



fermac risk

Challenges in Risk Modeling for 2024

Fermac Risk Whitepaper

May 2024





Foreword

In the rapidly evolving financial landscape of 2024, risk modeling has become more crucial and complex than ever before. The global financial crisis, economic volatility, and unpredictable geopolitical events have underscored the need for robust, adaptive, and forward-thinking risk management strategies. As financial institutions grapple with these challenges, they must navigate a landscape of radical uncertainty, technological advancements, and heightened regulatory scrutiny.

This white paper aims to explore the multifaceted challenges facing risk modeling today and provide insights into the innovative approaches being developed to address them. We delve into the limitations of traditional models, which often rely heavily on historical data and fail to account for the rapidly changing economic conditions. The advent of new technologies such as machine learning, quantum computing, and advanced probabilistic models offers promising solutions.

We highlight the necessity for frequent validation and recalibration of models to ensure they remain relevant in a dynamic environment. Integrating probabilistic and robust machine learning techniques enables more accurate predictions and better uncertainty handling. Furthermore, we discuss the potential of quantum computing to revolutionize risk modeling by solving complex optimization problems and simulating a broader range of scenarios at unprecedented speeds.

Banks and financial institutions must also contend with radical uncertainty, which demands a pivot from conventional risk management approaches to more adaptive and flexible strategies. Scenario-based strategic planning, continuous learning, and real-time adaptability are now essential components of effective risk management.

Through this white paper, we aim to provide a comprehensive overview of the current state of risk modeling, identify the key challenges, and propose actionable strategies for navigating these complexities. We aim to equip financial institutions with the knowledge and tools to enhance their risk modeling capabilities and foster a more resilient and responsive financial system.

We extend our gratitude to the contributors and experts whose insights have been invaluable in shaping this paper. As we look ahead, we remain committed to advancing the field of risk modeling and to supporting the financial industry in its pursuit of stability and innovation.

1. Challenges in Risk Modeling for 2024



The COVID-19 pandemic led to exceptional circumstances that caused IFRS 9 models to deviate from their usual assumptions. This resulted in increased use of overlays to adjust IFRS 9 risk parameters or the final ECL amount. Moving forward, it is important to monitor the use of overlays in banking institutions to understand if and to what extent institutions will modify their ECL models to account for the effects currently addressed by overlays or manual adjustments, how many overlays will be maintained, and for how long.

Geopolitical tensions from the Ukraine-Russia war persisted until May 2024, and tensions increased due to the conflict between Israel and Gaza. It seems that we are living in very uncertain times.

Banks are grappling with a new breed of risk management challenges. The factors at play, such as climate change, geopolitical

shifts, digitalization, and demographic changes, are complex and difficult to quantify and price. Traditional risk models are proving to be ineffective in capturing these new risks. This calls for a paradigm shift in our approach to risk modeling.

The performance of financial models is expected to worsen, despite modeling and supervisory methods improvements. The increasing frequency of unexpected events will be the main factor influencing this trend. This will affect advanced internal models and complex regulatory rule-based approaches, leading to simplification demands and increased risk assessment transparency. Firms will need the capability to assess many scenarios and achieve more cohesive integration across different types of risks. The document outlines several key factors shaping the future of models in banking:

The primary reasons prompting banks to change their models include:

- **Interest Rate Environment:** The shift from a low interest rate environment to one with higher inflation and interest rates necessitates model changes to accurately reflect the new dynamics of deposit withdrawals and interest margins.

- **Macroeconomic Shifts:**

The global economic landscape is undergoing significant changes, with weakened growth projections and higher inflation rates. In light of these shifts, banks must urgently reassess and adjust their models to ensure they are capturing the latest economic realities. The need for adaptation is pressing, and the time to act is now.

- **Technological Advancements:**

Improved IT and operational infrastructures are crucial, as outdated systems hinder banks' ability to compete in an increasingly digitalized economy and strengthen their resilience against cyberattacks.

- **Regulatory Requirements:**

Regulatory expectations and supervisory findings prompt banks to revise their models to comply with updated standards and better manage risks identified by regulatory bodies.

