Model Risk Management

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Agenda

- History of model risk: failures and regulation
- Our interpretation of a model
- How to assess model risk
- Examples of high-risk models
- Vendor models: risks and validation differences
- Model risk matrix
- Takeaway: validation as a learning tool
- Questions

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History of Model Risk

Institutional failures and the evolution of supervisory guidance

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When Models and Controls Fail

Two decades of lessons: the same root causes keep reappearing

FREDDIE MAC 2003

- Announced a ~$5B restatement of 2000–2002 earnings
- Sophisticated interest-rate risk modeling paired with weak operations and accounting controls
- Regulator (OFHEO) found operational risk neglected while earnings were being smoothed

FANNIE MAE 2004

- OFHEO special examination found accounting for derivatives and hedging did not comply with GAAP
- Estimates and amortization managed to hit earnings targets; inadequate internal controls
- Both GSEs were placed into conservatorship in 2008

NANO BANC 2026

- March 2026 order (issued upon consent) required a review of liquidity stress-testing assumptions
- Also required an ACL model effectiveness process, a full CECL framework assessment, and an independent third-party CECL validation
- Closed Sept. 25, 2026 with tangible equity at ~0.82% of assets

Common thread: unsupported assumptions, weak governance over model outputs, and a lack of effective challenge – not a lack of models.

The Evolution of Model Risk Guidance

From model validation to a risk-based, tailored MRM framework

OCC 2000-16

First supervisory guidance on model validation (May 30, 2000)

SR 11-7 / OCC 2011-12

Enterprise MRM: development, validation, governance; "effective challenge" (Apr. 4, 2011)

FDIC FIL-22-2017

FDIC adopts SR 11-7 for state non-member banks

SR 21-8

Interagency statement on MRM for BSA/AML systems (Apr. 9, 2021)

SR 26-2 / OCC 2026-13

Revised guidance supersedes SR 11-7 and SR 21-8 (Apr. 17, 2026)

Direction of travel: Validation of individual models (2000) → enterprise-wide MRM program (2011) → specialized BSA/AML expectations (2021) → proportional, materiality-driven MRM with explicit vendor/third-party considerations (2026).

Sources: OCC Bulletin 2000-16; FRB SR 26-2 (Apr. 17, 2026); OCC Bulletin 2026-13; FDIC press release (Apr. 17, 2026).

What Changed Across the Three Generations

Core principles persisted; scope, tailoring, and expectations evolved

Dimension	OCC 2000-16	SR 11-7 / OCC 2011-12	SR 26-2 / OCC 2026-13
Focus	Validating computer-based financial models	Full model lifecycle: development, use, validation, governance	Risk-based MRM tailored to model risk profile, size, and complexity
Model definition	Models used for risk, valuation, and strategy	Quantitative method with input, processing, and reporting components	Principles retained; emphasis on materiality of model exposure and purpose
Validation	Independent review, data and process checks	Conceptual soundness, ongoing monitoring, outcomes analysis; effective challenge	Rigor scaled to materiality; focus effort on highest-impact models
Vendor models	Limited treatment	Vendor models subject to same principles	Dedicated vendor and third-party considerations, including validation
BSA/AML	Not addressed	SR 21-8 added in 2021	SR 21-8 rescinded; BSA/AML systems fall under the general framework
AI	Not addressed	Not addressed	Generative and agentic AI explicitly out of scope
Applicability	National banks	All supervised institutions (FDIC adopted in 2017)	Most relevant above $30B; may apply below where model risk is significant

