Exploring internal ratings based models

Addressing key challenges and barriers to adoption

2026

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Understanding the IRB landscape

The EBA's Internal Rating Based (IRB) Repair Programme, launched in 2016, is a significant initiative to restore trust and comparability in credit risk models under the Capital Requirements Regulation (CRR). It aims to tackle undue variability in risk-weighted assets (RWAs) by enforcing stricter standards and harmonised methodologies for three key risk parameters: probability of default (PD), loss given default (LGD), and credit conversion factors (CCF).

While IRB models offer a more sensitive and bespoke view of a bank's credit risk, which can ultimately reduce capital requirements, they're inherently complex to develop and maintain. They're also subject to regulatory approval, which can take time and increase the cost of compliance compared to the standardised approach (SA). IRB banks also face changes through reforms from Basel 3.1 and the upcoming CRR III, namely:

- Changes in eligibility for advanced IRB approaches, for example restrictions for large corporate and financial institutions.
- Enhanced requirements for validation, governance, data quality, and margin of conservatism (MoC).
- Extended timelines for LGD and CCF changes in low-default portfolios, acknowledging data scarcity challenges.

Crucially, Basel 3.1 introduces a new output floor, set at 72.5% of RWA calculated using the SA. To establish where that floor sits, IRB-banks must effectively apply both models – putting greater pressure on resources and compliance costs moving forward.

Our findings at a glance

Recognising these challenges, we surveyed a small sample of banks and building societies (including two that are currently seeking regulatory approval) to understand the key barriers and challenges around IRB adoption.

Approval timelines: For 78% of banks with approved IRB models, the process (from model development to approval) took more than 18 months.

AI/ML adoption: 67% are in favour of applying advanced modelling techniques to IRB models, for specific use cases.

Regulatory feedback for non-approved models: 33% waited for over two years to receive regulatory feedback, and when they did, 33% weren't clear on what was required to achieve approval.

Low default portfolios (LDP): LDP modelling remains fragmented, with 33% of firms defining LDPs by annual default counts and 22% by lifetime portfolio defaults, reflecting the absence of a clear best practice amid data scarcity.

From these responses, three themes stand out:

1. Regulatory engagement remains critical – Firms seek greater clarity and consistency in approval processes, particularly for IRB submissions.
2. Operational strain is real – Resource constraints are a recurring challenge, especially for smaller institutions navigating complex model development and validation requirements.
3. Innovation is inevitable – Banks are actively exploring automation and advanced technologies, including generative AI, to enhance modelling efficiency and accuracy.

How widespread is IRB adoption?

Most big banks use IRB

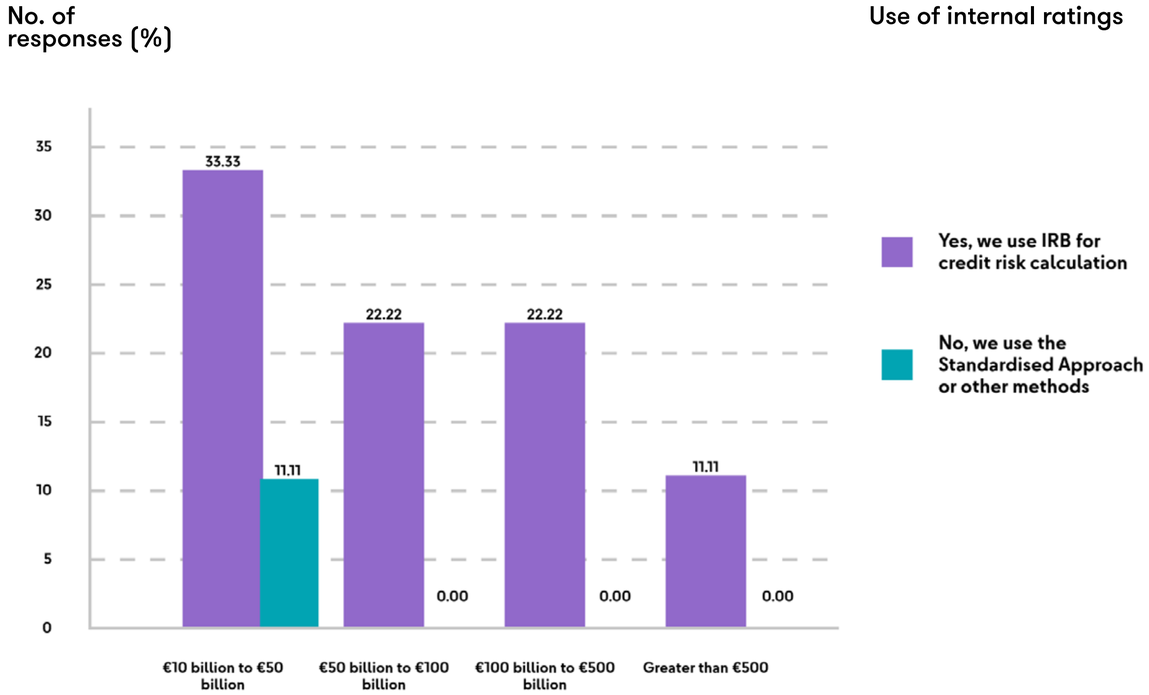
IRB adoption is widespread, particularly for larger banks, and its use is increasing. Of the nine firms we surveyed, just three (all with total assets under €50bn) currently use the SA, and two of those are applying to become IRB firms. Only one firm planned to continue using SA in the longer term.