- **Risk of Climate Change and Environmental Factors:**

The growing awareness of climate risks and the need for a sustainable transition influence banks to integrate environmental factors into their complex risk models, which require innovative approaches to measure and manage effectively.

- **Geopolitical Risks:**

Increasing geopolitical uncertainties, such as conflicts and trade tensions, necessitate adjustments in risk models to account for potential disruptions and their impacts on the financial sector.

- **Market Volatility and Liquidity:**

Market stress experiences, particularly during the pandemic, have highlighted the importance of having models that can predict and manage liquidity risks and market volatility.

- **Competition for Deposits:**

As interest rates rise, banks face increased competition for deposits. This requires models that can accurately predict customer behavior and the effects of competitive pressures on interest margins and deposit rates.

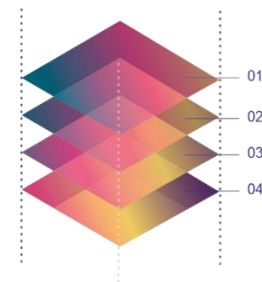
- **Non-Performing Loans (NPLs):**

Changes in asset quality, including the rise of non-performing loans in certain sectors, require banks to adjust their models to predict better and manage credit risks associated with different economic conditions.

- **Shift in Funding Sources:**

The transition from quantitative easing to quantitative tightening has led to changes in banks' funding mixes, requiring models that can account for shifts in market funding and the associated risks.

2. How can I make improvements to strengthen banking models?



These issues underscore banks' need to consistently update and enhance their models to remain robust and competitive in an ever-evolving financial landscape. Here is a list of improvements for strengthening banking models.

- **Improved Reflection of Customer Behavior:**

Banks must enhance their models to better reflect customer behavior, particularly during rising interest rates. Many existing models are based on data from low interest rate periods and fail to account for dynamics like deposit withdrawals during interest rate hikes.

- **Frequent Validation and Recalibration:**

Models must be validated, backtested, and recalibrated more frequently to remain accurate and relevant. In some instances, current models have unjustified assumptions that do not align with customer behavior.

- **Assessment of Indirect Effects:**

A well-defined framework is needed to assess the indirect effects of interest rate changes, such as increased competition for deposits and deteriorating asset quality. Many banks' models currently overlook these aspects, which are critical in managing the cost of risk and understanding shifts in saving behavior.

- **Adapting to Radical Uncertainty ¹:**

Banks face "radical uncertainty," meaning that conventional risk management approaches relying on historical data are insufficient. This requires a pivot towards scenario-based strategic planning and adaptive governance that allows for rapid response to unexpected market changes. Continuous learning and flexibility are emphasized as essential components of this strategy.

- **Integration of New Risks:**

Banks must integrate new risks such as climate change, geopolitical factors, digitalization, and demographic changes into their risk models. These risks are often difficult to quantify and price, necessitating innovative modeling approaches and resilience-building measures.

¹ Bridges to the future: managing bank risk amid Uncertainty, Claudia Buch, Chair of the Supervisory Board of the ECB



- **Enhanced Scenario Planning:**

Using alternative scenarios and dynamic planning is becoming more prevalent, reflecting lessons learned from recent global challenges like the pandemic and geopolitical events. This approach helps banks prepare for various possible futures rather than relying on a single predictive model.

By addressing these areas, banks can develop more robust and adaptable models to navigate the complexities and uncertainties of the future financial landscape.

3. Machine Learning for modeling customer behavior



AI, Generative AI, robust machine learning (ML), and quantum computing offer several advantages over traditional models for developing banking models.

Machine learning (ML) can significantly improve the reflection of customer behavior, especially in the context of rising interest rates. Here are some ways ML can enhance models to capture these dynamics better:

Dynamic Customer Segmentation:

Behavioral Clustering: ML algorithms like k-means clustering, hierarchical clustering, or DBSCAN can segment customers based on their behavioral patterns rather than static attributes. By continuously updating these clusters, banks can identify customers likely to withdraw deposits during interest rate hikes.

