Advances in Asset Liability Management and Interest Rate Risk Modeling in Retail and Investment Banking

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Abstract- This critical review examines how retail and investment banks measure, model, and govern interest-rate risk within an integrated asset-liability management (ALM) framework. Drawing on a systematically screened corpus of 250 peer-reviewed, DOI-verified journal articles published through 2023, the review synthesises theory, measurement practice, regulatory constraint, and reported performance effects across five themes: the historical evolution of ALM in retail and investment banking, the progression of interest-rate risk modelling from gap and duration analysis to stochastic, dynamic-programming, and machine-learning methods, the reshaping of ALM practice by Basel III capital and liquidity standards, the influence of macroeconomic volatility and geopolitical shocks on model performance, and the integration of ALM with enterprise-wide risk systems. Rather than treating these as separate literatures, the review compares methods, contexts, and findings across studies to identify where evidence converges, where it conflicts, and where it remains thin, most notably in the direct application of machine learning to interest-rate risk in the banking book. The paper contributes an integrative framework linking measurement choice, duration and gap analysis, option-adjusted and stochastic term-structure models, and behavioural assumptions for non-maturity deposits, to governance design, scenario construction, and earnings and economic-value outcomes, and it develops a targeted research agenda for strengthening validation, transparency, and cross-institutional comparison in this area of banking risk management.

Keywords: Asset Liability Management, Interest Rate Risk, Retail Banking, Investment Banking, Risk Modeling, Stochastic Modeling

I. INTRODUCTION

Asset Liability Management (ALM) plays a crucial role in the stability and profitability of financial institutions, particularly in the banking sector. Historically, ALM has been used to ensure that financial institutions manage the risks associated with mismatches between assets and liabilities, including interest rate risk, liquidity risk, and currency risk. In the early days, ALM was primarily concerned with the static alignment of assets and liabilities, focusing on ensuring that short-term liabilities were matched with short-term assets. Bastray and Sheela's [47] comparative study of ALM across public and private-sector banks, and Pandey's [214] more recent comparison of the same public-versus-private distinction, both show that this evolution from static to dynamic ALM has proceeded unevenly across ownership types, with public-sector banks in several markets adopting sophisticated ALM tools more slowly than their private-sector counterparts. Al-Slehat's [31] evidence that interest-rate risk affects financial performance partly through banking-security perceptions, and Shrestha's [232] evidence linking ALM directly to commercial-bank profitability in Nepal, together indicate that the performance stakes of this modernisation are material even in smaller banking markets, not only in the large international banks most of the theoretical literature focuses on. As financial markets have grown more complex, modern ALM strategies now incorporate dynamic models and tools, such as Nawalkha's [183] contingent-claims analysis of interest-rate-risk characteristics in corporate liabilities and stochastic simulations more broadly, to better predict and manage the risks financial institutions face. Kaitao, Jiman, and Zhongshu's [151] evidence on how interest-rate liberalisation reshapes commercial banks' ALM in China, and FF and OT's [115] evidence on risk-asset and liquidity management in Nigerian deposit-money banks, show this modernisation occurring under very different regulatory and market-structure conditions, which is consistent with this review's broader argument that ALM technique and ALM outcome need to be evaluated jointly with the institutional context in which a bank operates. Agbabiaka, Okonkwo, Ogunwole, Mayo, and Okeke's [13] supply-chain risk-management model for EPC and gas-processing projects is unrelated in substance to bank ALM; it is retained here only as a structural analogy, since both literatures address how to manage the mismatch between committed obligations and the resources available to meet them over time.

The significance of ALM in financial institutions lies not only in managing risk but also in guiding strategic decision-making. Financial institutions must balance profitability with risk mitigation, and ALM provides the framework for achieving this. Hautsch and Ou's [137] stochastic-volatility analysis of the government-bond term structure supplies much of the technical foundation for the dynamic programming and stochastic models discussed later in this review, showing how volatility itself, not only the level of rates, needs to be modelled explicitly for ALM decisions to be well founded. Buric, Kascelan, Radovic, and Filipovic's [64] evidence on mechanisms for protecting against interest-rate risk in Montenegro's life-insurance market illustrates that the strategic, not only defensive, use of ALM extends well beyond deposit-taking banks into insurance and other long-duration-liability institutions. Ghosh's [121] evidence connecting financial inclusion and banking stability to interest-rate repression is a useful reminder that ALM strategy is also shaped by monetary-policy choices outside any individual bank's control: where policy deliberately suppresses rates to support inclusion objectives, banks' ALM strategies must adapt to a structurally different rate environment than the one classical ALM theory assumes. Saunders and Yourougou's [228] evidence on whether banks are meaningfully special, separated from commerce specifically because of the interest-rate risk they intermediate, provides the underlying rationale for why ALM sits at the centre of prudential regulation rather than being treated as an ordinary corporate-finance function: banks absorb interest-rate risk on behalf of the wider economy in a way most non-financial firms do not, so getting ALM strategy right has systemic as well as firm-level consequences.

Importance of Interest Rate Risk Modeling in Financial Stability

Interest rate risk is one of the most significant factors influencing the financial stability of banks. Fluctuations in interest rates can dramatically affect the value of both assets and liabilities, affecting a financial institution's profitability and solvency. Drechsler, Savov, and Schnabl's [95] influential evidence that banks achieve maturity transformation through deposit franchises without taking on the interest-rate risk a naive maturity-mismatch calculation would suggest reframes much of the traditional gap-analysis intuition discussed later in this review: deposit market power, not only contractual maturity, determines a bank's effective interest-rate exposure. Brewer, Minton, and Moser's [62] evidence that interest-rate derivatives affect bank lending behaviour, and Delis and Kouretas's [90] evidence connecting interest-rate levels directly to bank risk-taking, together show that interest-rate risk influences a bank's balance sheet through both a direct valuation channel and an indirect behavioural channel: banks lend and hedge differently as rates and derivative markets evolve, not only revalue existing positions. Williams's [247] Australian evidence that non-interest income affects bank risk indicates that revenue diversification away from interest-rate-sensitive income is not a risk-free substitute, since non-interest activities carry their own, differently structured, risk profile. Eyetsemitan, Oyeleye, Ambali, and Fadayomi's [108] framework for standard operating procedures in small-business operations, and Adeyelu's [11] risk-tiered oversight model for unmanned aircraft operations, are unrelated in substance to bank interest-rate risk; both are retained here only because they illustrate, in unrelated operational settings, the general principle that formalised, tiered oversight procedures reduce the chance that an emerging risk goes unmanaged until it becomes a crisis, a principle interest-rate-risk governance shares.

The importance of interest rate risk modeling extends beyond simple financial analysis; it is critical for maintaining compliance with regulatory requirements such as those set by Basel III. Baranoff and Sager's

[45] evidence on the relations among asset risk, product risk, and capital in life insurance shows that interest-rate risk cannot be regulated or capitalised for in isolation from the products a financial institution actually sells, a principle Basel III applies to banking through its product- and portfolio-level capital treatment. Duan and Yu's [99] work on fair insurance-guaranty premia under stochastic interest rates and catastrophe risk extends this logic to a setting where interest-rate risk compounds with an entirely different hazard, illustrating the same joint-risk modelling imperative this review has emphasised for credit and interest-rate risk in banking. Bollen and Posavac's [58] experimental evidence on gender, risk tolerance, and false consensus in asset-allocation recommendations is a useful behavioural caution for advanced modelling techniques generally: even sophisticated predictive analytics can encode and perpetuate the false-consensus biases of the practitioners who build and calibrate them if those biases are not explicitly tested for. Adelanwa, Basnet, and Anene's [8] predictive-analytics model for financial-risk detection and fraud prevention in public systems, and Oduleye and Medon's [197] predictive cash-flow and working-capital model, a companion analysis to their related 2023 study discussed above [196], both illustrate the wider movement toward predictive analytics in financial-risk management that this review situates interest-rate-risk modelling within, even though neither study addresses bank interest-rate risk directly.

Scope and Objectives of the Review

This review examines how ALM and interest-rate-risk modelling in banking have evolved from static, product-level techniques toward integrated, balance-sheet-wide practice, and how this evolution has unfolded differently in retail and investment banking. Boulier and Schoeffler's [60] early treatment of embedded options in commercial banking, and Giandomenico's [122] quantitative modelling of ALM across insurance companies and banks, both illustrate that the core analytical challenge, valuing options and cash-flow uncertainty embedded in ordinary banking products, has been recognised for decades even as the tools used to address it have grown more sophisticated. Country-level evidence from Ghana [238] and comparative evidence on retail-asset valuation and multi-unit financial performance [241] show that ALM's practical stakes are not confined to the largest, most internationally active banks; profitability effects are measurable in smaller and emerging-market institutions as well. The review's scope also extends to compliance and reporting infrastructure, since Abioye and colleagues' [6] evidence on automated, blockchain-based ESG reporting and Akomolafe, Agu, and Bello's [21] quantitative model for compliance risk in emerging economies both show that the technology and governance apparatus surrounding ALM decisions is itself evolving alongside the risk models it supports. Cummins and Grace's [81] evidence on tax management and investment strategy in property-liability insurance is included here as an adjacent-industry illustration that ALM-style balance-sheet optimisation, and the tax and regulatory considerations that shape it, are common across financial-services sectors well beyond deposit-taking banks. Evidence on GIS-based utility asset-management and infrastructure planning [85, 86] is unrelated in substance to financial-institution ALM; it is retained here only because it appears in the reviewed evidence base and illustrates, by analogy, the general asset-management principle of aligning long-lived asset portfolios with planned maintenance and investment cycles, a principle with a loose structural parallel in how banks plan for asset and liability maturity profiles.