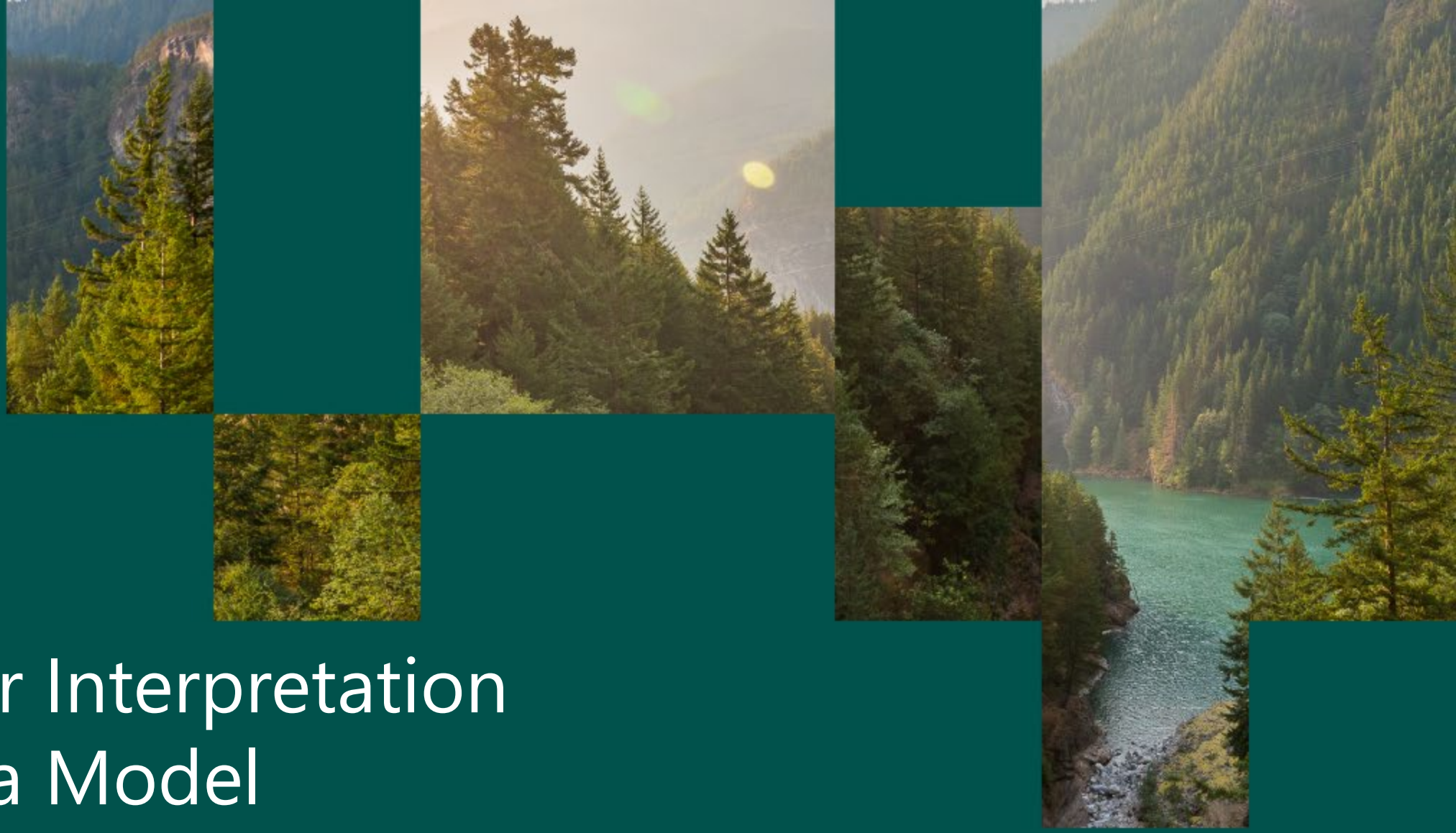
Sources: OCC Bulletin 2000-16; FRB SR 26-2; OCC Bulletin 2026-13; FDIC press release (Apr. 17, 2026).

The Duality of SR 26-2 for Community Banks

It reads like relief. In practice, the bar has moved from compliance to judgment.

What it appears to say	What it means in practice
"Most relevant above $30B in assets"	Still applies where models are prevalent, complex, or used outside traditional community banking
"Non-compliance will not result in supervisory criticism"	Examiners still cite unsafe practices; enforcement orders can require independent validation (Nano Banc CECL)
"SR 21-8 rescinded"	BSA/AML systems still must work; failures surface as BSA program violations
"Tailor MRM to your risk profile"	You must document and defend why your tailoring is sufficient
"Vendor products are addressed"	The bank still owns the risk of every vendor model it uses

Sources: FRB SR 26-2; OCC Bulletin 2026-13 (Note for Community Banks); CA DFPI Order to Nano Banc (Mar. 6, 2026).