Adaptive Segmentation: Using techniques like reinforcement learning, banks can adjust customer segments dynamically as new data comes in, ensuring that models remain relevant even as customer behavior changes.

Time Series Analysis:

Historical Trend Analysis: Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks can analyze historical customer behavior data to identify trends and predict future actions in response to interest rate changes.

Seasonality and Trend Decomposition: ML models can decompose time series data to separate out trends, seasonal effects, and random noise, providing clearer insights into how interest rates impact customer behavior.

Predictive Analytics:

Churn Prediction Models: Supervised learning techniques, such as logistic regression, decision trees, or gradient boosting, can predict the likelihood of customers withdrawing their deposits. These models can be trained on features such as account balances, transaction history, and interest rate changes.

Scenario Analysis: ML models can simulate various interest rate scenarios to predict their impact on customer behavior. Techniques like Monte Carlo simulations combined with ML can provide probabilistic forecasts of deposit withdrawals.

Anomaly Detection:

Unusual Activity Monitoring: ML algorithms can detect deviations from normal customer behavior. Anomalies such as sudden large withdrawals or changes in transaction patterns during interest rate hikes can be flagged for further investigation.

Early Warning Systems: By identifying unusual patterns early, banks can proactively engage with customers to understand their needs and mitigate potential withdrawals.

Personalized Customer Engagement:

Targeted Communications: ML models can help banks identify which customers will most likely be impacted by interest rate changes and tailor communications accordingly. Personalized messages can address customer concerns and offer tailored financial products.

Product Recommendations: Banks can use collaborative filtering and other recommendation algorithms to suggest more attractive products in a rising interest rate environment, such as fixed-term deposits or alternative investment options.

Feature Engineering:

Interest Rate Sensitivity Features: ML can help identify and create features that capture customers' sensitivity to interest rate changes, such as the ratio of variable to fixed-rate products they hold or their past responses to rate changes.

Behavioral Indicators: Features such as transaction frequency, changes in saving patterns, and customer interactions with the bank (e.g., visits to interest rate-related web pages) can enhance predictive models.

Model Retraining and Validation:

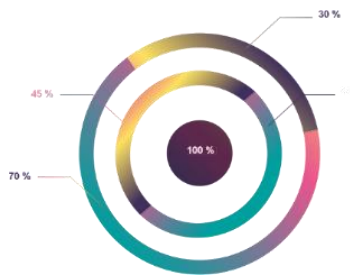
Continuous Learning: Banks can implement ML models that continuously learn and adapt to new data, ensuring predictions remain accurate over time. This is particularly important in dynamic environments like rising interest rates.

Model Validation: ML can automate validating models against historical data, ensuring they accurately reflect customer behavior in various interest rate scenarios.

By leveraging these ML techniques, banks can develop more accurate and responsive models that better reflect customer behavior during periods of rising interest rates. This allows for more effective risk management and customer engagement strategies.



4. Robust machine learning and machine learning for validating and recalibrating models



Machine Learning (ML) and Robust ML can greatly enhance the process of frequent validation and recalibration of models, ensuring they remain accurate and relevant. Here's how they can help:

Automated Model Validation

- **Continuous Monitoring:** ML systems can continuously monitor model performance by tracking key metrics such as accuracy, precision, recall, and mean squared error. Automated alerts can be set up to notify data scientists when performance degrades.
- **Back-Testing:** ML can automate back-testing processes by comparing model predictions with actual outcomes over historical data. This helps assess the robustness and reliability of models under different market conditions.

Adaptive Learning and Online Learning

- **Incremental Learning:** With online learning algorithms, models can be updated incrementally as new data arrives, ensuring they stay relevant without needing complete retraining from scratch.
- **Real-Time Adjustments:** Adaptive learning techniques allow models to adjust in real-time to new patterns in the data, ensuring they remain accurate even as customer behavior shifts.

Robust ML Techniques

- **Handling Outliers and Noise:** Robust ML algorithms are designed to handle outliers and noisy data, which can skew model predictions. Techniques such as robust regression and regularization help create models less sensitive to anomalies.
- **Assumption Validation:** Robust ML can help validate models' underlying assumptions. For instance, robust statistical methods can identify whether assumptions about data distributions or relationships hold true over time or must be revised.