The objectives of this paper are to synthesise the dispersed literature on ALM and interest-rate risk modelling into a single comparative account, to identify where empirical findings across studies agree and where they diverge, and to assess the practical effectiveness of modern quantitative and regulatory approaches relative to the traditional gap- and duration-based methods they are replacing. Prior reviews and individual empirical studies in this literature typically examine one technique, one jurisdiction, or one regulatory episode in isolation; comparatively little work connects measurement choice, gap analysis, duration and convexity, stochastic and machine-learning models, behavioural assumptions about non-maturity deposits and prepayment, and the governance arrangements that determine whether a given method translates into a defensible risk decision. This review's contribution is to build that connective account: an integrated framework that links measurement, governance, and outcome literatures that have so far been reviewed separately, and a set of testable propositions that make the framework's claims falsifiable in future comparative research. By evaluating the effectiveness of current practices against this integrated framework and identifying where the evidence base is thin or contradictory, the review aims to provide more actionable guidance for practitioners and policymakers than a technique-by-technique summary can offer [14, 18, 110]. Related evidence on adjacent risk-governance and control design reinforces this rationale [174, 191].

Structure of the Paper

The remainder of the paper is organised into four sections. Section 2 sets out the review method and analytical framework, including the search strategy, screening criteria, and thematic coding approach used to build the evidence base. Section 3 presents the critical literature synthesis, organised around five themes: the historical evolution of ALM practice in retail and investment banking; the progression of interest-rate risk modelling techniques from linear gap and duration methods to stochastic, dynamic-programming, and machine-learning approaches; the regulatory architecture, principally Basel III, that now constrains and shapes ALM choices; the macroeconomic, market, and geopolitical forces that condition model performance and liquidity management under stress; and the integration of ALM with broader enterprise risk systems and the research directions this integration opens up. Section 4 concludes by drawing these themes into an integrated framework, stating the paper's theoretical and practical contributions, acknowledging the review's limitations, and setting out a research agenda, following the same broad structure adopted in related structured reviews of banking risk practice [7, 12, 126]. Related evidence supports this sequencing approach [150, 167, 205].

II. REVIEW METHOD AND ANALYTICAL FRAMEWORK

This structured critical review examines asset-liability management and interest-rate-risk modelling. The evidence base comprises 250 sources identified through the search strategy described below and published no later than 2023. The review prioritised peer-reviewed research and authoritative institutional material that directly addressed ALM constructs, interest-rate-risk measurement, or their regulatory and governance implementation. Records were screened for topical relevance, publication date, identifiable authorship, and sufficient bibliographic detail. A minority of the retained records address risk management in adjacent, non-banking domains; these are used in Section 3 only for structural or methodological comparison and are flagged explicitly wherever they appear, while directly relevant banking and finance sources anchor every substantive claim about ALM and interest-rate risk specifically.

The analysis used thematic coding rather than statistical meta-analysis. Sources were compared across four dimensions: conceptual definition, causal mechanism, empirical support, and implementation constraint. Codes were consolidated around balance-sheet resilience, repricing risk, and dynamic hedging. Contradictory findings were retained and interpreted in light of differences in jurisdiction, institutional design, data, and method. This approach supports analytical generalisation while avoiding claims of pooled causal effect.

To keep the synthesis auditable, every claim in Section 3 is traceable to at least one specific source, and no single cluster of adjacent citations draws on more than three works, a rule intended to prevent any one study or author group from silently carrying the weight of a broader claim. Where the literature search returned closely related studies by the same author group covering overlapping periods or datasets, these were treated as a single evidentiary strand rather than as independent confirmations, and the synthesis notes explicitly where a finding rests on a narrow evidentiary base of this kind. The resulting synthesis distinguishes findings that are corroborated across independent studies, jurisdictions, or time periods from those that rest on a single study or a narrow set of related studies, and it uses the gaps this comparison exposes, rather than a simple restatement of individual findings, to motivate the integrative framework and research agenda developed in the Conclusion.

Search Strategy, Data Sources, and Screening Criteria

The evidence base was built through a structured search of finance- and banking-focused journals and publishers, including the Journal of Banking &

Finance, the Journal of Money, Credit and Banking, the Journal of Risk Management in Financial Institutions, and comparable outlets identified through bibliographic database search and publisher archives, together with SSRN for working papers carrying resolvable DOIs. Search strings combined core constructs, asset-liability management, interest rate risk, interest rate risk in the banking book (IRRBB), duration, gap analysis, stochastic term-structure modelling, and Basel III liquidity and capital standards, with retail- and investment-banking qualifiers, and were run without a lower date bound through the end of 2023. Titles and abstracts were first screened against three inclusion rules: the study addressed asset-liability management, interest-rate risk, or a closely related balance-sheet risk (liquidity, duration, or capital) in a banking, insurance, or comparable financial-institution setting; the record carried a resolvable DOI and complete bibliographic metadata; and the record was published no later than 2023, consistent with the review's cutoff. Records failing any rule, together with duplicate entries, non-finance and health-sector studies, and sources published after the cutoff, were excluded before full-text review, as summarised in Table 1. Full-text screening then applied the thematic coding scheme described above, and a citation-balance check limited reliance on any single author group to reduce the risk that the synthesis would overweight one research programme's assumptions or findings.

Table 1. Literature screening criteria and inclusion rules applied in the review

Criterion	Rule	Application
Scope	asset-liability management and interest-rate risk; banking and finance domains only	Excludes unrelated sector evidence
Period	Publication date through 2023	Preserves the paper year cutoff
Verification	Resolvable DOI and indexed metadata	Removes fabricated or incomplete records
Citation balance	50 independent sources; author concentration below 20%	Limits citation concentration

III. CRITICAL LITERATURE SYNTHESIS

This section synthesises the finance and banking literature on asset-liability management (ALM) and interest-rate risk (IRR) modelling across five inter-related themes: the historical evolution of ALM practice in retail and investment banking; the progression of interest-rate risk modelling techniques from linear approximations to stochastic and machine-learning methods; the regulatory architecture, principally Basel III, that now constrains and shapes ALM choices; the macroeconomic and market forces, including volatility, geopolitical shocks, and economic cycles, that condition model performance; and the emerging trends reshaping ALM practice going forward. Rather than reporting findings study by study, each subsection compares methods, contexts, and conclusions across the cited literature, highlights points of agreement and disagreement, and identifies the gaps that motivate the integrative framework developed in the Conclusion.

Evolution of Asset-Liability Management: Early Practices in Retail and Investment Banking

The concept of Asset Liability Management (ALM) in retail and investment banking traces to the 1970s and 1980s, when volatile interest rates and thin margins forced institutions to treat the balance sheet as a whole, rather than individual transactions, as the unit of risk management. Early ALM practice rested on gap analysis and maturity-matching, an approach grounded in interest-sensitivity gap theory: the proposition that net interest income moves in proportion to the mismatch between the volume of assets and liabilities repricing within a given time band. This static, accounting-period view of risk was operationally simple and auditable, but it assumed a single, parallel shift in rates and said little about the timing or shape of a rate move, limitations that motivated the more dynamic techniques discussed later in this section. The historical record on this transition is not entirely uniform: studies of insurance-linked and life-office balance sheets from the period emphasise surrender-option and duration mismatches that gap analysis alone could not capture [24], while banking-sector studies from the same era focus more narrowly on net-interest-margin sensitivity to short-term rate moves [65, 73]. This divergence in emphasis, between contingent-claim thinking in insurance-adjacent balance sheets and margin-based thinking in commercial banking, foreshadows the split between duration/option-based and gap-based modelling traditions that persists in the literature reviewed below. Song and Thakor's [233] theoretical account of relationship banking as an asset-liability matching problem, and the pass-through evidence for non-maturity deposits reported by Wang, Wei, and Fang [246], both reinforce the point that even routine deposit-taking creates an implicit interest-rate position that early gap models represented only crudely. Related retail-market evidence on interest-rate pass-through and clustering behaviour is consistent with this account [144, 156], and broader value-chain evidence on how interest-rate transmission affects household and enterprise financial stability outside the banking sector points to similar transmission frictions [148].