Four of our respondents are significant institutions – and these firms all apply the IRB approach for credit risk calculations, typically for more than 70% of exposures.

Of the remaining five (non-significant institutions), just two currently use the IRB approach – but they use it as extensively as significant institutions.

Looking ahead, 56% of banks expect their IRB usage to increase over the next few years. That includes 66% of firms currently using the SA approach (both already planning to migrate), and 40% of firms that are already using it for over 70% of exposures.

IRB adoption vs bank size



Size of bank: What is the approximate total assets of your institution? (%)

Understanding the barriers to adoption

For a broader view of IRB usage, firms were invited to give free-form feedback over barriers to adoption. They highlighted recurring themes around the length and complexity of the regulatory approval process, with an average timeframe of over 18 months. Some firms also noted challenges around PRA feedback structures, and evolving regulatory views. Data availability is also problematic in some instances.

One firm noted that “the application process is very long and costly, however, it does enable better holistic risk management – but requires a lot of commitment”. Given the effort required for IRB authorisation, it’s reasonable to expect significant benefits from it, but only two firms viewed IRB models as a key driver of strategic decision-making, with 44% saying that although they’re important to strategic decision-making, they’re primarily used for regulatory compliance.

IRB resources vary considerably

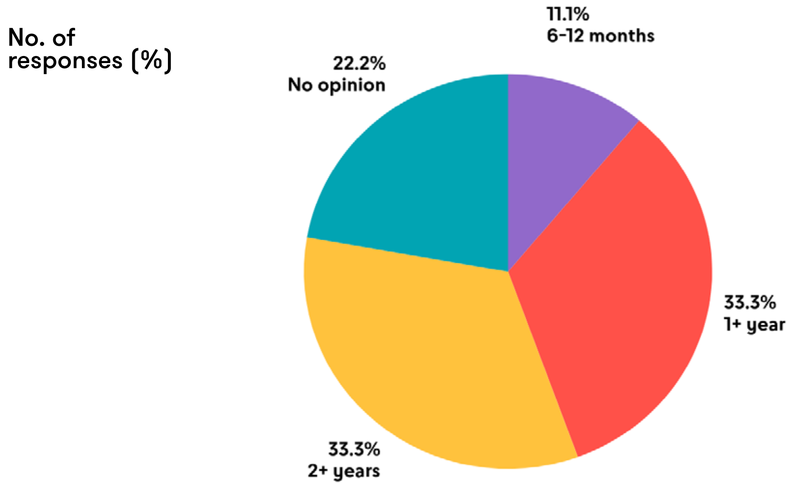
Full time employees (FTEs) dedicated to IRB model development, monitoring and validation varied considerably:

- For development FTEs ranged from 3-75, with one firm noting that their team doubled to support specific modelling activities.
- For monitoring, FTEs ranged from 2-50.
- For validation, FTEs ranged from 1-50.

The reason for the variation is unclear and there's no demonstrable correlation between size of organisation, portfolio types, or IRB coverage in relation to the number of dedicated FTEs working these models. For example, the bank with the highest total number of FTEs had an IRB coverage (by exposure) of 30-50%, compared to the next biggest employer, which had less than half the dedicated staff, with a coverage of over 70%.

The variation could potentially be due to the structure of the question, which was split by stages of the model lifecycle and, in practice, people may work across more than one area – leading to undercounting or double counting.

Feedback time for rejected model



Time taken to receive feedback on non-approved IRB attestation models?