Frequent Recalibration

- **Parameter Tuning:** ML models can use techniques like grid search, random search, or Bayesian optimization to

recalibrate model parameters, ensuring optimal performance frequently.

- **Hyperparameter Optimization:** Automated hyperparameter tuning can be conducted regularly to adjust model complexity and improve predictive accuracy.

Model Explainability and Transparency

- **Interpretable ML Models:** Techniques like SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) can provide insights into model decisions, helping to identify unjustified assumptions and areas for improvement.
- **Explainability Tools:** Robust ML often includes tools for model explainability, which help understand how different features contribute to predictions. This makes it easier to spot and correct flawed assumptions.

Scenario Analysis and Stress Testing

- **Robust Scenario Analysis:** ML models can simulate various economic scenarios to test model performance under different conditions, ensuring they remain robust and relevant.
- **Stress Testing:** Robust ML can enhance stress testing by evaluating how models perform under extreme but plausible conditions, identifying potential weaknesses and areas for recalibration.

Regular Data Updates and Retraining

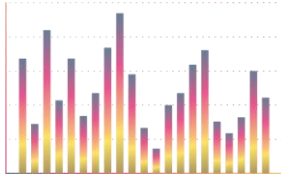
- **Automated Data Pipelines:** Establishing automated data pipelines ensures that models are regularly updated with the latest data, which is crucial for frequent validation and recalibration.
- **Scheduled Retraining:** Implementing scheduled retraining processes ensures that models are periodically updated, reducing the risk of performance degradation over time.

Performance Metrics and Feedback Loops

- **Comprehensive Metrics:** Robust ML includes comprehensive performance metrics that go beyond accuracy to include measures like robustness, stability, and reliability.
- **Feedback Loops:** Creating feedback loops where model predictions are compared with actual real-time outcomes helps improve model accuracy and relevance.



5. Probabilistic ML and quantum computing for modeling uncertainty.



Probabilistic ML and Quantum Computing can significantly enhance banks' ability to adapt to radical uncertainty by facilitating more flexible, adaptive, and robust risk management strategies. Here's how these technologies can help:

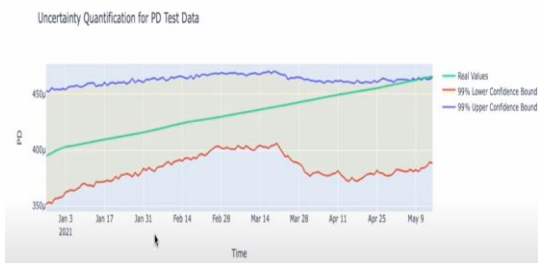
Probabilistic Machine Learning

Scenario-Based Strategic Planning

- **Probabilistic Modeling:** Probabilistic ML can create models that distribute possible outcomes rather than single-point estimates. This allows banks to explore a range of scenarios and their associated probabilities, helping to plan for various potential future states.
- **Bayesian Networks:** These models can incorporate prior knowledge and continuously update beliefs based on new data, making them well-suited for scenario analysis and decision-making under uncertainty.

Quantifying Uncertainty

- **Uncertainty Quantification:** Probabilistic ML models, such as Gaussian Processes and Bayesian Neural Networks, quantify uncertainty in predictions. This helps banks understand the confidence level of their models and make informed decisions under uncertainty.
- **Risk Assessment:** Probabilistic ML helps assess and manage risks more effectively by providing probability distributions for outcomes, offering insights into worst-case, best-case, and most-likely scenarios.



The above graph shows a time series of the PD, and for 6 months, the actual values are within the confidence intervals. This forecast uses the Bayesian neural network of long and short-term memory, BLSTM, which quantifies the epistemic uncertainty. The graph shows

that for 6 months, the actual values are within the confidence intervals.