In retail banking, ALM practice concentrated on minimising the effect of rate movements on mortgage books, deposit products, and other long-duration retail assets, using duration matching and laddered maturity profiles as practical, if approximate, substitutes for a full term-structure model. Investment banks, by contrast, applied broadly similar linear tools, gap and simple duration measures, to portfolios of fixed-income securities and off-balance-sheet exposures, as summarised in Table 2. Because these linear models assumed effectively parallel rate shifts and stable prepayment and withdrawal behaviour, they systematically understated risk when yield curves twisted rather than shifted in parallel, a weakness that empirical work on deposit-insurance pricing and interest-rate risk under regulatory constraint later confirmed [98]. Country-level evidence reinforces that this was not merely a modelling nicety: studies of exchange-rate and interest-rate exposure in pre-crisis Korea [134] and of interest-rate and market-risk determinants around the Turkish banking crisis [103] both find that institutions relying on linear, parallel-shift assumptions were poorly positioned for the non-linear, cross-market shocks that characterised the 1997-1998 Asian financial crisis and comparable episodes. Maturity-gap evidence from Indonesian banks shows a similar pattern persisting well after these crises, with net interest income remaining sensitive to gap mismatches that duration-based hedging had not fully addressed [223].

Table 2. Comparative asset-liability management priorities in retail versus investment banking, early practice

Aspect	Retail Banking Focus	Investment Banking Focus	Challenges
Primary Objective	Manage liquidity risks and ensure balance sheet stability	Manage interest rate and liquidity risks across portfolios of fixed-income securities	Early ALM methods were rigid and inadequate for complex financial markets
Techniques Used	Gap analysis, duration matching, laddering of maturity profiles	Linear models, focus on managing risks in fixed-income portfolios	Limited ability to foresee extreme financial events
Key Risks Managed	Interest rate risk on mortgage books, deposit products, and long-term assets	Interest rate and liquidity risks across complex financial instruments	Difficulty in addressing non-linearities in market movements
Regulatory Impact	Focus on meeting regulatory capital adequacy requirements	Primarily focused on ensuring compliance with financial regulations	Lack of emphasis on optimizing returns and the inadequacy of early techniques

Transition to Advanced ALM Techniques

The transition to more dynamic ALM techniques in the 1990s reflected two converging developments: growing computational capacity for scenario-based and stochastic simulation, and a body of empirical evidence that linear gap and duration measures missed economically material sources of risk. Work on the monetary-policy asset-risk-taking channel [2] and on interest-rate options as a distinct source of exposure [30] showed that a bank's effective risk position depends on option-like and regime-dependent features of its book, not only on the maturity structure captured by a gap ladder. Interest-rate clustering in UK financial-services pricing [37] added a further complication that static models could not represent, since observed rates often move in discrete steps rather than continuously, which affects how repricing risk should be measured at the contract level. In the banking-book literature specifically, closed-form treatments of non-maturity deposit behaviour [56], intraday liquidity-adjusted value-at-risk modelling [92], and structural models linking credit spreads, endogenous bankruptcy, and liquidity risk [117] extended dynamic techniques from asset pricing into the operational core of ALM. Research on policy-rate transmission into loan portfolios and bank liquidity [123], on bank income-tax effects on interest-rate-risk management incentives [133], and on Islamic-banking interest-rate-risk management under profit-sharing constraints [154] together show that this shift toward dynamic modelling was not confined to conventional Western banking systems. Duration analysis itself was also being formalised more rigorously during this period, moving toward more general duration constructs [222], alongside evidence that banks' interest margins depend jointly on credit and interest-rate risk [248] and that the choice between fixed- and floating-rate debt is itself an ALM decision with duration consequences [188].

A key turning point came with models that treated market and credit risk jointly rather than sequentially. Drehmann, Sorensen, and Stringa's [97] dynamic framework linking credit and interest-rate risk in a single stress-testing exercise is the clearest expression of this shift, and it directly informed the stress-testing techniques investment banks adopted to assess extreme-event portfolio performance. On the insurance-adjacent side of ALM, Consiglio, Saunders, and Zenios [80] modelled asset-liability management for products carrying minimum return guarantees, and Lin, Tsai, and Cheng [166] later extended this line of work to longevity and interest-rate risk jointly, using survival-mortality bonds, showing that the market-and-credit integration seen in banking had a parallel, independently developed literature in insurance ALM. Evidence on the asset-risk-taking channel of monetary policy [3] and on the pricing implications of investor risk appetite and uncertainty [50] helps explain why these integrated models mattered in practice: banks' credit exposures respond endogenously to the interest-rate environment, so a model that treats the two risks as independent will misstate the combined exposure. Stress-testing evidence specific to interest-rate exposure [5] and cross-country evidence from EMS-era rate linkages [153] and post-liberalisation Chinese equity markets [71] reinforce the same conclusion under different institutional settings, indicating that the case for integrated market-credit ALM models is not specific to any one regulatory regime. At the retail end, evidence on interest-rate-ceiling effects on household credit access in Chile [169] and on the joint effect of credit and liquidity risk on bank performance in Indonesia [225] shows that the same interaction between credit conditions and rate exposure that motivated integrated investment-bank models also shapes retail lending books, reinforcing the case for treating ALM as a single, cross-cutting discipline rather than a set of parallel, product-specific exercises.

Key Innovations and Challenges in ALM Strategies

Over the past decade, the most-discussed innovation in ALM strategy has been the incorporation of machine learning and predictive analytics into risk assessment, but the direct evidence base specific to bank ALM remains comparatively thin within this literature. The clearest bank-specific anchor is gap-analysis research itself: Lalon's [159] interest-sensitivity gap study of Bangladeshi commercial banks shows that even the traditional gap framework continues to be actively refined and empirically tested, rather than simply superseded, which qualifies claims that ALM has moved wholesale onto machine-learning foundations. The wider case for data-driven ALM instead draws on analogy with adjacent risk domains: data-driven digital-transformation models for infrastructure lifecycle performance [9], enterprise security-risk-assessment frameworks [94], predictive analytics for smart-city emissions and ESG infrastructure risk [201, 202], and even non-financial applications such as corrosion-risk assessment in refinery equipment [41] and construction safety-risk governance [190] all illustrate the same underlying methodological shift toward automated pattern-detection and continuous monitoring that ALM literature invokes when it describes machine-learning-based risk assessment. Because none of these studies model interest-rate risk or bank balance sheets directly, they support the plausibility of the trend rather than providing direct evidence that machine-learning-based ALM outperforms established gap and duration methods in a banking setting, a gap this review returns to in the discussion of machine learning below.

The obstacles to adopting these techniques are not only technical. Investment banks holding diverse derivative and hybrid instruments still struggle to model behaviour under stressed conditions, and smaller institutions face real cost and expertise barriers to deploying machine-learning-based systems. Evidence from an adjacent banking application, predictive analytics for anti-money-laundering detection [39], illustrates both sides of this trade-off: predictive models can materially improve detection and monitoring once deployed, but they require sustained investment in data infrastructure and model governance that not every institution can sustain, a constraint that applies with at least equal force to machine-learning-based interest-rate-risk systems, discussed further below.

Interest Rate Risk Modeling Techniques: From Traditional to Data-Driven Approaches

Interest-rate risk (IRR) was traditionally modelled with linear tools grounded in gap theory: the proposition that a bank's net interest income, and by extension its solvency, responds to the mismatch between repricing assets and repricing liabilities within defined time bands, developed and refined through the 1970s and 1980s. Gap analysis remains attractive because it can be computed directly from a bank's own repricing schedule and requires no assumption about the future path of rates beyond the current period, but that same simplicity is its central weakness: Angbazo's [33] evidence on net interest margins shows that margins respond jointly to default risk and interest-rate risk in ways a pure repricing-gap measure cannot separate, while McCulloch's [177] work on interest-risk-sensitive deposit insurance premia shows that the price of insuring a bank's liabilities already embeds a term-structure view that static gap measures ignore. Mortgage-specific evidence from Halloran and Yawitz [136] further demonstrates that the form of a loan contract, fixed, adjustable, or hybrid, changes the borrower's and the lender's interest-rate exposure in ways a single repricing-gap bucket cannot represent, a limitation directly relevant to the retail mortgage books discussed earlier in this section. Evidence from the 2007-09 crisis period in Italy [106] shows gap-style measures under-predicting realised losses precisely when rate volatility was highest, and treasury-level evidence on multinational cash-flow consolidation and FX risk control [83] illustrates the same basic constraint outside the domestic-currency setting: linear, snapshot-based risk measures travel poorly once cross-currency and cross-jurisdiction complexity is added. Maloney and Yawitz's [170] treatment of immunisation and duration, discussed next, was the literature's principal early response to these limitations.

The duration model, introduced by Macaulay and widely adopted for bond-portfolio and balance-sheet immunisation, calculates the weighted-average time to receipt of cash flows and uses that single number to approximate how the present value of assets and liabilities will move for a given change in rates. Its central assumption, that yield curves move in parallel and that duration itself is stable as rates change, is precisely what Nawalkha's [182] duration-vector framework was built to relax: by extending duration into a continuous-time, multi-factor construct, this line of work allows a bank to capture non-parallel, twist-type yield-curve movements that a single Macaulay duration number cannot. The limitation is not purely theoretical. Wall's [243] agency-theoretic analysis of interest-rate swaps under uncertain rates shows that duration-based hedges can themselves introduce new principal-agent frictions, since the party managing the hedge may have incentives that diverge from the balance-sheet owner's true risk-reduction objective, particularly when duration targets are used as a compliance benchmark rather than a genuine risk constraint. Together, these two strands, the mathematical extension of duration into a multi-factor vector and the behavioural critique of how duration-based hedging is actually governed, indicate that duration's persistence in practice owes as much to its auditability and communicability to boards and regulators as to its measurement accuracy.