Our Interpretation of a Model

If it transforms data into outputs that drive decisions, govern it like a model

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Our View: Data In, Decisions Out = Model

Apply the input–processing–output test broadly; govern in proportion to risk

INPUTS	PROCESSING	OUTPUTS
• Internal and vendor data • Assumptions and parameters • Expert judgment and overlays	• Rules and thresholds • Statistics and econometrics • Fuzzy matching, ML, AI • Vendor / fourth-party logic	• Estimates and forecasts • Scores, alerts, flags • Automated decisions • Reports used by management

Often overlooked, but meets the test

- Rule-based transaction monitoring scenarios and thresholds
- Sanctions screening with fuzzy / phonetic name matching
- Spreadsheet CECL qualitative-factor workbooks
- RPA bots and digital workers that disposition alerts
- Vendor KYC and fraud decisioning platforms

From our work: A bank documented its vendor account-opening decisioning platform as having "no assumptions and no limitations" because it was rule-based. Our review identified four assumptions and limitations – including reliance on vendor data accuracy, vendor score thresholds, watchlist currency, and consistent manual review.

Rule-based does not mean assumption-free.

Model definition per SR 11-7 / SR 26-2 (input, processing, reporting components). Anonymized Cadmus Experience.

How to Assess Model Risk

A transparent framework for impact, likelihood, and controls

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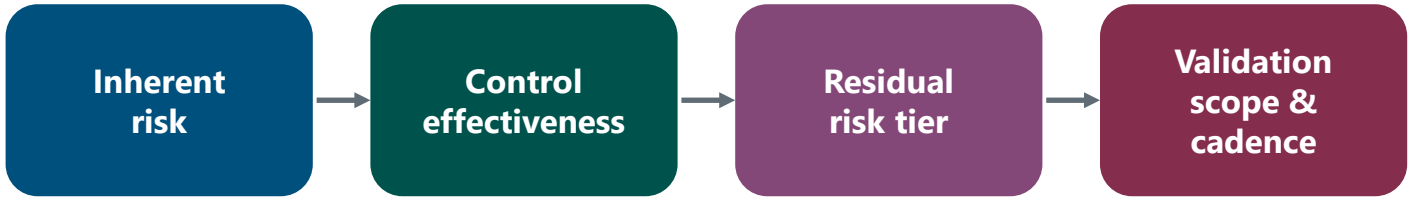
A Practical Model Risk Assessment Framework

Inherent risk = Impact × Likelihood; controls drive residual risk and cadence

IMPACT (illustrative weights)	
Financial / balance sheet impact	**50%**
Regulatory focus	**25%**
Aggregate / downstream model use	**15%**
Reputational & customer impact	**10%**

LIKELIHOOD (illustrative weights)			
Complexity	**45%**	Data inputs	**25%**
Explainability	**20%**	Frequency of use	**10%**



Residual tier	Full-scope validation	Between validations
High	Every 2 years	Annual review; semi-annual monitoring
Moderate	Every 3 years	Annual review and OPM results
Low	Every 4–5 years	Periodic review at MRM discretion

Dollar-threshold example: Impact is rated High when a model error could move the income statement by ≥ $5M or the balance sheet by ≥ $15M, or cause direct and significant reputational or strategic damage.

Why it matters: an inherently high-risk model with strong controls can carry less residual risk than a moderate model with none.

Framework synthesized from Cadmus client MRM programs (anonymized); weights and thresholds are illustrative and should be calibrated to each bank.

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Model Risk Assessment in Practice

Anonymized examples from recent Cadmus engagements

Model (anonymized)	Key impact drivers	Key likelihood drivers	Rating	Validation cycle
Sanctions screening (vendor), regional bank	Potential fines from $50K to tens of millions; enforcement and reputational exposure	Fuzzy / phonetic matching; daily use; automated feeds from multiple sources	**Moderate**	Full scope every 3 years; annual review
AML transaction monitoring (vendor), mid-size bank	Critical role in AML compliance; impact of control failures	Complex scenarios and tuning; multiple data sources	**High**	Every 2 years
CECL / ACL (vendor platform), commercial bank	Directly drives ACL, earnings, and capital	Vendor sub-models, macro forecasts, Q-factor overlays	**High**	Every 2 years plus quarterly governance
Customer due diligence risk scoring (vendor)	Lower direct financial impact	High complexity of scoring logic	**Moderate**	Every 3 years; annual internal review

Lesson: The rating must reflect how the bank uses the model – not the vendor's brand or the model's age. Re-assess when use, data, or configuration changes (e.g., retiring a business line from screening).

