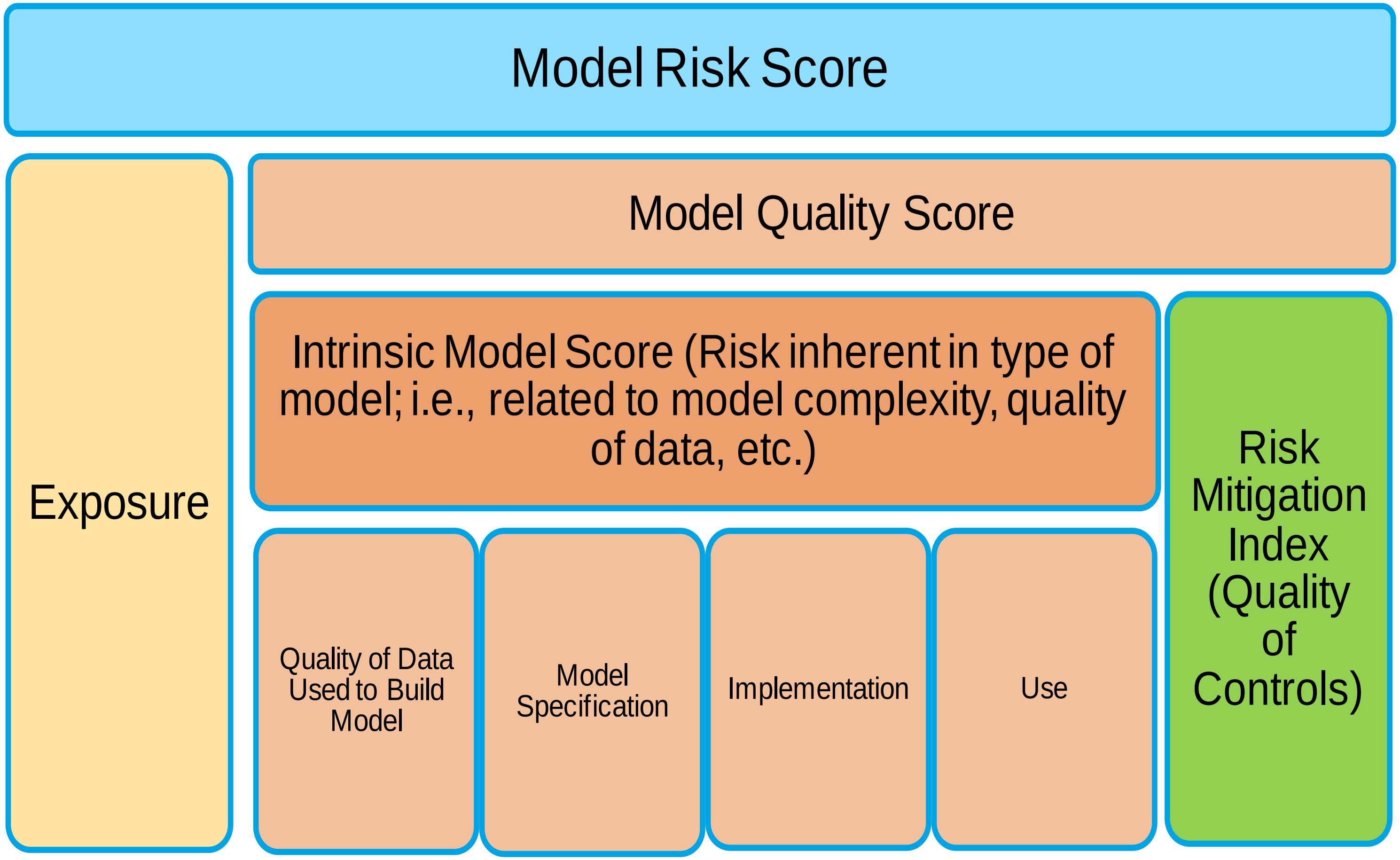
1. Enumerate bad outcomes
   - Losses (of different types), revenue drag, reputational damage, regulatory censure, etc.
2. Identify preference rank ordering, e.g.
   a. Don't fail CCAR
   b. Prevent headline "OpRisk" losses
   c. Enhance margins
   d. etc
3. Associate models with bad outcome potential
4. Enumerate modes of failure for model types
5. Associate failure modes with bad outcome likelihood

Management/BU developed

Risk Analytics developed

These components, along with their probability measures and weightings comprise the framework

Model-level Risk Scores can be produced as a by-product of an effective model validation process



To harvest risk component data from the validation process requires that process to be highly structured

But model-level risk scores have limitations

- Model-to-model effects
  - Risk propagation (amplification, neutral transmission, or mitigation) within a system
- Exposure attribution
- Weak link to financial metrics
- Redundant analyses/findings
- Poor subject matter expertise matching
  - All validators need to be data quality experts?