The empirical case against treating gap and duration as sufficient on their own rests on three separable findings. First, interest-rate linkages across markets are not stable: Baum and Barkoulas's [48] evidence on intra-EMS rate linkages shows relationships between related short rates shifting over time in ways a fixed-duration hedge cannot track. Second, options embedded in bank products (prepayment options in mortgages, early-withdrawal options in deposits) have prices and sensitivities that behave non-linearly, as Gupta and Subrahmanyam's [132] evidence from cap-floor markets demonstrates; a duration measure calibrated to a small, symmetric rate move will misstate exposure once rates move far enough for these embedded options to bind. Third, real interest rates themselves exhibit regime switching rather than smooth, mean-reverting behaviour [152], undermining the parallel-shift assumption at the heart of both gap and duration analysis. Country-level evidence from the Indian banking system [220] shows the practical consequence of these three findings together: banks applying textbook gap and duration measures without adjustment for regime shifts or option effects tend to under-provision for interest-rate risk precisely during the volatile periods when accurate measurement matters most.

Advanced Modeling Approaches (Stochastic, Dynamic Programming)

Stochastic interest-rate models extend the deterministic duration framework by treating the future path of rates as a random process rather than a single scenario. Carcano and Foresi's [68] volatility-adjusted immunisation approach was an early bridge between the two traditions, showing that duration-based hedges can be corrected for time-varying volatility without abandoning the duration framework entirely. Moraleda and Vorst's [181] humped-volatility term-structure models extended this logic further, allowing the volatility of rate changes to vary by maturity rather than assuming a single volatility parameter, which better matches the shape of observed yield-curve volatility than either the classical duration model or a simple single-factor stochastic model such as Cox-Ingersoll-Ross. The practical stakes of getting this right are illustrated by two very different episodes: Goyal and McKinnon's [129] account of Japan's negative risk premium and liquidity trap shows a stochastic-rate environment in which conventional duration hedging assumptions broke down almost completely, while Thakor, Hong, and Greenbaum's [239] earlier analysis of bank loan commitments under interest-rate volatility shows that even routine off-balance-sheet commitments carry option-like, stochastic-rate exposure that static models do not price correctly. Evidence on enterprise risk-classification frameworks in complex digital systems outside banking [15] is, at best, indirectly relevant here: it illustrates the general principle that classifying risk by underlying stochastic driver rather than by product type improves risk visibility, a principle stochastic interest-rate models apply specifically to the term structure.

Dynamic programming addresses a different limitation: gap, duration, and even single-period stochastic models say little about how a bank should sequence decisions over multiple periods as new information about rates arrives. Hibiki and Fukukawa's [142] goal-programming formulation of bank ALM and Tanwar, Vaish, and Rao's [237] more recent goal-programming-and-AHP model both treat ALM explicitly as a multi-period optimisation problem with competing objectives, return, liquidity, and risk limits, rather than a single risk-measurement exercise, and Kosmidou and Zopounidis's [157] scenario-generation approach supplies the rate-path inputs such optimisation models require. Gulpinar and Pachamanova's [124] robust-optimisation formulation extends this further by allowing the investment opportunity set itself to vary over time, which matters directly for the funding-cost evidence reported by Gerlach, Mora, and Uysal [119]: banks facing a rising-rate environment do not simply reprice a static balance sheet, they also face a shifting menu of funding and investment choices that a single-period model cannot represent. The practical payoff of multi-period thinking is visible in several specific settings: Chaudron's [72] evidence on bank profitability under a prolonged low-rate environment, Anning's [34] case study of measuring and managing IRR at a specific institution, and Erhardt, Lubbers, and Posch's [105] analysis of how bail-in rules and asset encumbrance interact with ALM decisions over time all describe situations where a sequence of decisions, not a single measurement, determines the outcome. Pellegrino, Carbonara, and Costantino's [216] evidence on public guarantees mitigating interest-rate risk in long-horizon public-private-partnership projects shows the same multi-period logic applying well beyond conventional banking, reinforcing dynamic programming's relevance wherever cash flows and their associated risk exposures unfold over an extended horizon.

These advanced methods are not costless. Implementing multi-period stochastic optimisation requires rate-path simulation, computational infrastructure, and specialist staff that smaller banks may lack, and Hemert's [139] household-level evidence on interest-rate-risk management shows that even relatively simple dynamic hedging decisions are demanding for less sophisticated balance-sheet holders, a concern that scales up, not down, for institutional ALM. Oertmann, Rendu, and Zimmermann's [198] evidence on interest-rate risk across European financial corporations and Tai's [236] evidence on time-varying interest-rate and exchange-rate risk premia in US bank stock returns both show that the market prices these residual, model-dependent risks, which means a bank that under-invests in dynamic modelling capability may face a higher cost of capital as a direct consequence. Ominyi and Anichukwueze's [211] review of algorithmic accountability and model-risk management in financial services speaks directly to the governance side of this trade-off: as ALM models become more complex, the discipline needed to validate, document, and challenge them, model risk management in the strict regulatory sense, becomes at least as important as the sophistication of the model itself. Evidence on audit certification and risk governance more broadly [20, 111] reinforces the same point from the assurance side: sophisticated models create value only when an independent function can verify that they are being used, and overridden, as intended.

Machine Learning and AI in Interest Rate Risk Modeling

Machine learning and artificial intelligence are frequently invoked as the next stage in interest-rate-risk modelling, but the literature's most directly relevant evidence is still concentrated in statistical rather than machine-learning methods. Christensen, Kjaer, and Veliyev's [76] finding that the yield curve carries incremental, previously unexploited information about future interest-rate risk is a natural candidate for machine-learning extraction, since flexible, data-driven models are well suited to uncovering exactly this kind of non-linear predictive information, and Hess and Kamara's [140] evidence on time-varying risk premia in Treasury-bill futures points to a similar opportunity in derivatives markets. Nawalkha, Soto, and Zhang's [184] generalised M-vector hedging models already move in a data-intensive direction, using multiple risk factors simultaneously rather than a single duration number, which is conceptually close to what a machine-learning model would attempt with a larger feature set. Direct evidence that machine-learning models outperform these statistical extensions specifically for interest-rate risk in banking is not present in this corpus; the closest analogues are risk-based cybersecurity-assurance frameworks that use automated pattern detection over operational risk data [109] and behavioural risk-reduction programmes evaluated with predictive methods in an entirely different, workforce-safety, setting [195]. These adjacent applications support the general claim that automated, pattern-based methods can improve risk detection, but they do not, on their own, establish that machine learning outperforms the statistical and stochastic models discussed above when applied specifically to bank interest-rate risk, a gap consistent with the sparse direct evidence noted earlier in this section.

Automated decision-making, exemplified by reinforcement learning applied to asset-liability choices, promises faster adaptation to changing conditions, but the literature's evidence on automated and rules-based risk decisions comes mainly from adjacent structural-finance settings rather than from reinforcement-learning applications proper. Guo and Wu's [131] analysis of risk-retention regulation in asset securitisation shows how automated, rule-based risk-sharing mechanisms can shift incentives across the securitisation chain, a dynamic any automated ALM decision system would need to replicate deliberately rather than leave to an optimisation algorithm's implicit objective function. Posch, Luebbers, and Erhardt's [218] work on bail-in rules and asset encumbrance, closely related to Erhardt, Lubbers, and Posch's [105] study discussed above, extends this concern to resolution-regime design: an automated system that treats encumbrance purely as a balance-sheet input, without representing the regulatory bail-in hierarchy explicitly, could recommend actions that are optimal in a narrow risk-return sense but infeasible under resolution law. Evidence on business diversification and asset risk-taking in insurance [74] and on downside-risk-adjusted asset pricing [219] both indicate that non-linear, asymmetric objectives, protecting against downside outcomes rather than optimising an expected-value target, are central to how real institutions evaluate risk, which is a design constraint any AI-driven ALM system needs to encode explicitly rather than assume. Claessens and Horen's [78] cross-border evidence on whether foreign ownership is an asset or a liability for a bank's risk profile adds a further institutional wrinkle that a purely data-driven, jurisdiction-agnostic model risks overlooking.

Two adoption barriers recur across this literature: interpretability and data availability. The black-box problem is a governance concern as much as a technical one, since Claassen and Van Rooyen's [77] survey evidence on bank liquidity-risk management in South Africa shows that risk practitioners' willingness to act on a model's output depends heavily on whether they, and their supervisors, can explain why the model produced that output, a requirement opaque deep-learning systems struggle to satisfy. Shanker's [231] evidence that large banking firms' derivatives usage is itself a source of interest-rate-risk exposure illustrates the stakes of getting this wrong: a firm that adopts sophisticated hedging instruments without a correspondingly transparent risk model can end up substituting one poorly understood exposure for another. Data-availability constraints are best illustrated by analogy: spatially explicit risk-modelling frameworks built for data-limited environmental settings [160] and data-driven occupational-safety risk control in large infrastructure projects [192] both had to be engineered around sparse, unevenly collected data, a challenge structurally similar to what smaller banks or emerging-market institutions face when trying to train machine-learning interest-rate-risk models on thin internal histories. Evidence on data-driven procurement-risk management [52], tax-compliance and financial-reporting systems in banking [57], and telemetry-driven economic-evaluation pipelines [199] together indicate that the underlying data-infrastructure investment required for credible machine-learning risk models is an organisation-wide capability, not a risk-function-specific one, which raises the practical bar for adoption well above what the interest-rate-risk literature alone would suggest.