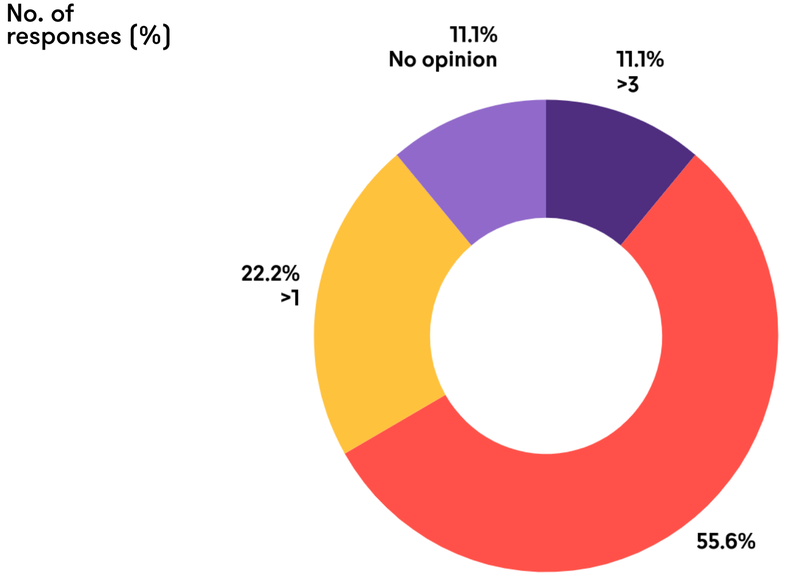
IRB model approvals take time

From our sample, the majority of firms had one or more model approved and only two had three or more. However, getting to that point is time consuming, with 78% of firms taking more than 18 months to develop the model and receive approval.

For those that aren't approved, a third waited over a year for feedback and a third waited more than two – but despite the long turnaround, 33% were still unclear on next steps to gain approval. Firms didn't go into detail over the areas of regulatory concern during the approval process, but some mentioned model cyclicality, and divergence between PRA guidance and ECB's expectations.

In addition to the approval timelines, IRB models can also be resource heavy with staffing estimates for development, monitoring and validation ranging from 1-75 full time staff members (with significant variation between firms). Moving forward, AI could be an integral tool to streamline workloads and increase the rate of development.

IRB attestation - approved models



How many submitted IRB attestation models were approved? (%)

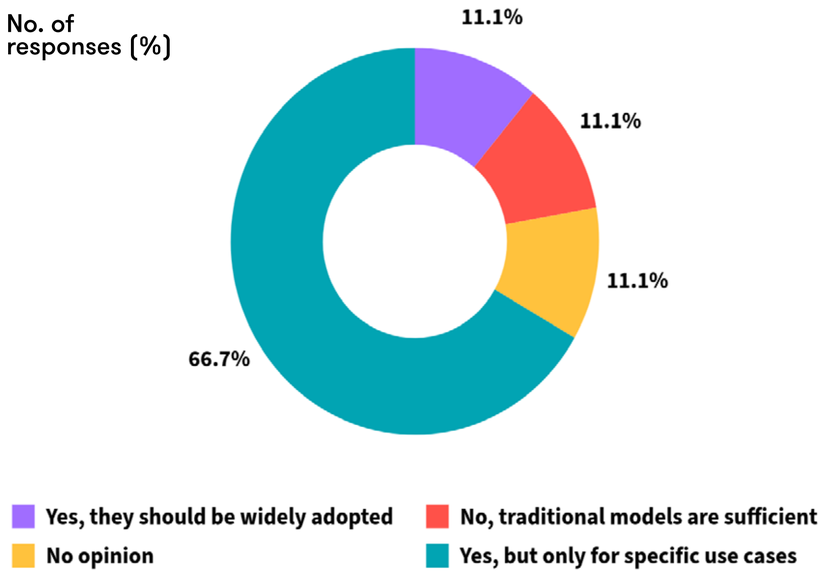
Use of AI

Implementing AI

Firms were broadly keen to adopt advanced modelling techniques using machine learning or artificial intelligence, and this could be a critical area for future developments in modelling. However, the regulatory position is still unclear and the direction of travel will likely emerge as the industry and regulators begin to establish good practice.