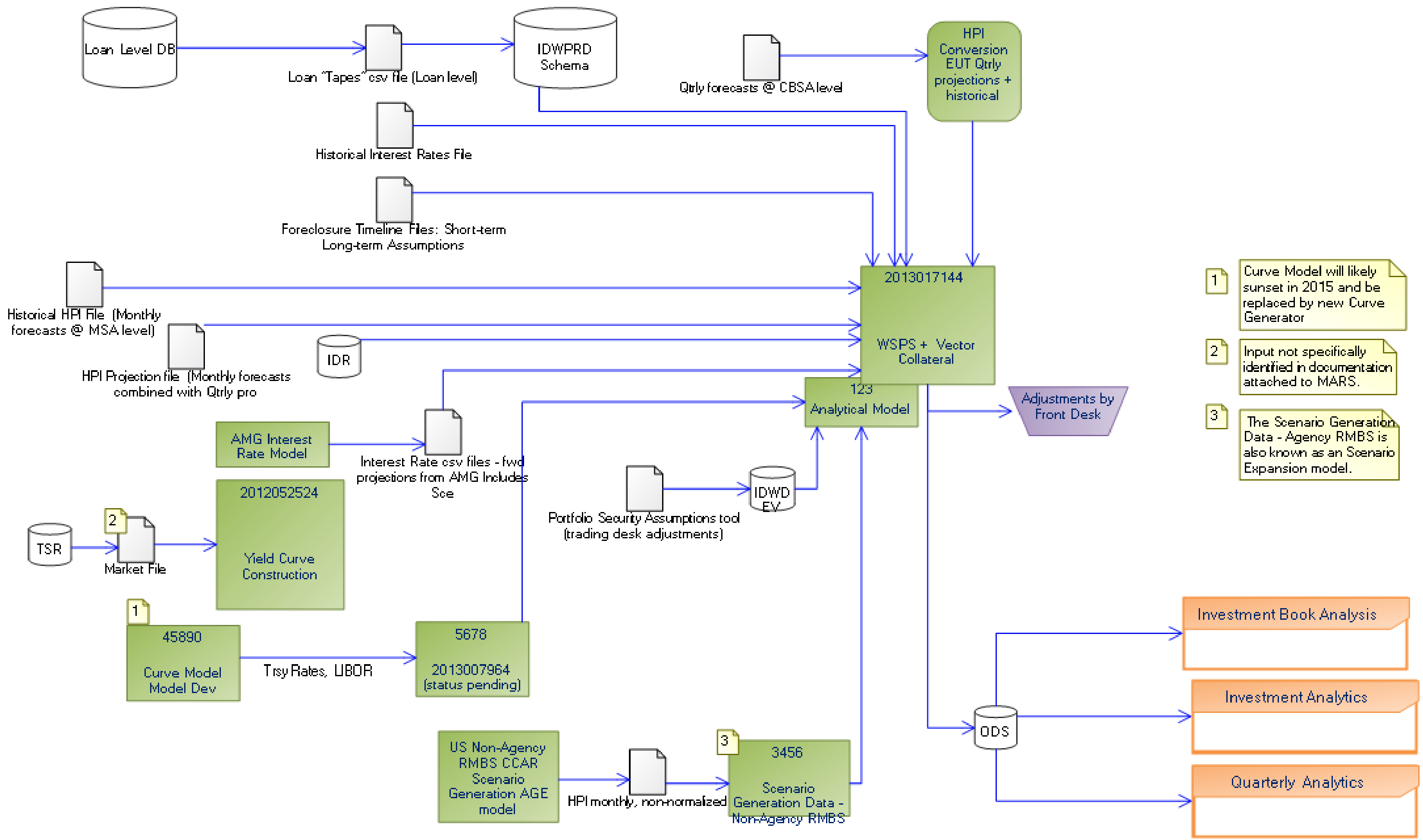
All of these issues are significantly ameliorated by elevating the unit of observation to the model stream level

What is a model stream?