Client names withheld. Ratings reflect each bank's own risk assessment framework at the time of review.

Examples of High-Risk Models

Where model errors translate directly into losses or enforcement

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Five High-Risk Model Families

High impact on financial statements, capital, liquidity, or regulatory standing

CECL

Drives the ACL, earnings, and capital

What goes wrong

- Unsupported Q-factors
- Lookback and forecast choices
- Manual hand-offs between teams

AML / CFT

Transaction monitoring, fraud, OFAC

What goes wrong

- Incomplete data feeds
- Stale thresholds and rules
- Outdated documentation

ALM / IRR

NII and EVE sensitivity

What goes wrong

- Deposit beta and decay assumptions
- Prepayment assumptions
- Weak back-testing

STRESS / LIQUIDITY

Capital and liquidity under stress

What goes wrong

- Unsupported stress assumptions
- Inconsistent scenario models
- Weak link to contingency funding

AI & AUTOMATION

ML models, RPA bots, digital workers

What goes wrong

- Limited explainability
- Drift and volume limits
- Unclear ownership

Nano Banc's 2026 order targeted two of these five directly: liquidity stress testing assumptions and the CECL framework.

Source: CA DFPI Order to Nano Banc (Mar. 6, 2026); Cadmus validation experience.

What We Find in Validations

Anonymized findings from recent engagements – and why they matter

Model type	Observation	Why it matters
Sanctions screening	A change in wire data formatting meant institution details for some foreign-currency wires (~$2.5M per month) did not flow to the screening tool; staff relied on a manual workaround	Data integrity gap in a regulatory control; required a reconciliation control
Sanctions + digital worker	A stricter screening setting was temporarily rolled back because the downstream RPA digital worker could not absorb the extra alert volume	Model interdependencies can quietly weaken controls
AML	No single bank-authored model document covering data, theory, assumptions, and limitations	Interpretability and governance risk; Medium finding
Capital stress testing	Scenario construction not documented; econometric models not applied consistently across scenarios	Differences should reflect scenario severity only
CECL / ACL	Process split across Credit Administration and Finance with manual files passed between teams	Higher error and key-person risk; consolidate and reconcile
Fraud (vendor)	Alert output lists the number of rules triggered, not which rules	Rule-level effectiveness and tuning cannot be assessed

All observations anonymized from 2025–2026 Cadmus model validations and reviews.

Validating AI Models: Approach and Methodology

ML-driven alert triage as a model: validation includes the pipeline, the data, and the human hand-off

Area	What we do	Why it matters for AI models
1. CONCEPTUAL SOUNDNESS & DATA		
Decompose the pipeline	Map each component – entity extraction, ML classifiers, name/address matchers, rules engine – and confirm which use ML vs. rules	Risk sits in the hand-offs between components, not just in one algorithm
Data & inputs	Trace source-to-model field mappings; test what upstream systems actually pass in (e.g., a wire amount read as a name)	An AI model is only as reliable as the fields and populations it receives
Scores & thresholds	Obtain the meaning and cut-offs of confidence and risk scores; test fit with screening cadence and lookback settings	Proprietary vendor scores stay opaque unless the bank documents them
2. OUTCOMES, USE & CONTROLS		
Outcomes analysis	Sample auto-closed and escalated alerts; independently re-adjudicate dispositions and review narratives	Tests false-negative risk in alerts no human reviewed
Human in the loop	Confirm escalation routing, QA of automated dispositions, and capacity when alert volumes rise	Human review is the key compensating control for limited explainability
Change & drift	Review vendor release and version control; monitor drift, volumes, and auto-close rates	Retraining or upgrades can change outputs without bank review

Fair Lending Models and Their Validation

Disparity testing under ECOA and the Fair Housing Act includes replication, not just the review

What the model does	What validation tests
Assigns protected class (BISG proxy, ≥50% probability) →	Proxy build and target vs. control group assignment
Builds base model from credit and loan factors →	Variables and bucketing vs. underwriting and pricing policy
Adds protected-class indicators to regressions →	Replication; statistical and economic significance
Flags focal points where disparities remain →	Independent focal-point identification and thresholds
Selects matched pairs for file review →	Pair selection and the bank's resolution process

From our work: a vendor HMDA fair lending model was submitted with no protected-class variables in its regressions – so the test was incomplete. Our replication surfaced two focal points (one underwriting, one pricing) for management review.