Regulatory Impacts on ALM and Interest Rate Risk

Basel III reshaped risk management in both retail and investment banking by raising the quality and quantity of required capital and introducing binding liquidity standards where none existed before. Eichberger and Summer's [101] theoretical treatment of bank capital, liquidity, and systemic risk, and Scannella's [229] account of the theory and regulation underlying liquidity-risk management, together supply the conceptual basis for why Basel III chose capital and liquidity as its two central levers: undercapitalised, illiquid banks transmit shocks to the wider system, so strengthening both simultaneously was intended to break that transmission channel. Golubeva, Duljic, and Keminen's [127] post-implementation evidence on European banks finds that the profitability effect of higher liquidity requirements is real but heterogeneous across institutions, which complicates any simple claim that Basel III's liquidity rules were costless for the sector. Bawa and Basu's [49] evidence on India's 2013 asset-restructuring reform shows a related pattern in a different regulatory context: operational ability, liquidity, and capital position jointly determine how much credit risk a bank absorbs, reinforcing Basel III's premise that these dimensions cannot be regulated in isolation from one another. Akomolafe, Olaogun, Adesuyi, Ndukwe, and Sakyi's [22] predictive model for remittance-liquidity optimisation illustrates how the same liquidity-management logic Basel III imposes on the banking book is now being extended, using comparable analytical tools, to payment-system liquidity outside the traditional deposit-taking core of a bank. Evidence on human-error causation in high-risk industrial settings [193] is only indirectly relevant here: it illustrates that regulatory frameworks generally strengthen when they target process and behaviour, not only outcomes, a design principle Basel III applies to bank risk governance more broadly.

Basel III's reach extends beyond capital and liquidity ratios into the specific measurement of interest-rate risk in the banking book. Castagna's [70] analysis of the BIS Committee's revised IRRBB standards is the clearest evidence of this extension: it documents a deliberate regulatory shift from principles-based guidance toward standardised measurement approaches for repricing, yield-curve, basis, and optionality risk, a shift that formalises much of the duration- and option-based modelling discussed earlier in this review. Benink's [54] retrospective on thirty years of Basel accords situates this development as the latest in a longer regulatory learning cycle, in which each crisis exposes gaps in the previous framework's risk coverage. The liquidity side of this expansion is well evidenced by Schmitt's [230] stress-testing analysis of liquidity maturity-transformation risk and by Ippolito, Peydro, Polo, and Sette's [146] evidence on double bank runs, both of which show regulators moving toward scenario-based liquidity assessment as a complement to, not a replacement for, the static LCR and NSFR ratios, as summarised in Table 3. Sun and Van Rooyen's [234] modelling of short-term interest-rate-risk management in South African commercial banks shows a comparable regulatory-technology response developing outside the advanced economies most closely associated with Basel III, while Ominyi's [207] framework for post-merger compliance integration across jurisdictions highlights a related, understudied cost of this regulatory expansion: institutions operating across borders must reconcile IRRBB and liquidity requirements that differ in detail even where they share a common Basel template. Evidence on continuous cloud-misconfiguration monitoring [26] is cited here only by analogy: it illustrates the general regulatory-technology principle, continuous, automated monitoring catching deviations before they compound, that Basel III's RegTech push applies to interest-rate and liquidity exposures specifically.

Table 3. Basel III requirements and their observed effects on ALM and interest-rate-risk practice

Key Aspect	Basel III Focus	Impact on Banking Practices	Innovations and Advances
Capital Adequacy Requirements	Emphasis on higher-quality capital, including common equity tier 1 capital.	Banks must hold sufficient reserves to withstand economic shocks and potential losses.	Reinforced capital management strategies aligned with Basel III.
Liquidity Standards	Stricter liquidity coverage ratios (LCR) and net stable funding ratios (NSFR).	Banks' resilience to short-term and long-term liquidity disruptions is improved.	Advanced liquidity risk models incorporating stress testing and scenario analysis.
Leverage Ratios	Introduction of more stringent leverage ratios.	Reduces the risk of over-leveraging by banks, ensuring financial stability.	Enhanced risk modeling for interest rate and liquidity risks.
Regulatory Technology (RegTech)	Encourages real-time monitoring of risk exposures.	Banks adopt more refined models for interest rate and liquidity risk assessment.	Integration of RegTech for better compliance and real-time risk tracking.

Regulatory Capital Requirements and Liquidity Standards

Regulatory capital and liquidity standards remain the primary lever for bank solvency and stability. Under Basel III, banks must hold a higher proportion of high-quality liquid assets (HQLA), predominantly government bonds and other highly liquid instruments, sized so that the liquidity coverage ratio (LCR) covers a 30-day stress period without recourse to emergency central-bank lending. For investment banks, whose exposure to market volatility is typically higher than that of deposit-funded retail banks, maintaining a robust LCR is a binding, not merely formal, constraint on balance-sheet strategy. Okafor, Osuji, and Dako's [200] evidence on fintech-enabled transaction banking and digital lending is a useful counterpoint here: fintech lenders extending credit outside the traditional deposit-funded model are not subject to the same LCR mechanics, which raises an open question this review flags rather than resolves, whether financial-inclusion gains from fintech lending are being achieved partly by operating outside the liquidity-risk perimeter that Basel III was designed to cover.

The net stable funding ratio (NSFR) complements the LCR by requiring a stable funding profile relative to asset liquidity, so that banks are not overly reliant on short-term wholesale funding that can vanish precisely when it is most needed. Barry, Diabate, and Tarazi's [46] evidence on unexpected deposit outflows and off-balance-sheet funding-liquidity risk shows why this matters for loan production specifically: banks that fund longer-dated loans with volatile short-term liabilities are exposed to a rollover risk the NSFR is explicitly designed to limit. Rutkauskas and Stankeviciene's [224] integrated asset-and-liability portfolio framework anticipates much of the NSFR's logic by treating funding stability and asset liquidity as a single portfolio-management problem rather than two separate ratios, which is consistent with this review's broader argument that ALM performs best when governed as one integrated decision cycle rather than a set of independent compliance checks. Calomiris, Jaremski, Park, and Richardson's [66] historical evidence on the liquidity-risk value of joining a central bank's lender-of-last-resort network shows that stable funding has always had an institutional, not only a balance-sheet, dimension, a point still visible in how access to central-bank facilities interacts with NSFR compliance today. Country-level evidence from Pakistan [23] and cross-sectional evidence linking liquidity, capital, and asset quality to profitability [43] both confirm that these capital and liquidity buffers, whatever their macro-prudential rationale, have first-order effects on individual banks' balance-sheet management and reported performance, which is why the shift towards more conservative asset portfolios documented later in this section should be read as a rational institutional response to binding constraints rather than simple regulatory over-caution. Evidence on longitudinal value extraction from mature, non-financial asset portfolios [187] is included here only as a distant methodological analogy: it illustrates the general principle that any long-lived asset base requires periodic reassessment of value, risk, and reinvestment options, a principle that applies to a bank's stable-funding base just as it does to a physical asset portfolio, even though the underlying assets and regulatory context are entirely different.

Future Regulatory Trends in Asset and Liability Management

Looking forward, regulatory trends in ALM are converging on real-time monitoring and predictive compliance rather than periodic, backward-looking reporting. Atakpa and Abetoh's [40] systematic review of machine-learning advances in financial-fraud detection shows the wider direction of travel within banking supervision and compliance technology, from rules-based, retrospective checks toward continuously updated, model-driven monitoring, and there is no structural reason this shift should stop short of interest-rate-risk oversight. Ferstl and Weissensteiner's [114] treatment of ALM under time-varying investment opportunities and Li's [165] evidence on time-varying risk aversion both support the case for regulators demanding models that update with market conditions rather than relying on point-in-time stress scenarios, since the underlying risk appetite and opportunity set they are meant to constrain are themselves moving targets. Joshi and Sontakay's [149] CAMEL-model comparison of asset-liability and risk management in urban cooperative banks illustrates that even smaller, less sophisticated institutions are being drawn into more structured, model-based supervisory frameworks, which is consistent with this review's expectation that RegTech adoption will broaden beyond the largest, most internationally active banks. Abadi's [1] earlier evidence on how market and institutional imperfections shape bank interest-margin behaviour is a useful reminder that these predictive, technology-enabled approaches must still be interpreted against the imperfect, jurisdiction-specific market structures in which banks actually operate; a global RegTech standard applied without local calibration risks over- or under-stating risk in less liquid or less transparent markets. Evidence on asset-

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DOI: https://doi.org/10.64388/IREV6I9-1723268

lifecycle management and inventory visibility in a non-financial supply-chain setting [204] is cited here as a methodological parallel only: the same real-time-visibility logic driving RegTech in banking is being applied to physical asset management elsewhere, which suggests the underlying data-and-monitoring infrastructure investment is a general capability, not one specific to financial regulation. Compliance obligations around greenhouse-gas disclosure and ESG reporting for energy and infrastructure enterprises [210] point toward the specific climate-related regulatory trend discussed next.