- A group of models *and their infrastructure* related by
  - Function
  - Dependence (nesting)
  - Common data sources
  - Common platform
- The stream includes all movements of data and calculated values
- It includes data transfer/processing/transformation components as well as models
- It is wing-to-wing: data sources to final use/reporting

Risk measurement at the stream level can directly embed data quality risks and model risks adjusted for interdependencies

Stream view example – a modeling complex for a certain asset class



What would we like to know about a model stream?

- Product outlook
  - Core/non-core, Growth/Stable/Shrinking
  - Profitability, Peer profitability
  - Performance Volatility
  - Product evolution (dynamism, segmentation)
- Tactical Objectives
  - Objective 1 (e.g. improve risk segmentation, predictive power)
  - Objective 2 (e.g. improve implementation – more controlled production application, ease of use, more automated data capture)
  - Objective 3 (e.g. consolidate related models)
  - Etc.
- Economic assessment
  - Known suite deficiencies
  - Key effected margins
    - Expenses
    - Loss avoidance
    - Pricing power/adverse selection/elasticity
    - Market share/product differentiation/client service potential
  - Potential impact – Cost/Benefit, Combined ratio effect, etc.

Strategic and tactical action based on this information *is* model risk management

Strategic View of the Overall Information Processing Complex

Requires the following components:

- **Model based view**
  - Wing-to-wing independent validation (data, performance, controllership, technology)
  - Risk score (based on comprehensive model risk assessment framework)

Basic underlying analysis

- **Stream based view**
  - Assessment based on use/scope/corporate function
  - Clear executive ownership
  - Includes an appropriate measurable definition of model exposure alternatives

Supports the development of a strategy

- **Meta view**
  - Explicit mapping of all system components: data, applications, models, reports & other uses
  - Typically will lie between "model" and "block" based views
  - Assessment throws off:
    - Aggregated Model Risk measure
    - Risk-based data quality measure
    - Explicit tactical remediation plans

Enables the implementation of the strategy

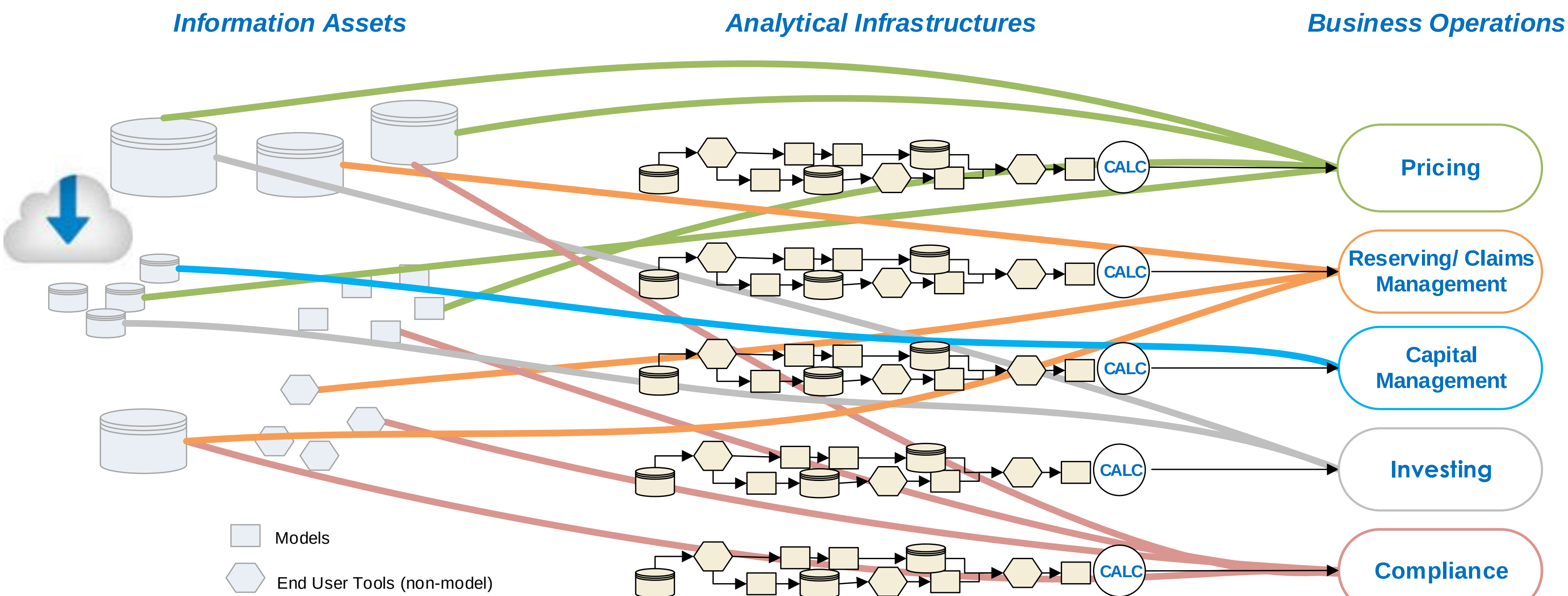
Model Risk Management that includes the interrelationship of all analytic components is holistic and simplifies reporting and strategic planning