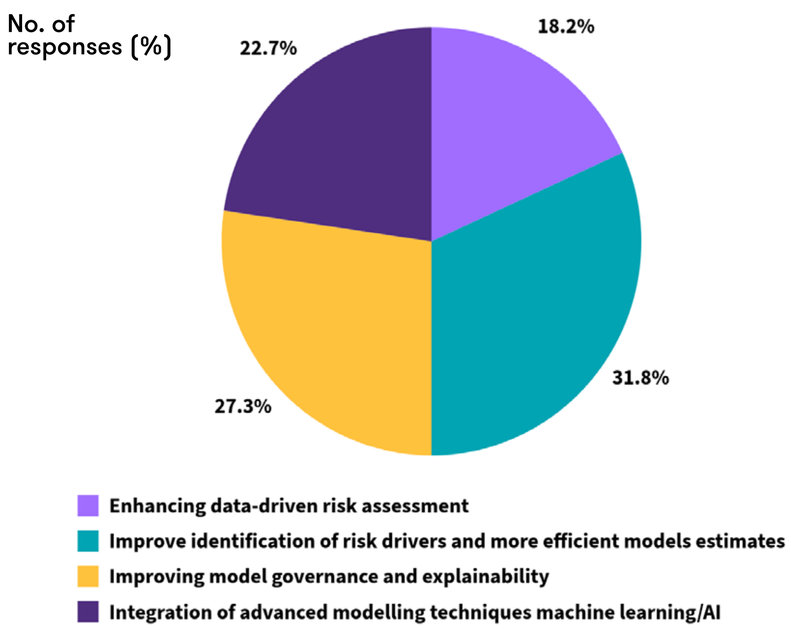
11% of respondents were keen to see advanced modelling techniques widely adopted, while 67% were in favour of using them for specific use cases only, with perceived benefits including better informed modelling decisions, enhanced stress testing and scenario analysis and improved predictive accuracy.

Support for AI/ML models



Are you in favour of introducing advanced modelling techniques or AI into bank IRB models? (%)

Critical innovation areas in modelling

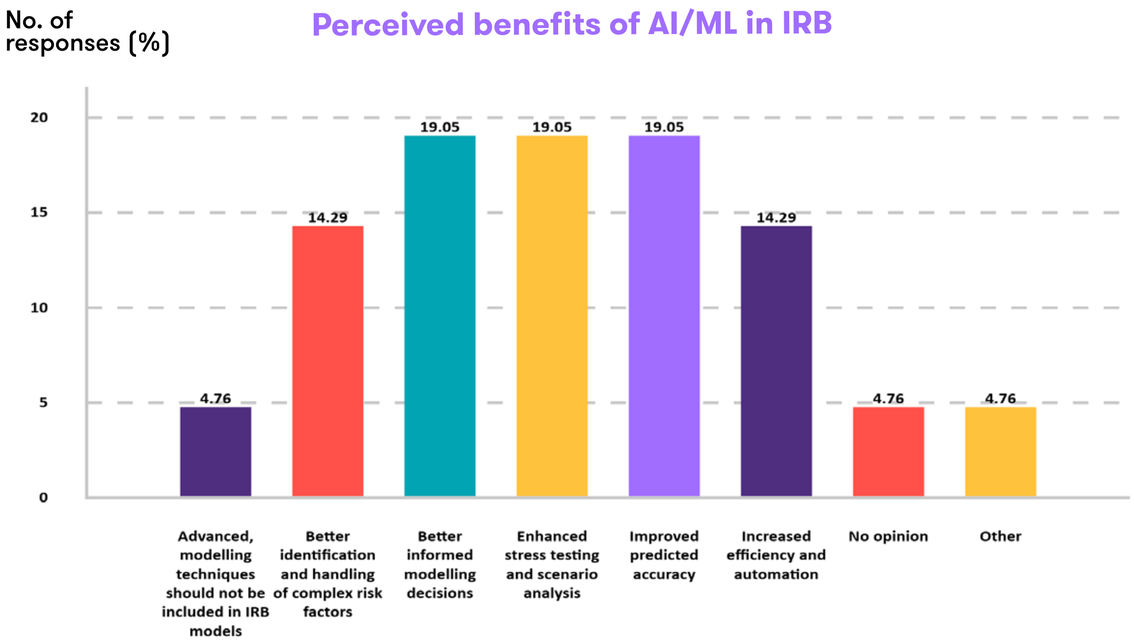


Which areas of internal modelling will need the most innovation in the coming years? (%)

Benefits of using AI

When asked about which areas of modelling were the most critical in terms of innovation, 32% cited a need to improve identification of risk drivers and more efficient model estimates, while 27% cited improving model governance and explainability as a key benefit.

When considering potential portfolios for inclusion, retail lending and high default portfolios took the lead, perhaps due to increased sensitivity that AI modelling could potentially offer.