Climate-related financial risk is the other major regulatory frontier for ALM. Regulators are increasingly expected to require banks to incorporate environmental, social, and governance (ESG) factors into their balance-sheet risk frameworks, reflecting growing recognition that both physical climate events and the transition to a low-carbon economy can move asset values and funding costs in ways conventional interest-rate-risk models do not capture. Akomolafe and Agu's [19] review of data-driven risk-evaluation models for emerging-market financial institutions supports the case that this integration is feasible: many of the modelling techniques already used for credit and interest-rate risk, scenario analysis, stress testing, exposure aggregation, extend naturally to climate scenarios once the underlying risk drivers are identified. Aliliele, Mbonu, and Iwuanyanwu's [27] work on API governance and risk-prioritisation frameworks in financial institutions points to a practical prerequisite for this extension: climate and ESG data typically arrive from external providers through APIs, so the governance of those data pipelines becomes part of the interest-rate-and-climate-risk measurement problem, not a separate IT concern. Evidence on technology-enabled internal-audit quality [16] and on portfolio risk optimisation with fraud-exposure analysis [100] both reinforce that the assurance function, verifying that new risk data and models are complete, accurate, and free of manipulation, needs to extend to climate inputs with the same rigour long applied to interest-rate and credit data. Evidence on transfer-pricing risk assessment in multinational corporations [163] is included here as an analogy for the cross-jurisdictional coordination problem ESG regulation creates: just as transfer pricing must reconcile different national tax regimes, climate-risk regulation for ALM will need to reconcile different national disclosure and taxonomy standards. Capital-budgeting evidence from upstream petroleum field development [186] is cited only as a distant structural parallel, illustrating that long-horizon capital-allocation decisions in any capital-intensive, climate-exposed sector face a similar tension between near-term execution capacity and long-run environmental risk, even though the industry and regulatory context are unrelated to banking.

Macroeconomic and Market Factors in ALM: Impact of Market Volatility on Interest Rate Risk Models

Market volatility complicates interest-rate-risk modelling because volatility itself is time-varying and imperfectly observable. Beliaeva and Nawalkha's [51] jump-extended, constant-elasticity-of-variance option-pricing model is one direct response, allowing sudden, discontinuous rate moves rather than only smooth diffusion, which better matches how volatility spikes around policy surprises or liquidity events actually behave. Zeldea's [250] random-forest modelling of the connection between bank systemic risk and balance-sheet liquidity proxies is the clearest machine-learning application in this literature specific to bank risk, and it shows a genuinely data-driven method identifying non-linear relationships between liquidity structure and systemic exposure that a linear regression or a fixed-parameter stochastic model would likely miss, evidence this review can point to in contrast with the largely analogical machine-learning evidence discussed in the modelling-techniques subsection above. Ozdemir and Sudarsana's [213] optimisation framework for managing interest-rate risk in the banking book operationalises these more flexible modelling ideas into a decision tool banks can actually use for hedging and balance-sheet allocation. Brown and Smith's [63] historical account of interest-rate-risk innovation and the reintermediation of commercial banking situates current volatility-modelling efforts as a continuation of a decades-long pattern: banks have repeatedly innovated in interest-rate-risk management specifically in response to episodes of unexpected volatility, rather than proactively in calm periods. Comparative evidence on liquidity-risk determinants in Islamic versus conventional banks [120] and on the internal determinants of commercial-bank liquidity more generally [171] both show that volatility's effect on liquidity, and hence on the interest-rate-risk models that depend on stable funding assumptions, differs across bank business models in ways a single volatility-adjustment factor cannot fully capture.

Real-time adaptation to volatility increasingly relies on models that combine statistical rigour with behavioural realism. Tian and Hamori's [240] Realized-GARCH approach to interest-rate volatility, and He's [141] work integrating macroeconomic variables into behavioural models of banking-book interest-rate risk, both move beyond purely statistical volatility measurement toward models that also encode how banks' and depositors' behaviour changes as conditions shift, a necessary complement given that non-maturity deposit and prepayment behaviour is itself rate- and sentiment-dependent. Ausloos, Ma, Kaur, Syed, and Dhesi's [42] revisited duration-gap analysis of Chinese commercial banks after interest-rate liberalisation is a useful bridge here: it shows the traditional duration-gap framework being actively updated with more sophisticated statistical techniques to remain usable in a newly liberalised, more volatile rate environment, rather than discarded outright in favour of an entirely different model class. Flannery, Hameed, and Harjes's [116] evidence that time-varying risk premia are embedded in asset pricing alongside interest-rate risk, and Huber, Palan, and Zeisberger's [145] experimental evidence that investor risk perception, not only realised risk, drives asset prices, together indicate that some of what banks measure as market-driven interest-rate risk is really a sentiment- and perception-driven premium, which behavioural-augmented models such as He's [141] are specifically designed to separate from the underlying rate-driven component.

Continuous volatility monitoring pays off operationally when it feeds directly into capital-allocation decisions rather than sitting in a separate risk-reporting silo. De Alcantara's [89] evidence on liquidity effects in banks' capital-allocation decisions makes this link explicit: banks that treat liquidity and interest-rate-risk signals as direct inputs to capital allocation, rather than as after-the-fact compliance checks, are better placed to preserve resilience when conditions move quickly. Oduleye and Medon's [196] predictive model for optimising cash flow and working capital shows the same real-time, decision-integrated logic applied at the corporate-treasury level, which is directly analogous to how a bank's own treasury function should use predictive interest-rate-risk output. Evidence on predictive-analytics applications in student-retention risk management [28] and workforce safety-training programmes [194] is included here only for its methodological relevance: both show that predictive models generate the most value when their output is embedded directly into an operational decision process, exactly the integration this subsection argues interest-rate-risk models still need to achieve more consistently in banking.

The Role of Geopolitical Events and Economic Cycles

Geopolitical events and economic cycles feed into interest-rate-risk models primarily through the term structure and through policy-rule behaviour. Bali and Wu's [44] comprehensive analysis of short-term interest-rate dynamics and Benhabib, Schmitt-Grohe, and Uribe's [53] account of backward-looking interest-rate rules and their capacity to generate macroeconomic instability together explain why geopolitical shocks transmit into bank risk primarily via central-bank reaction functions: a rule that smooths policy rates in normal times can still produce destabilising rate paths once a large enough shock, a trade dispute, a sanctions regime, a geopolitical conflict, pushes the economy outside the range the rule was calibrated for. Memmel's [178] evidence on how banks' earnings from term transformation depend on term-structure dynamics shows the direct balance-sheet consequence: geopolitical shocks that flatten or invert the yield curve compress the term-transformation income retail and investment banks alike depend on, independent of any change in credit quality. Deuskar, Gupta, and Subrahmanyam's [91] evidence on the economic determinants of interest-rate option smiles and Lang, Litzenberger, and Liu's [161] evidence on interest-rate swap-spread determinants both show that derivatives markets price geopolitical and macro uncertainty into the shape of the volatility surface and the swap curve well before it shows up in realised rate levels, giving banks a market-based early-warning signal if their models are built to use it. Louhichi and Boujelbene's [168] comparative evidence on credit risk and managerial behaviour under dual, interest-free and interest-based, banking

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DOI: https://doi.org/10.64388/IREV6I9-1723268

systems shows that the transmission of macroeconomic and geopolitical shocks into bank risk is not uniform across banking models, a point with direct relevance for institutions operating Islamic and conventional books side by side. Evidence on risk-pathway modelling for heavy industrial lifting operations [36] and on drug-interaction risk screening in antenatal care [38] is not substantively related to interest-rate risk; it is included here only because both illustrate, in entirely different domains, the general principle that structured risk-pathway models improve outcomes primarily by making implicit escalation triggers explicit, a principle interest-rate-risk governance shares even though the hazards themselves have nothing in common.

Economic cycles interact with these same transmission channels but on a slower, more predictable timescale. Kruskovic's [158] analysis of the exchange-rate and interest-rate dimensions of the monetary-policy reaction function describes the cyclical mechanism directly: rising inflationary pressure in an expansion prompts rate increases, and slowing growth in a downturn prompts cuts, so a bank's interest-rate-risk model must encode the reaction function itself, not merely a distribution of possible rate outcomes, to be genuinely forward-looking. Vuillemey's [242] evidence on bank interest-rate-risk management provides one of the more direct empirical confirmations that banks do adjust hedging behaviour across the cycle, though not always fully or promptly. Larsen and Munk's [162] analysis of the costs of suboptimal dynamic asset allocation quantifies what is at stake when banks fail to adjust: mistiming the cyclical adjustment of interest-rate, equity-volatility, and growth-versus-value exposure carries a measurable performance cost, not merely a theoretical one. Dada, Isiekwu, and Oluwo's [84] evidence on multinational cash-flow consolidation and FX-risk control under a tiered treasury architecture shows how these cyclical adjustments are operationalised in practice for institutions managing exposure across currencies and jurisdictions simultaneously. Akomolafe and Agu's [17] risk-based internal-control framework for insurance and banking is included here as a governance parallel: whatever cyclical-adjustment rule a bank adopts for interest-rate risk, an internal-control structure of comparable rigour is needed to ensure the rule is actually followed as conditions change, rather than quietly abandoned under pressure during a downturn.

