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Posted Date: 23 April 2026

doi: 10.20944/preprints202604.1628.v1

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Article

Making Sense of Expected Credit Losses: A Qualitative Analysis of IFRS 9 Compliance Strategies in an Emerging Market

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Abstract

Following the global financial crisis, the transition to IFRS 9's forward-looking Expected Credit Loss (ECL) model has introduced significant implementation complexity, particularly in emerging markets facing data limitations. This study investigates the heterogeneous ECL compliance strategies adopted within the Cambodian banking sector during a period of heightened credit stress, marked by a system-wide non-performing loan ratio of 8.6%. Utilizing a multiple-case study design and replication logic, a qualitative content analysis was conducted on the 2024 audited financial statements of 13 representative institutions, ranging from market leaders to international subsidiaries. The findings reveal a pronounced technical divide: market leaders utilize advanced internal statistical methods, such as cohort analysis, while international subsidiaries rely on top-down parent-group proxy models to bridge local data gaps. A "macro-correlation paradox" was identified, where certain institutions prioritize faithful representation by excluding macroeconomic variables when statistical links to historical defaults remain weak. Furthermore, a significant transparency gap exists, where granular disclosures are leveraged as strategic communication tools to signal institutional safety. These results suggest that ECL compliance in data-limited environments is a strategic management choice rather than a standardized technical exercise, highlighting the need for regulatory standardization of modeling assumptions to improve inter-bank comparability.

Keywords: banking sector; Cambodia; disclosure quality; ECL; emerging markets; IFRS 9; macro-correlation paradox; management overlays; strategic communication

1. Introduction

In the aftermath of the 2008 global financial crisis, international accounting standards (IAS) for financial instruments, specifically IAS 39 *Financial Instruments: Recognition and Measurement*, faced intense scrutiny from regulators and standard setters. Critics widely condemned the Incurred Credit Loss model for its "too little, too late" approach, where credit losses were recognized only upon clear evidence of default, a delay that exacerbated the crisis by failing to provide timely information about asset quality (Azhar, 2022). In response, the International Accounting Standards Board issued IFRS 9 *Financial Instruments*, representing a fundamental shift from a rule-based to a principle-based standard designed to ensure the earlier recognition of impairment. This new regime centers on the Expected Credit Loss (ECL) model, a forward-looking framework that requires financial institutions to recognize impairment losses before a default event occurs by incorporating past events, current conditions, and reasonable forecasts (Azhar, 2022).

The transition to ECL modeling introduces substantial implementation complexity for banks, as it necessitates the integration of Forward-Looking Information (FLI) and the estimation of complex Macroeconomic Variables (MEVs). Under IFRS 9, financial assets migrate through a three-stage algorithm based on their credit quality: Stage 1 for assets with minimal credit risk (12-month ECL), Stage 2 for those showing a Significant Increase in Credit Risk (SICR) since initial recognition (lifetime ECL), and Stage 3 for credit-impaired assets. While this model is intended to minimize the cliff-effect

and reduce procyclicality, its operationalization relies on sophisticated statistical parameters, including Probability of Default (PD), Loss Given Default (LGD), and Exposure at Default (EAD).

The inherent flexibility of a principle-based standard means that estimating ECL is fundamentally subjective and relies heavily on management judgment. This subjectivity can lead to significant inconsistencies in how banks apply the standard and report their financial resilience, potentially undermining the comparability and transparency of financial statements. In an emerging market context, these challenges are compounded by data limitations and unique regulatory settings. Cambodia's banking sector serves as a compelling case study; while the nation fully adopted Cambodian International Financial Reporting Standards (CIFRS)—equivalent to International Financial Reporting Standards (IFRS)—with mandatory implementation for banks beginning in 2019 (IFRS Foundation, 2025), the industry currently faces significant economic headwinds.

The Cambodian financial system is navigating a period of heightened credit stress, with system-wide non-performing loans (NPLs) jumping to a ratio of 8.6% in 2025 (National Bank of Cambodia, 2026, p. iii). This surge in problem loans, coupled with a sluggish real estate sector and high capital funding costs, places immense pressure on bank management to maintain adequate provisioning. Despite these pressures, there is a profound lack of empirical research exploring how banks in developing economies actually define and operationalize their ECL compliance strategies during times of economic stagnation. Without a clear understanding of institutional modeling choices and disclosure practices, primary users—including investors and regulators—may struggle to distinguish between genuine credit resilience and the masking of underlying model deficiencies through management overlays.