What are the key benefits for introducing advanced modelling techniques in IRB models? (%)

Firms aren't there yet

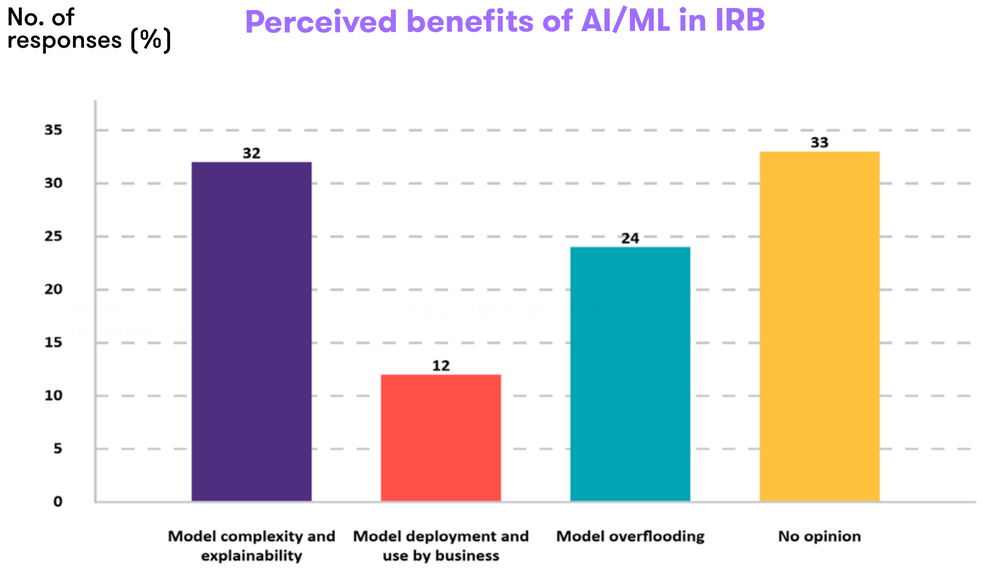
While many firms can see the benefits of advanced modelling techniques, ambition currently outstrips capabilities and firms' associated risk management. 11% of respondents had developed AI or ML models, but none had gained regulatory approval to use them. A further 22% were considering developing AI or ML models, but hadn't put them into action yet.

However, a significant 56% said they weren't in scope for development and firms could foresee a range of risks associated with AI modelling techniques. 32% saw model complexity and explainability as a potential barrier, with a further 32% citing regulatory compliance.

To close these gaps and support advanced modelling capabilities, 44% of firms noted a need for closer collaboration between the regulator and industry.

However, firms were divided in terms of what the regulators' role should be. 25% believed the industry should lead the innovation, in line with prudent and sound principles, while 31% believed that further regulatory guidance is needed before full adoption.

These concerns were echoed in another question, where we asked firms about the key areas in which they would like to see more prescriptive regulation. 67% of firms noted the use of AI and ML, while 22% wanted more prescriptive guidance on calibration techniques.



What key risks have you observed (or do you expect to observe) from using advanced modelling techniques? (%)

Approaches to low-default portfolios

Taking a proportionate approach

Under Basel 3.1, banks can no longer use advanced IRB models for low-default portfolios (LDPs), meaning firms must move to the foundation IRB or standardised approach.

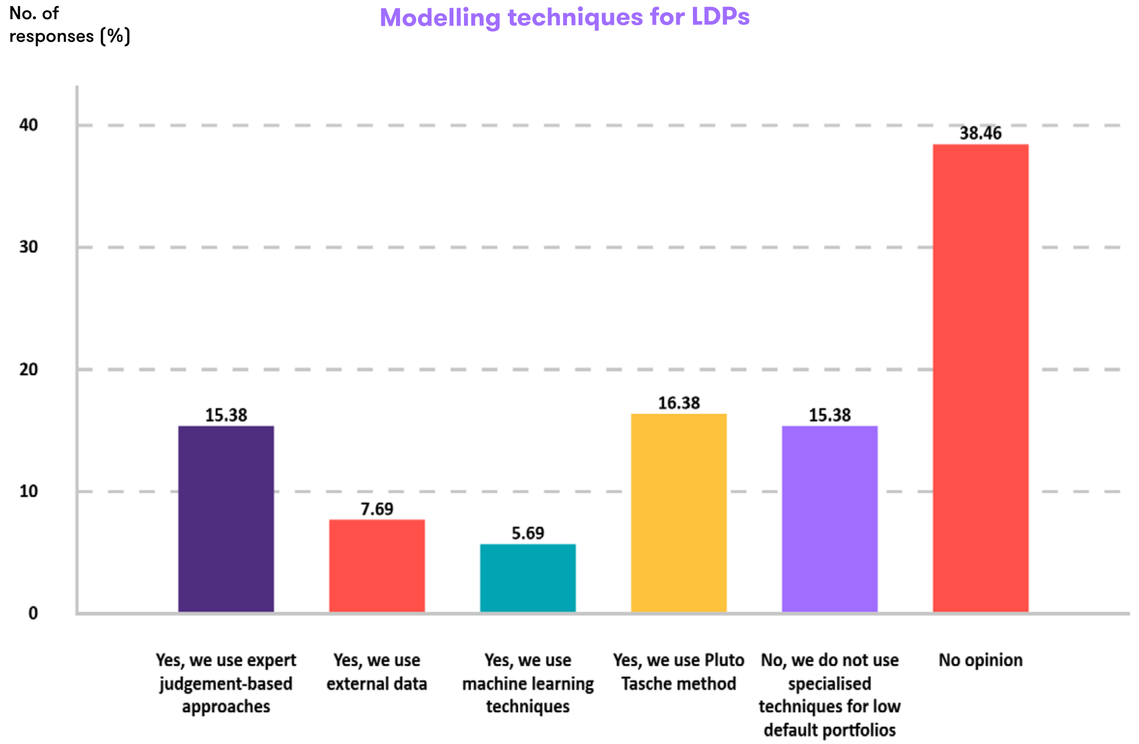
Current classifications vary: 33% define LDPs by the number of defaults per year and 22% by defaults across the portfolio's history, with a typical threshold of 20 or fewer defaults across either time horizon.