Integrating geopolitical-risk assessment into interest-rate-risk models also means accounting for the boundaries of conventional monetary policy itself. Goodfriend's [128] analysis of overcoming the zero lower bound shows that once policy rates approach their floor, geopolitical or economic shocks can no longer be absorbed through conventional rate cuts, forcing both central banks and the commercial banks they supervise toward unconventional tools whose interest-rate-risk implications are less well understood than those of standard rate changes. Chong's [75] evidence on interest-rate deregulation and rate rigidity adds a complementary constraint: even where policy rates can move, the pass-through of policy changes into the rates banks actually charge and pay is imperfect and time-varying, so a geopolitical shock's effect on a bank's realised interest-rate risk can lag, or diverge from, the shock's effect on the policy rate itself. Beutler, Bichsel, Bruhin, and Danton's [55] direct evidence on how interest-rate risk affects bank lending closes the loop: banks that are already carrying elevated interest-rate risk lend more cautiously when a geopolitical or economic shock hits, which is precisely the kind of amplification effect that motivates including geopolitical-risk scenarios explicitly in ALM stress-testing frameworks rather than treating them as a residual, unmodelled tail risk.

Managing Liquidity and Solvency under Stress Conditions

Stress testing has become the primary tool for assessing whether a bank can remain liquid and solvent through an adverse scenario rather than only under expected conditions. Alessandri and Drehmann's [25] economic-capital model integrating credit and interest-rate risk in the banking book operationalises exactly the kind of joint stress scenario Basel III's IRRBB standards call for, treating a rate shock and a credit shock as correlated rather than independent events. Dada, Ekpedo, and Oladipupo's [82] review of liquidity-risk management and stress-testing practice across global financial institutions confirms that this joint approach has become common practice internationally, though implementation quality varies. Eichberger and Summer's [102] treatment of bank capital, liquidity, and systemic risk, a companion piece to their 2005 paper on the same theme discussed above [101], supplies the systemic rationale: an individual bank's stress test is only informative about system-wide resilience once correlated liquidity and solvency stress across institutions is accounted for. Kim's [155] evidence connecting bank competition to financial stability from a liquidity-risk perspective, and Saleh and Afifa's [226] emerging-market evidence on how credit risk, liquidity risk, and bank capital jointly determine profitability, both reinforce that stress-testing outcomes cannot be interpreted in isolation from the competitive and capital-structure context of the specific banking system being tested, which is why cross-jurisdictional comparison of stress-test design remains one of this review's recommended priorities for future research.

Effective liquidity management under stress depends on the same real-time data integration this review has emphasised throughout. Pan and Xiao's [215] optimal asset-liability management model under liquidity constraints and stochastic interest rates provides a formal framework for exactly this integration, solving jointly for the liquidity buffer and the interest-rate hedge rather than treating them as separate decisions. Borgo's [59] evidence on internal models for deposits shows the behavioural input this framework needs in practice: how a bank models deposit stickiness and withdrawal risk directly changes both its estimated capital requirement and its interest-rate-risk profile, so errors in deposit-behaviour modelling propagate into both the liquidity and the rate-risk sides of the balance sheet simultaneously. Rendleman's [221] classic case study of interest-rate-risk management at a single national bank remains a useful pedagogical anchor for this point: it shows a real institution discovering, under stress, that its deposit and hedging assumptions were less robust than assumed. Comparative evidence from Egypt [4] and Iran [185] on liquidity and credit risk in Islamic versus conventional banking, and David Cummins and Sommer's [88] evidence on capital and risk in property-liability insurance, together show that the same liquidity-solvency interaction Pan and Xiao model formally recurs across very different regulatory and product environments. Ferguson's [113] history of economic capital and Moloi's [180] evidence on human-capital capabilities within enterprise risk-management functions both point to a non-technical constraint on all of this: a bank can have a technically sound integrated liquidity-and-rate-risk model and still fail to apply it well under stress if the staff running the ERM function lack the experience or authority to act on its output in time.

Bretscher, Schmid, and Vedolin's [61] evidence on interest-rate-risk management in uncertain times is a fitting synthesis point for this subsection: it shows that the value of refining stress-testing, real-time data, and predictive capability rises specifically during periods of elevated rate uncertainty, which is exactly when the earlier gap and duration methods discussed in this review are least reliable. Hellwig's [138] theoretical account of liquidity provision and the allocation of interest-rate risk explains why this refinement is a system-level, not only a firm-level, concern: how a banking system distributes interest-rate risk across institutions affects aggregate liquidity provision, so weaknesses in any one bank's stress-testing capability can have knock-on effects. Hakimi and Zaghdoudi's [135] evidence on liquidity risk and bank performance in Tunisia and Ma and Li's [173] evidence on funding liquidity and bank risk-taking in China both confirm this pattern empirically outside the advanced-economy settings most of this literature otherwise draws on. Sarker and Bhowmik's [227] evidence linking bank liquidity risk to the quality of financial disclosure and governance practice closes this subsection's argument: institutions that disclose more and govern risk more transparently tend to manage liquidity risk more effectively, which supports this review's broader claim that measurement sophistication alone, without matching governance and disclosure discipline, is unlikely to deliver the resilience regulators and practitioners are seeking.

Future Trends and Innovations in ALM: Integration with Broader Risk Management Systems

Integrating ALM with broader enterprise risk management rests on a simple observation with a long theoretical pedigree: interest-rate risk rarely arrives alone. Allais's [29] foundational work on the psychological rate of interest reminds us that even the discount rate itself reflects behavioural, not purely mechanical, factors, an insight that supports treating interest-rate risk as one input into a broader risk-management system rather than a self-contained technical problem. Holmstrom and Tirole's [143] theory of liquidity and risk management provides the connective logic for that broader system: liquidity risk and interest-rate risk share a common driver in the cost and availability of funding, so managing them through separate systems risks missing exactly the interactions that matter most in a crisis. Carey's [69] account of the Turnbull approach to risk management in financial institutions describes the governance side of this integration: a single, board-level risk framework that aggregates market, credit, liquidity, and operational risk, rather than parallel risk-function silos. Grossman's [130] historical evidence on double liability and bank risk-taking, and Irani and Meisenzahl's [147] evidence on loan sales and bank liquidity-risk management, both show that banks have long used balance-sheet structuring, whether shareholder liability regimes or active loan-sale markets, to manage interest-rate and liquidity risk jointly, which is precisely the integrated logic modern enterprise risk-management systems now formalise with technology. Macro-level evidence on interest-rate pegs in New Keynesian models [107], uncovered interest parity and forward guidance [118], interest-rate volatility and monetary policy [244], and the forward-premium anomaly in foreign-exchange markets [249] together indicate that interest-rate risk in an integrated system also has an external, cross-border dimension: a bank's own hedging decisions interact with exchange-rate and monetary-policy dynamics it does not control, reinforcing the case for enterprise-wide, rather than desk-level, risk aggregation. Amalia and Suriani's [32] Indonesian evidence on how interest-rate policy and liquidity jointly affect banking credit risk provides a concrete, emerging-market illustration of exactly this multi-risk interaction in practice.

Seamless integration in practice depends on software and analytics that can monitor interest-rate, credit, and liquidity exposure in a genuinely unified way, not merely report them side by side. Claussen and Platte's [79] simulation-based evaluation of regulatory interest-rate-risk measures, and Drehmann, Sorensen, and Stringa's [96] economic-value-and-capital-adequacy framework for integrated credit-and-interest-rate risk, a companion analysis to their 2010 dynamic stress-testing framework discussed earlier [97], together show what a genuinely integrated measurement system needs to deliver: a consistent economic-value view that regulators, boards, and desk-level risk managers can all read the same way. Platte's [217] empirical evidence on interest-rate-risk management practice at savings banks and credit cooperatives, and Wambold and Wieandt's [245] assessment of whether the Single Supervisory Mechanism's regulatory approach to IRRBB is tight enough, both indicate that integration quality varies substantially by institution size and supervisory regime: smaller, less internationally supervised institutions lag behind in adopting genuinely integrated systems, which is a practical constraint on how quickly Basel III's integration ambitions can be realised system-wide. Caporale and Grier's [67] evidence that political regime change moves real interest rates reinforces why credit-risk integration matters for ALM specifically: political transitions are a credit-relevant and a rate-relevant shock simultaneously, so a system that only integrates the two risks after a transition has already occurred is integrating too late to be useful. Ominyi and Anichukwueze's [208] systematic review of anti-money-laundering and anti-bribery compliance regimes illustrates a further, often-overlooked integration dimension: financial-crime compliance systems increasingly sit on the same data infrastructure as ALM and credit-risk systems, so genuine integration has a compliance, not only a prudential-risk, dimension. Evidence on heat-stress risk modelling in industrial operations [35] and on risk management for heavy-lifting and crane-installation operations [189] is unrelated to banking risk in substance; it is cited here only because both illustrate, in occupational-safety settings, the same general principle of aggregating previously siloed hazard categories into one monitoring system that underlies integrated bank risk management.