This paper seeks to address these critical gaps by investigating the diverse ECL compliance strategies adopted within Cambodia's banking sector. Specifically, the study addresses two primary Research Questions (RQ):

RQ1: How do Cambodian banks define and operationalize compliance with IFRS 9, particularly regarding the qualitative and quantitative triggers for a SICR and the modeling of PD, LGD, and EAD?

RQ2: Why does ECL disclosure quality vary significantly across the sector, with some institutions providing granular technical notes while others remain technically opaque despite asserting compliance?

The objective of this research is to perform a rigorous qualitative content analysis of 2024 audited financial statements from 13 representative institutions, including market leaders, international subsidiaries, and specialized banks. By applying replication logic, the study aims to identify sector-wide patterns and technical divides in ECL modeling, providing a Level Two inference regarding how institutions navigate complexity through a blend of quantitative modeling and qualitative management overlays.

The significance of this study is rooted in its contribution to both academic literature and practical banking supervision in emerging economies. Literarily, this research covers a notable gap by providing one of the first empirical examinations of IFRS 9 implementation using real-world data from a developing country during a period of heightened credit stress. It enhances the understanding of the relationship between ECL disclosure quality and strategic communication, illustrating how banks use technical transparency to signal institutional safety.

From a practical perspective, the findings provide vital information for the National Bank of Cambodia (NBC) and other supervisory authorities regarding the impact of IFRS 9 on financial stability and inter-bank comparability. By highlighting the transparency gap and the diverse ways institutions integrate forward-looking information, the study supports recommendations for the regulatory standardization of modeling assumptions and macroeconomic variables. Furthermore, for primary users like investors and lenders, this analysis bridges the gap between complex statistical outputs and the qualitative realities of the Cambodian market, promoting more informed economic decision-making.

The remainder of this paper is organized to provide a comprehensive analysis of the identified issues. Section 2 establishes the institutional and theoretical context, reviewing the Cambodian regulatory environment and the IFRS 9 ECL disclosure requirements. Section 3 details the materials and methods, justifying the multiple-case study design and the replication logic used for data extraction. Section 4 presents the results, categorized by institutional clusters to reveal technical sophistry and divergence across the sector. Section 5 discusses the transparency gap, management overlays, and the policy and management implications of the findings. Finally, Section 6 concludes the paper with a summary of findings, limitations, and specific recommendations for future research.

2. Institutional and Theoretical Context

The Cambodian regulatory landscape is defined by a comprehensive shift toward international alignment, spearheaded by the Accounting and Auditing Regulator and the NBC. Cambodia fully adopted the IFRS without modification, renaming them CIFRS. Mandatory implementation of these standards for the banking sector became effective for periods beginning on or after 1 January 2019 (IFRS Foundation, 2025). As the primary supervisory authority, the NBC plays a critical role in maintaining financial stability and fostering international confidence in the domestic financial system.

To support this transition, the NBC has modernized its supervisory reporting framework, increasing the number of required reporting templates to 51 to ensure data quality remains consistent across the sector (National Bank of Cambodia, 2026, p. 22). Furthermore, the regulator has moved beyond traditional manual reporting through the pilot of the NBC Portal, which facilitates automated data verification and real-time analysis of the system's financial health (National Bank of Cambodia, 2026, p. 22). Supervision under this regime is characterized by a risk-based and forward-looking framework that utilizes regular off-site and on-site inspections focused heavily on credit quality and provisioning adequacy (National Bank of Cambodia, 2026, p. 18).

Regulatory updates in 2025 have further tightened oversight, with the NBC issuing new regulations (Prakas) on early intervention measures and revised requirements for capital buffers to ensure the system continues to align with international Basel standards (National Bank of Cambodia, 2026, p. iii). These measures are particularly vital as the Cambodian banking system navigates heightened global uncertainties and localized economic headwinds (National Bank of Cambodia, 2026, p. ii).