To manage these challenges, banks already use a mix of specialist techniques, including expert judgement, the Pluto-Tasche method, external data and limited machine learning, while only 15% report using no specialised approaches. Views on advanced analytics are mixed: 22% believe AI or machine learning can materially improve accuracy, whereas 11% still see traditional techniques as more reliable.

With limited data available for low-default portfolios, we asked banks about their use of external data in IRB models. 44% confirmed that they are using external data to offset deficiencies and biases, but how firms used that data varied, with key methods including:

- 33% using external data for risk quantification (calibration) purposes
- 13% using it for benchmarking
- 13% using it for risk differentiation

In terms of applying external data to key risk parameters, 45% used it to inform probability of default calculations and 18% used it to assess loss given default.



Are low-default modelling techniques used, and which are the most common? (%)

Use of external data

Applying the standardised approach

Despite the challenges in applying IRB models to LDPs, banks were divided on the merits of moving these portfolios to the standardised approach:

- 22% felt that partial standardisation is beneficial, but flexibility is needed
- 11% felt the standardised approach was necessary to avoid risk underestimation
- 22% felt the standardised approach is necessary to optimise costs associated with LDP model development and monitoring

Maintaining model quality

IRB firms need to ensure their models are supported by strong governance and oversight, using a range of processes to identify potential deficiencies. To achieve this:

- 41% monitor key performance indicators
- 37% carry out regular back-testing and validation
- 23% review regulatory feedback and benchmarking

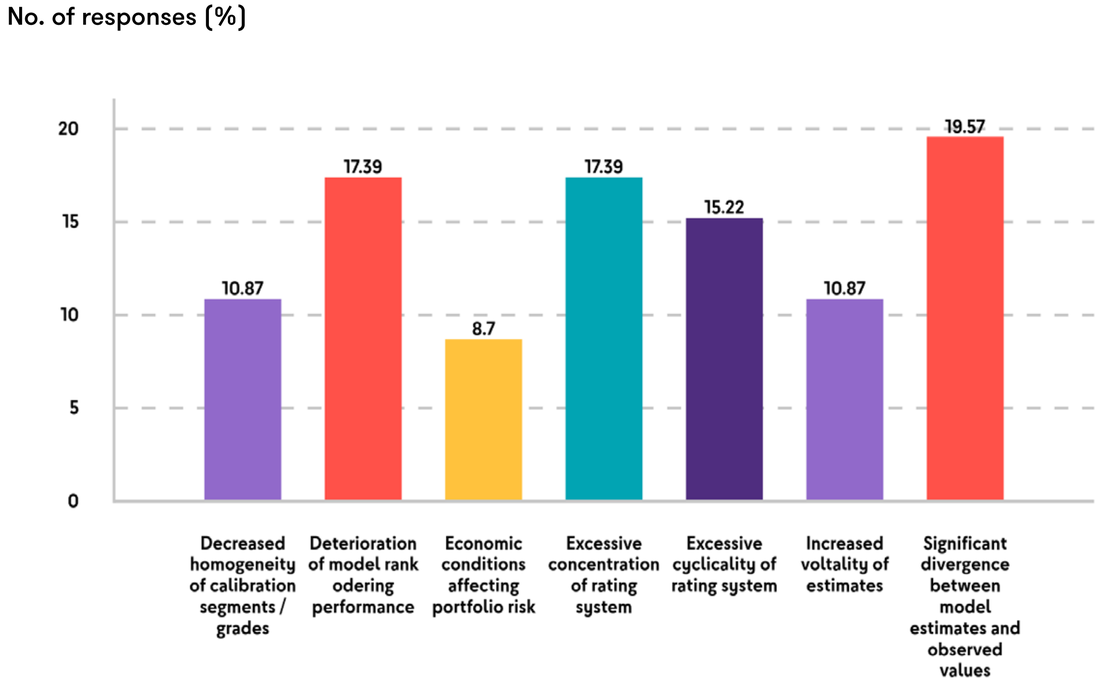
Among those using KPIs, there was no clear consensus on what should trigger recalibration, though common indicators included significant divergence between estimates and observed values, excessive risk concentrations, and deterioration in rank-ordering performance. Banks were also split on when recalibration should occur, with 38% basing it on model complexity and materiality, and 38% waiting until significant deficiencies arise.