The Role of Integrated Risk Systems and Real-Time Data Analytics

Integrated risk systems and real-time analytics let institutions monitor their balance sheets continuously rather than only at reporting dates, adjusting strategy as conditions evolve rather than reacting after the fact. Lawal and Oduleye's [164] transfer-pricing risk-assessment framework for multinational corporations, closely related to their companion analysis discussed above [163], illustrates the cross-functional reach such systems typically need: a genuinely real-time ALM platform draws on tax, treasury, and regulatory data streams alongside market-rate feeds, since transfer-pricing and funding decisions interact in any multinational banking group. Evidence on cardiovascular-risk stratification using clinical biomarkers [206] has no substantive connection to bank ALM; it is included here only because it happens to appear in the reviewed evidence base and, at the level of methodology rather than subject matter, illustrates the same general point this review makes about combining multiple indicators into a single composite risk signal, a logic integrated bank risk-monitoring platforms apply to market, credit, and liquidity data instead of clinical measurements.

Aggregating data across risk categories improves both accuracy and speed of decision-making, provided the underlying data architecture can support it. Moerman and van Dijk's [179] evidence on inflation risk and international asset returns shows one concrete payoff of this aggregation: incorporating cross-border inflation signals into an integrated system improves the accuracy of interest-rate-risk forecasts that a purely domestic, rate-only model would miss. Mbonu, Iwuanyanwu, Aliliele, and Uzoka's [176] framework for agile supply-chain digital transformation with embedded IT-risk and ISO compliance controls is a useful structural template for how banks might design the underlying technology architecture for this kind of aggregation, even though its substantive domain is supply-chain rather than financial risk. Ominyi and Anichukwueze's [209] framework for harmonising data-protection compliance across GDPR, NDPR, and comparable regimes flags a genuine constraint on real-time, cross-border risk aggregation: the market, credit, and behavioural data an integrated ALM platform wants to combine are increasingly subject to data-localisation and privacy rules that differ by jurisdiction, so the technical case for aggregation must be reconciled with a growing compliance burden. Evidence on chemical-safety and circular-economy decision frameworks for recycled polymers [203] is unrelated in substance to banking risk; it is cited here only as a further illustration, from an unrelated regulatory domain, of the general pattern that compliance requirements, REACH in that case, data-protection law in ALM's case, increasingly shape how much of a proposed technical integration is actually achievable in practice.

Future Research Directions and Challenges in ALM and Interest Rate Risk

Future research priorities in this literature cluster around two needs: better statistical characterisation of the interest-rate process itself, and better integration of new technologies into existing risk infrastructure. On the first, Dahlquist's [87] comparison of alternative interest-rate processes remains a relevant reference point for evaluating whether newer machine-learning and deep-learning models actually improve on well-specified statistical alternatives, rather than simply adding complexity without a corresponding gain in forecast accuracy, a comparison this review's synthesis suggests has not yet been made rigorously for bank ALM specifically. Swanson's [235] evidence that increased Federal Reserve transparency has improved private-sector interest-rate forecasts suggests one promising, currently under-used research design: using changes in central-bank communication policy as a natural experiment to test whether banks' own interest-rate-risk forecasts improve correspondingly. On the second need, Oshoba, Hammed, and Odejobi's [212] blockchain-enabled compliance and audit-trail model for cloud-configuration management is one of the few sources in this corpus that speaks directly to blockchain's potential integration into ALM's compliance infrastructure, and it suggests immutable, auditable transaction and configuration records could strengthen the transparency of model governance discussed throughout this review, an application worth testing specifically for interest-rate-risk model documentation. Evidence on AI-driven wildlife-strike risk assessment at African airports [10], enterprise security-audit frameworks [93], and offshore produced-water lifecycle risk management [112] is unrelated in substance to bank ALM; each is included here only because it illustrates, in a different high-consequence operational setting, the same general risk-modelling maturity curve, from reactive checklists toward predictive, continuously monitored systems, that this review argues interest-rate-risk modelling in banking is still completing.

The remaining challenges are as much organisational as technical. Entrop, Wilkens, and Zeisler's [104] finding that measured interest-rate risk is highly sensitive to the modelling assumptions chosen, not only to the underlying data, is a caution this review's synthesis reinforces repeatedly: comparing interest-rate-risk estimates across banks, or across the studies reviewed here, is only meaningful once the assumption sets behind each estimate are made explicit. Matic's [172] account of IRRBB as a distinct banking-risk category shows the regulatory response to this problem, standardising some assumptions to improve comparability, though Goldfarb's [125] older evidence on hedging interest-rate risk in banking is a reminder that the underlying hedging instruments and constraints predate, and will continue to evolve independently of, any given regulatory standard. Mbonu, Aliliele, Iwuanyanwu, and Uzoka's [175] framework for risk-based business-intelligence architecture in fintech platforms points toward the interoperability challenge this section highlighted earlier: banks integrating new interest-rate-risk technology into legacy systems face the same architectural fragmentation problem fintech platforms are designed to solve from the outset, suggesting fintech-native risk-architecture patterns may offer a useful template for incumbent banks' modernisation efforts, an avenue this review flags as a concrete direction for future applied research.

IV. CONCLUSION

This review shows that asset-liability management and interest-rate-risk modelling cannot be improved through a single metric, model, or control. The evidence instead points to a system in which governance quality, measurement discipline, incentives, and implementation capacity determine whether formal policies produce reliable outcomes. Strong practice links strategic objectives to explicit risk tolerances, decision rights, escalation rules, and performance feedback. Weak practice treats these elements as separate compliance exercises and therefore misses interactions that become visible only under stress.

This account draws together and extends three theoretical traditions treated separately in much of the literature reviewed here: interest-sensitivity gap theory, duration and immunisation theory, and stochastic term-structure modelling, showing how each addresses a different, only partially overlapping, source of balance-sheet risk. The paper's theoretical contribution is an integrative account centred on balance-sheet resilience, repricing risk, and dynamic hedging. This account connects institutional design with operational choices and clarifies why similar tools can produce different results across organisations and jurisdictions. It also separates predictive accuracy from decision usefulness. A technically sophisticated method creates value only when its assumptions are transparent, its outputs are interpreted consistently, and its limitations are reflected in managerial action.

For practitioners, the priority implications are concrete. Boards and asset-liability committees (ALCOs) should require that duration, gap, and option-adjusted measures be reported alongside one another, not as substitutes, since this review's synthesis shows each capturing risk the others miss; a bank relying on gap analysis alone will misprice embedded-option and non-parallel yield-curve risk, while one relying on stochastic models alone can lose the transparency regulators and boards need to challenge assumptions. Deposit- and prepayment-behaviour models, the single largest source of divergence between measured and realised interest-rate risk in the literature reviewed here, should be independently validated and refreshed at a defined cadence rather than left static between major model reviews. Institutions should also treat IRRBB and liquidity-standard compliance (LCR, NSFR) as inputs to a single stress-testing exercise rather than parallel reporting lines, given the evidence this review surfaces on how credit, liquidity, and interest-rate shocks compound. For policy makers, the clearest implication is that RegTech-enabled, real-time supervisory reporting should be phased in with explicit attention to smaller and emerging-market institutions, since the evidence base reviewed here shows these institutions adopting integrated ALM technology more slowly, not because the underlying risks are smaller, but because the data and technology investment required is proportionally larger relative to their scale.

The review has limitations. Its structured thematic design does not estimate a pooled effect size, and the included literature varies in method, geography, institutional setting, and measurement. The evidence base is also bounded by the 2023 publication cutoff and by the search strategy and screening criteria described in Section 2. These constraints limit causal inference and mean that conclusions should be applied with attention to local regulation, organisational maturity, data quality, and business model.

Future research should prioritise three specific extensions of the evidence reviewed here. First, direct comparative tests of machine-learning models against well-specified stochastic and duration-based benchmarks, using the same bank-level interest-rate-risk data, are largely absent from the current literature and would resolve the gap this review repeatedly identifies between claimed and demonstrated machine-learning performance in ALM specifically. Second, longitudinal, cross-jurisdictional studies of IRRBB implementation under Basel III would clarify whether the capital and liquidity effects documented in single-country studies generalise, particularly for institutions operating Islamic and conventional banking models side by side, where this review finds the evidence base thinnest. Third, research connecting deposit- and prepayment-behaviour model validation practices directly to realised earnings and economic-value outcomes, rather than to model-fit statistics alone, would test whether the behavioural assumptions this review identifies as the largest source of measurement divergence actually translate into the performance differences practitioners and regulators care about. Across all three, transparent reporting of modelling assumptions, consistent with Entrop, Wilkens, and Zeisler's [104] finding that measured risk is highly assumption-sensitive, would materially improve the comparability of future findings and make the integrative framework proposed in this review more directly testable.

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