The analysis of ECL compliance is theoretically grounded in the IFRS *Conceptual Framework*, which identifies relevance and faithful representation as the fundamental qualitative characteristics of useful financial information (IFRS Foundation, 2024a, *Conceptual Framework*, para. 2.5). Information is deemed relevant if it possesses predictive or confirmatory value (IFRS Foundation, 2024a, *Conceptual Framework*, para. 2.7), particularly regarding a bank's future cash flows and risk exposures. In the context of ECL, relevance is achieved by integrating FLI (IFRS Foundation, 2024a, *Conceptual Framework*, paras. 2.2–2.3) to ensure that loss provisions are anticipatory rather than merely historical.

Faithful representation requires that financial disclosures are complete, neutral, and free from error (IFRS Foundation, 2024a, *Conceptual Framework*, para. 2.13). For Cambodian banks, this necessitates moving beyond numerical outputs to provide granular descriptions of the methodologies used for staging and impairment assessments. This theoretical lens also incorporates the concept of management commentary as a strategic communication tool; the quality of a bank's disclosure often reflects management's willingness to provide technical transparency regarding internal modeling assumptions.

Furthermore, this study applies replication logic to derive Level Two inferences from institutional management practices (Yin, 2018a). By systematically comparing representative clusters of banks, the research seeks to uncover how different institutions interpret the balance between providing relevant technical notes and maintaining a faithful representation of their risk profile during periods of economic uncertainty.

The core of IFRS 9 is the three-stage ECL algorithm, which requires institutions to recognize impairment based on the migration of credit risk. Stage 1 encompasses assets with no SICR since initial recognition, requiring a 12-month ECL (IFRS Foundation, 2024b, IFRS 9, para. 5.5.5). Stage 2 includes assets showing an SICR, requiring the recognition of lifetime ECL (IFRS Foundation, 2024b, IFRS 9, para. 5.5.3). Stage 3 consists of credit-impaired or non-performing assets (IFRS Foundation, 2024b, IFRS 9, Appendix A). Interest income is typically calculated on the gross carrying amount for Stages 1 and 2, shifting to the net carrying amount once an asset is credit-impaired in Stage 3 (IFRS Foundation, 2024b, IFRS 9, para. 5.4.1(a)–(b)).

Despite the structured nature of this algorithm, ECL modeling introduces substantial implementation complexity due to management subjectivity (IFRS Foundation, 2024c, para. BC5.84). Defining what constitutes a SICR is inherently judgmental (IFRS Foundation, 2024c, paras. BC5.154–BC5.158), relying on qualitative triggers such as loan restructuring (forbearance), bankruptcy filings, or specific industry headwinds (IFRS Foundation, 2024b, IFRS 9, para. B5.5.17). Management must also make critical assumptions when modeling technical parameters, including PD, LGD, and EAD.

Existing literature on IFRS 9 in emerging markets has largely focused on quantitative assessments of bank performance or the broad impact on financial stability such as the study conducted by Azhar (2022). Previous studies have yielded mixed results across different countries (Azhar, 2022), but few have conducted empirical examinations using post-implementation data from the Cambodian context. Specifically, there is a profound lack of qualitative research exploring how financial institutions actually operationalize the principle-based flexibility of IFRS 9 during times of heightened credit stress.

This study fills these critical gaps by providing a qualitative content analysis of audited financial statements, moving beyond numerical impacts to uncover institutional modeling choices. It identifies a significant technical divide between market leaders using advanced internal statistical methods and international subsidiaries relying on global proxy models provided by head offices. Furthermore, by highlighting the transparency gap between granular and opaque disclosures, the research provides vital evidence for the NBC regarding the potential need for regulatory standardization of modeling assumptions and MEVs to enhance inter-bank comparability.

3. Materials and Methods

This study employs a multiple-case study design to investigate the heterogeneous ECL compliance strategies adopted by Cambodian banks. As posited by Yin (2018a), evidence derived from multiple cases is generally considered more robust and compelling than that from a single-case design. Rather than adhering to the sampling logic typical of survey-based research, this study utilizes replication logic, wherein cases are selected to either predict analogous results (literal replication) or produce contrasting outcomes for theoretically anticipatable reasons (theoretical replication) (Yin, 2018a).