Adaptive Governance

- **Real-Time Learning:** Probabilistic models can adapt in real-time to new data, ensuring that risk assessments and strategic plans remain current as market conditions change.
- **Decision Support Systems:** Integrating probabilistic ML into decision support systems allows for dynamic strategy adjustment based on the latest data and emerging trends.

Stress Testing and Sensitivity Analysis

- **Stress Testing:** Probabilistic ML can enhance stress testing by simulating various extreme but plausible scenarios and evaluating their impact on the bank's portfolio and financial health.
- **Sensitivity Analysis:** These models can identify which variables significantly impact outcomes, helping banks focus on key risk drivers and improve their risk management practices.

Quantum Computing

Enhanced Optimization

- **Complex Optimization Problems:** Quantum computing can solve complex optimization problems more efficiently than classical computers. This capability is particularly useful in risk management, where optimal resource allocation under uncertainty is critical.
- **Portfolio Optimization:** Quantum algorithms can optimize large and complex portfolios by quickly identifying the best combination of assets to minimize risk and maximize returns under different scenarios.

High-Fidelity Simulations

- **Market Simulations:** Quantum computers can simulate financial markets with high fidelity, capturing intricate interactions and dependencies that classical simulations might miss. This helps in understanding the potential impact of radical changes in market conditions.
- **Scenario Generation:** Quantum computing can generate many scenarios at unprecedented speed, providing a broader and more detailed view of possible future states.



Adaptive and Flexible Models

- **Quantum Machine Learning:** Combining quantum computing with ML can lead to developing adaptive models that learn and evolve rapidly in response to new data and market changes.
- **Real-Time Adaptation:** Quantum-enhanced ML models can adapt in real-time, providing up-to-date insights and allowing for immediate adjustments to strategies and risk management practices.

Robust Decision-Making

- **Enhanced Data Processing:** Quantum computing can process large datasets more efficiently, extracting valuable insights that inform strategic decisions. This is particularly useful in understanding and responding to unexpected market changes.
- **Improved Forecasting:** Quantum algorithms can improve the accuracy of forecasting models by identifying complex patterns and correlations in the data that are not apparent with classical methods.

Integrating Both Technologies

Hybrid Approaches

- **Combining Strengths:** Banks can leverage both technologies' strengths by integrating probabilistic ML with quantum computing.
- Probabilistic ML provides robust uncertainty quantification, while quantum computing offers powerful optimization and simulation capabilities.
- **Enhanced Risk Management:** The combined approach allows for more comprehensive risk management strategies that are both adaptive and capable of handling radical uncertainty.

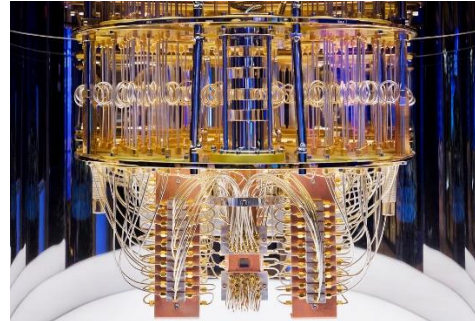
Continuous Learning and Flexibility

- **Adaptive Systems:** Systems that continuously learn from new data and adapt their models accordingly ensure that banks remain flexible and responsive to market changes.
- **Dynamic Governance:** Incorporating these technologies into governance frameworks allows banks to dynamically adjust their strategies, policies, and risk management practices in real-time, maintaining resilience in the face of radical uncertainty.

By leveraging probabilistic ML and quantum computing, banks can enhance their ability to adapt to radical uncertainty, ensuring

more resilient and flexible risk management and strategic planning processes.

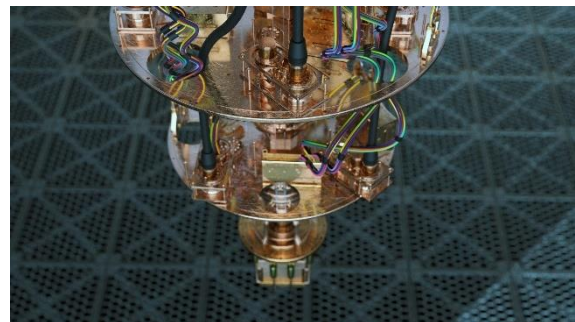
6. Do you need to understand quantum physics to use quantum computing?