Vendor-Developed Models

Most small and mid-size banks buy rather than build – but they still own the risk

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Vendor Models: Where the Risk Hides

Buying a model transfers the development work, not the model risk

Black box
Proprietary logic limits review of conceptual soundness and code

Generic calibration
Default settings and pooled data may not fit the bank's portfolio or customers

Bank-owned configuration
Thresholds, rules, segmentation, and overrides are set by the bank

Fourth-party chains
Platforms often aggregate other vendors' scores and data

Vendor "validation"
Vendor testing is useful input but is not independent validation

Release & change risk
Upgrades and patches can change outputs without bank review

Data interfaces
Mapping and feed errors between core systems and the vendor tool

Concentration & exit
Limited contingency if the vendor or product is discontinued

Sources: SR 26-2 vendor and third-party considerations; Cadmus validation experience (e.g., KYC decisioning platform integrating five third-party data providers).

Validating Vendor vs. In-House Models

Same principles, different emphasis: governance and controls carry more weight

Area	In-house model	Vendor model: where to focus
1. GOVERNANCE		
Governance & ownership	Developer and owner inside the bank	Named bank model owner; vendor due diligence; contract rights to documentation
Model documentation	Full development evidence available	Bank-authored document covering use, configuration, assumptions, and limitations – not just vendor manuals
Ongoing performance monitoring (OPM)	Developer-designed metrics	Bank-defined thresholds; alert volumes, dispositions, back-testing; vendor release review
2. CONTROLS		
Data	Direct access to development data	Source-to-vendor reconciliation, field mapping, rejected records
Change & access	Code-level change control	Configuration change logs, approval evidence, user access reviews
Outcomes	Replication and benchmarking	Outcomes analysis, sensitivity testing, and challenger / benchmark where logic is opaque

Source: Cadmus validation methodology; approach for externally developed models consistent with client MRM procedures and SR 26-2.

Model Risk Matrix

Where the risks concentrate by model type and validation category

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Model Risk Matrix

Typical risks by model type and validation category

Validation category	CECL	AML / CFT	ALM	Stress / Liquidity	AI / Automation
Data	Loan-level history gaps; segmentation; peer / proxy data	Incomplete feeds; field mapping; core-to-vendor reconciliation	Instrument and deposit attributes; repricing data	Cash-flow and funding data; scenario variables	Training data quality and representativeness
Conceptual soundness	Lookback period; R&S forecast; unsupported Q-factors	Scenario coverage vs. BSA/AML risk assessment	Deposit beta and decay; prepayment assumptions	Unsupported stress assumptions; scenario severity	Fit for purpose; explainability
Methodology / mathematics	Loss-rate, PD/LGD, DCF implementation; reversion	Thresholds; above/below-the-line tuning; match scoring	Discounting; option modeling; EVE / NII calculation	Inconsistent econometric models across scenarios	Overfitting; drift; threshold calibration
Governance (documentation, OPM)	Overrides; committee challenge; back-testing	Outdated docs; missing OPM; change logs	ALCO assumption approval; back-testing	Board approval; link to contingency funding plan	Inventory; ownership; human-in-the-loop; vendor changes

Takeaway

Validation is a learning experience,

not a checkbox

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Validation That Helps Banks Avoid Losses

The value is in what the bank learns about using its models better

Check-the-box validation		Value-adding validation
Confirms documents exist	→	Tests whether the model works for this bank's use
Relies on vendor testing	→	Independently tests data, outcomes, and configuration
Generic, boilerplate findings	→	Specific, actionable recommendations tied to business impact
Report filed; findings age	→	Findings drive remediation, tuning, and training
Same scope every cycle	→	Scope follows risk, changes, and prior findings

Right-sized MRM for small-medium banks: know your inventory, rate risk honestly, focus validation on high-impact models, own your vendor models, and treat every validation as an opportunity to use models better – and avoid losses.

Thank You / Questions

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Sources

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- Stanford Securities Class Action Clearinghouse, Fannie Mae Securities Litigation case summary
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- Client examples are drawn from Cadmus engagements and anonymized.