- Models are typically embedded in systems/processes that include data sources, inter-related models, platforms, and other model-delivery systems – *they all contribute to risk and to return*
- Effective model validation requires some consideration of this broader context/infrastructure anyway – putting structure on this part of the process will increase efficiency
- Business strategic planning to enhance analytic capabilities is typically done at the stream level – this planning is also critical contextual input for the validators
- Model risk measures aggregated to the stream level will be more meaningful and more actionable

Why is a Meta Infrastructure Needed?

Typically:

- Each business line has its own infrastructure, sometimes linked, but not explicit or visible.
- Development of calculations are siloed and independently managed.
- Data & calc lineages are not easily determined.
- Analytic infrastructures require forensic analysis to determine components and assess controllership, performance gaps and outputs.

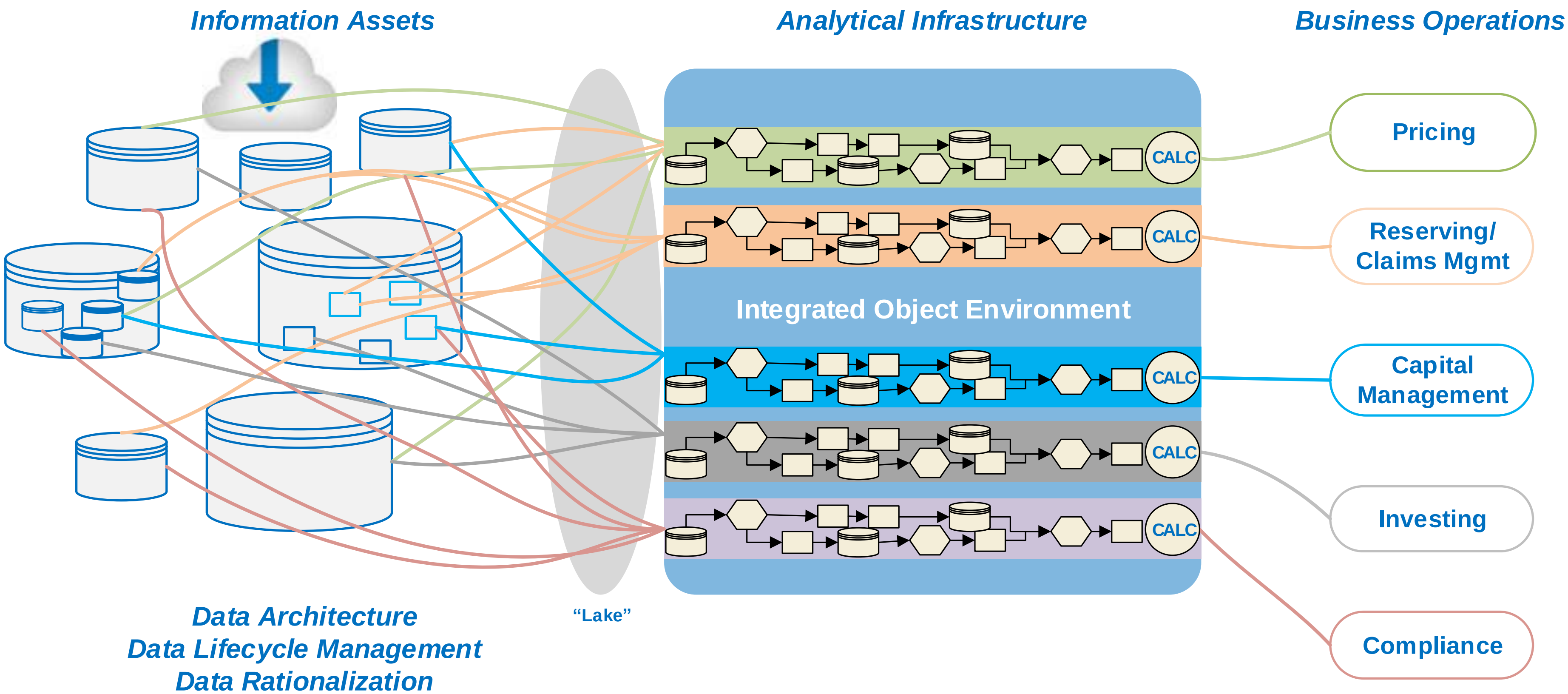


Model Risk
Data Governance, Standards, Quality & Risk
Database Rationalization

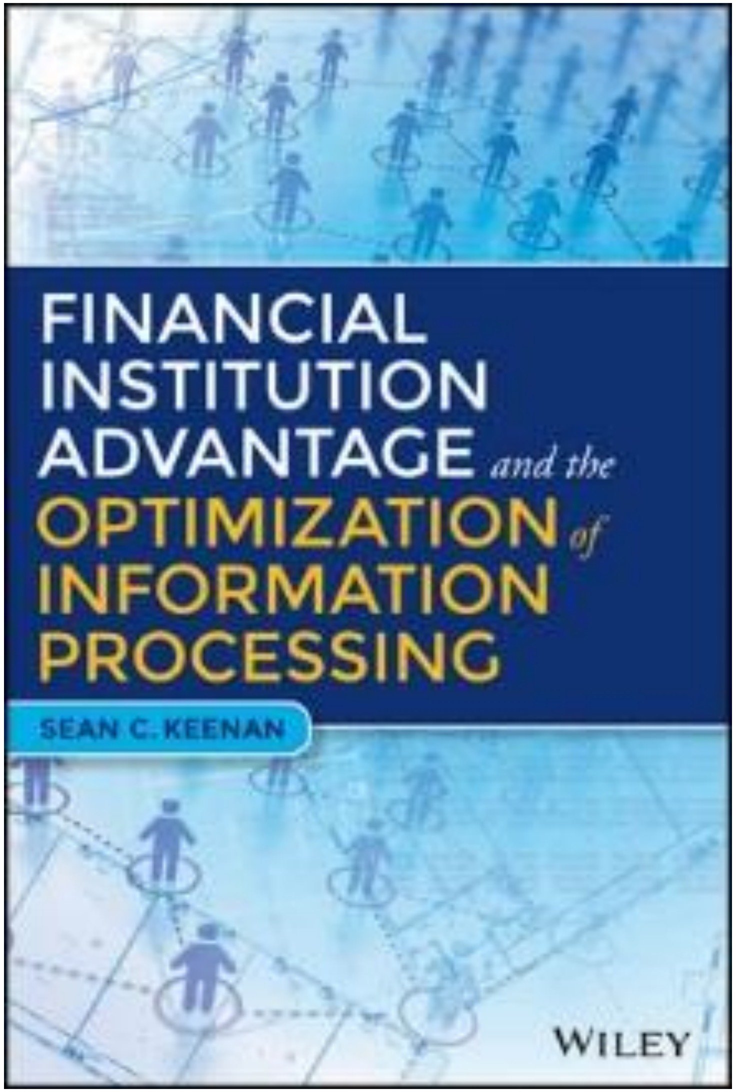
The Analytics "Supply Chain and Factory"

With a Meta Infrastructure in place:

- Analytical linkages established and maintained data, models, platforms, end uses.
- Makes the infrastructure "streams" visible with insight into cost, controls, and profitability.
- Contains its own embedded analytic & reporting capabilities for management.
- Surgical approach to scale and to extension.



For a more detailed discussion of these and related topics please see.....

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