No, you don't necessarily need an in-depth understanding of quantum physics to use quantum computing. While a basic understanding of quantum principles can be helpful, many quantum computing frameworks and libraries, such as IBM's Qiskit, Pennylane, or Google's Cirq, provide high-level abstractions that allow you to work with quantum algorithms without delving deeply into the underlying physics.

However, a solid foundation in mathematics, particularly linear algebra, and familiarity with classical computing concepts will be beneficial.

7. A bank needs to wait 10 years from now to use quantum computing models.



Quantum computing is a rapidly evolving field, but it is not yet at the stage where it can be widely adopted for commercial use, including in banking. However, banks do not necessarily need to wait 10 years to start leveraging quantum computing. Here's a nuanced view of the timeline and how banks can start preparing now:

Current State and Near-Term Opportunities

Early Adoption and Experimentation

Pilot Projects: Banks can begin experimenting with quantum computing through pilot projects and collaborations with



quantum computing companies like IBM, Google, and D-Wave. These projects can help banks understand the potential applications and limitations of quantum computing.

Quantum Simulators: Even though fully operational quantum computers are not yet mainstream, quantum simulators running on classical hardware can help banks start developing and testing quantum algorithms.

Hybrid Approaches

Quantum-Inspired Algorithms: Banks can use quantum-inspired algorithms that run on classical computers. Quantum computing principles influence these algorithms and can improve performance over traditional methods.

Integrated Systems: Combining classical and quantum computing in hybrid systems can offer enhanced capabilities. For example, classical computers handle tasks they are well-suited for, while quantum computers tackle specific complex problems.

Partnerships and Collaboration

Collaborations with Tech Companies: Form partnerships with leading tech companies and research institutions that are at the forefront of quantum computing. These partnerships can provide access to cutting-edge technology and expertise.

Consortiums and Industry Groups: Join consortiums and industry groups focused on quantum computing to stay informed about the latest developments and contribute to shaping the technology's future.

Preparing for the Future

Skills Development

Training and Education: Invest in employee training programs to build quantum computing expertise. Encourage participation in online courses, workshops, and conferences.

Recruiting Talent: Hire or collaborate with quantum computing experts and researchers to build an internal knowledge base.

Research and Development

In-house R&D: Establish an in-house research and development team dedicated to exploring quantum computing applications relevant to banking, such as risk management, portfolio optimization, and fraud detection.

Innovation Labs: Set up innovation labs or centers of excellence focused on quantum computing to foster experimentation and innovation.

Infrastructure and Investment

Technology Infrastructure: Start investing in the necessary infrastructure to support quantum computing. This includes hardware, software, and cloud-based quantum computing services.

Financial Investment: Allocate a portion of the budget for quantum computing research and pilot projects, considering it as a long-term strategic investment.

Use Cases Identification

Targeted Use Cases: Identify specific use cases where quantum computing can provide a competitive advantage. Potential areas include complex financial modeling, high-frequency trading, and optimization problems.

Proof of Concept: Develop proofs of concept for these use cases to demonstrate the potential benefits and build a business case for further investment.

Long-Term Outlook

Monitoring Technological Progress

Staying Updated: Keep abreast of advancements in quantum computing technology, including breakthroughs in qubit stability, error correction, and quantum algorithms.

Technology Roadmap: Develop a technology roadmap that includes milestones for adopting quantum computing based on its maturity and relevance to the bank's strategic goals.

Regulatory and Compliance Considerations

Engage with Regulators: Work with regulatory bodies to understand the implications of quantum computing and ensure compliance with evolving regulations.

Security and Privacy: Focus on the security and privacy aspects of quantum computing, particularly in the context of quantum cryptography and its impact on current encryption standards.

While quantum computing is not yet ready for widespread commercial deployment, banks can begin taking steps now to prepare for its future integration. By investing in skills development, research, and strategic partnerships, banks can position themselves to take advantage of quantum computing advancements as they become available.