When managing model risk more broadly, firms highlighted challenges around maintaining model relevance and spotting emerging risks:

- 44% used hybrid rating philosophies
- 33% used through-the-cycle or point-in-time approaches
- 11% applied explicit lifetime adjustments in PD and LGD

To identify emerging risks, 50% applied robust periodic risk assessment, with a further 29% conducting industry benchmarking.

KPIs triggering model recalibration



Which KPIs should serve as the primary triggers for recalibration/model risk? (%)

Alignment with IFRS 9

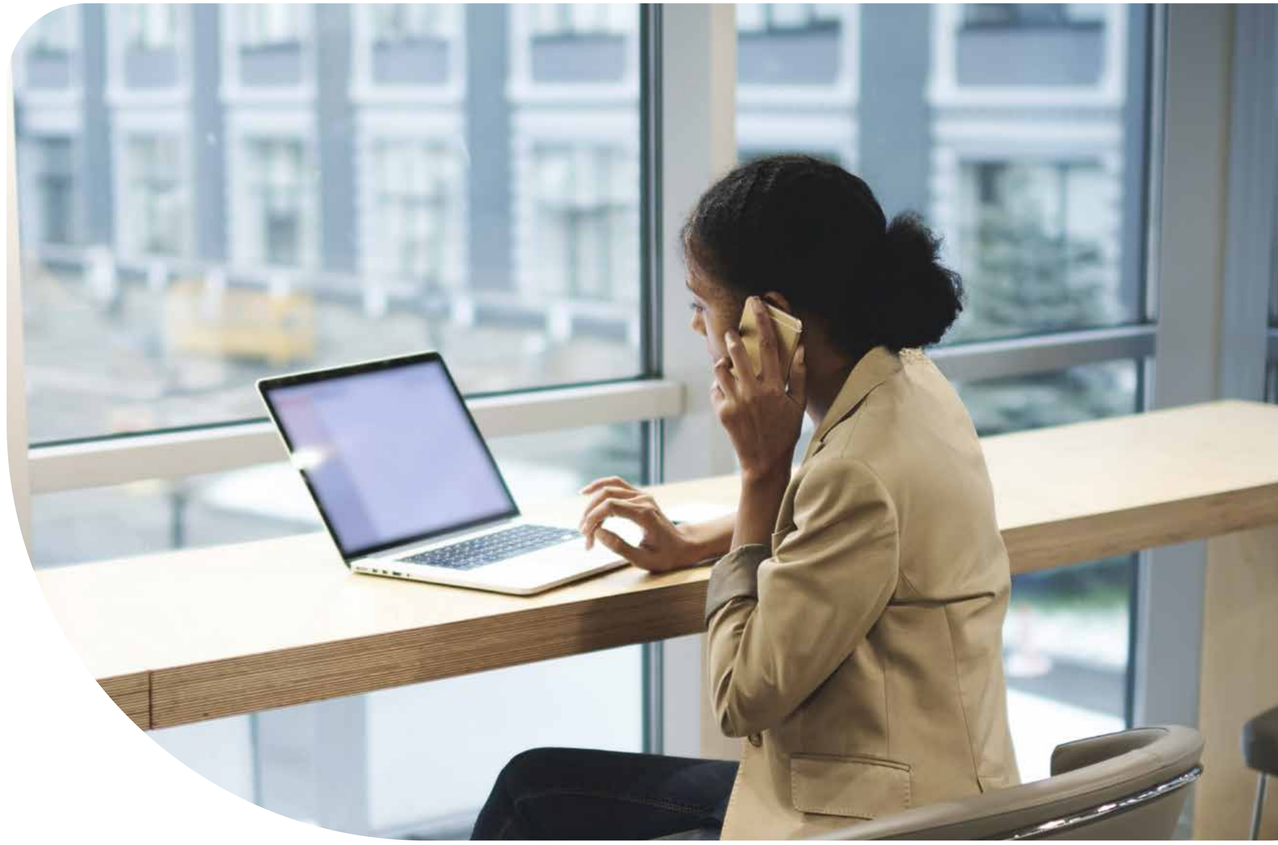
Addressing data gaps

Variations in methodologies, combined with different outlooks from expert judgement, could result in significant variations in firm's IRB model output, with a knock-on effect on supervisory comparability.

When asked about model risk practices in relation to IFRS 9, our respondents noted a broad range of challenges, with the most consistent being the lack of internal risk data and default observations.

However, many firms also cited challenges around the difficulty in forward-looking estimates, and representativeness in point in time and lifetime estimations, among others.

With these ongoing challenges, it was interesting to note that 33% of banks felt an alternative standardised approach should exist for certain portfolios to support IFRS 9 calculations.



Estimating probability of default

Estimating probability of default in low-default portfolios was particularly challenging and banks used a range of methods to supplement their data, but there was no real consensus on best practice or preferred approach. Some firms leveraged additional techniques to address the issues:

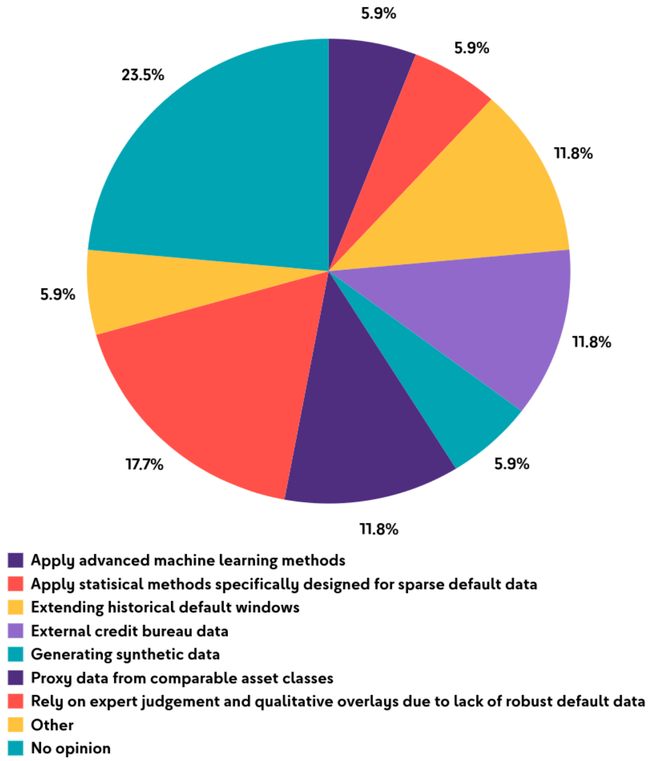
- 20% used through-the-cycle (TTC) outputs, transformed using macroeconomic overlays
- 10% used hybrid TTC/point-in-time calibration (for example anchored methodologies)
- 20% used alternative non-IRB approaches, for example machine learning
- 10% used pure point-in-time estimation, with expert judgement

Estimating loss given default

On a comparable note, firms used a range of methods to estimate loss given default (LGD) in low-default portfolios:

- 18% rely on internal recovery data only (despite its limitations), and applying further expert judgement
- 9% apply downturn LGD floors from regulatory frameworks
- 9% leverage the regulatory LGD model, but remove conservative floors or margins
- 9% supplement internal data with external LGD benchmarks or pooled industry/recovery data
- 9% used other approaches

Data supplementation methods for PD estimation under IFRS9



Do you use external data to calibrate PDs for low-default portfolios under IFRS 9?(%)

Our survey reflects the challenges banks face around implementing IRB models, including significant operational strain, uncertainty over the regulatory approvals process and gaps in data. Despite these challenges, banks feel that the IRB approach still offers a clearer view of their risk. As such, banks want to keep using it but recognise that there is room for greater regulatory support and improved clarity throughout the approvals process.

Moving forward, AI and machine learning will undoubtedly play an important role in model development, validation and risk management – but we aren't there yet. There is considerable work ahead, from the regulators and financial sector, to establish what good looks like and robustly apply it to these crucial models.

Contact us

Kantilal Pithia
Partner
D +44 (0)20 7865 2688
E kantilal.pithia@uk.gt.com

Vivian Lagan
Managing Director
D +44 (0)20 7865 2240
E vivian.lagan@uk.gt.com

Grant Thornton

GRANTTHORNTON.CO.UK