The methodological design is specifically embedded, facilitating a multi-layered analysis within each institutional case (bank). While the primary unit of analysis is the institutional compliance strategy, the embedded subunits focus on the granular technical parameters of the ECL models—specifically PD, LGD, and EAD—alongside the integration of FLI. This framework allows for a rigorous cross-case synthesis, enabling the researcher to preserve the holistic characteristics of each bank's management practices while systematically comparing technical patterns across the sector.

The primary data for this research were sourced from published annual reports and audited financial statements for the fiscal year ending December 31, 2024. In case study research, documentary information serves as a critical source of evidence because it is stable, unobtrusive, and contains precise technical nomenclature and details (Yin, 2018b). Data were manually extracted to ensure the capture of nuanced technical notes and management commentary that are frequently omitted in aggregated quantitative datasets.

To provide a faithful representation of IFRS 9 ECL compliance within the Cambodian banking sector, a representative stratified selection of 13 key institutions was analyzed from a total population

of 59 commercial banks (National Bank of Cambodia, 2026, p. 1). The first group, *Market Leaders and Systemically Important Banks*, includes Advanced Bank of Asia (ABA Bank), ACLEDA Bank, and Canadia Bank, which serve as primary benchmarks for digital innovation and financial reporting. ABA Bank is recognized as the nation's largest commercial bank, reporting USD 13.8 billion in total assets for 2024 (Advanced Bank of Asia Ltd., 2025), while ACLEDA Bank remains a top-tier domestic institution and the only Cambodian bank ranked in the "Top 1,000 World Banks 2024" (ACLEDA Bank Plc., 2025). Canadia Bank rounds out this group as a leading local full-service institution with over three decades of market experience (Canadia Bank Plc., 2025).

The second cluster consists of *Major International Subsidiaries*, which offer insight into how global parent company standards influence local implementation. This category includes Maybank (Cambodia) and CIMB Bank, both subsidiaries of major Malaysian banking groups (CIMB Bank PLC, 2025; Maybank (Cambodia) Plc., 2025). Shinhan Bank (Cambodia) represents the first Korean bank to invest in the Cambodian market Shinhan Bank (Cambodia) Plc., 2025), while Woori Bank (Cambodia) recently transitioned to a full commercial banking license (Woori Bank (Cambodia) Plc., 2025a). This group is completed by Cambodian Public Bank (Campu Bank), a subsidiary of Malaysia's Public Bank Berhad that has maintained operations in Cambodia since 1992 (Cambodian Public Bank Plc., 2025).

The third group includes *Key Locally Incorporated and Specialized Institutions* with deep local roots or specific market orientations. The Foreign Trade Bank of Cambodia (FTB) serves as the country's first local commercial bank, established in 1979 (Foreign Trade Bank of Cambodia, 2025). Sathapana Bank, formed by a 2016 merger involving a microfinance institution, now operates an extensive network across all 25 provinces (Sathapana Bank Plc., 2025). KB Prasac Bank is a significant entity created by the 2023 merger of PRASAC Microfinance and Kookmin Bank Cambodia (KB Prasac Bank Plc., 2025). This group also features Chip Mong Commercial Bank, established in 2019 (Chip Mong Commercial Bank Plc., 2025), and the 100% Cambodian-owned Vattanac Bank, which focuses on retail and SME banking (Vattanac Bank, 2025).

The analytic strategy involved the manual extraction of textual and quantitative ECL disclosures from the *Notes to the Financial Statements*, followed by a cross-case synthesis to identify sector-wide patterns. A central component of this analysis is the three-stage impairment approach, where banks must define "performing" (Stage 1), "underperforming" (Stage 2), and "non-performing" (Stage 3) categories. This coding process identified whether interest revenue is calculated on the gross carrying amount for Stages 1 and 2 or shifts to the net carrying amount (amortized cost) for Stage 3 assets, while also monitoring the treatment of Purchased or Originated Credit-Impaired (POCI) assets.

Model inputs were coded by examining the specific methodologies used to estimate the core components of the ECL formula: PD, LGD, and EAD. The analysis focused on whether the PD utilized a "point-in-time" approach through models such as cohort analysis or migration matrices. For LGD, the coding captured estimation methods like "workout style" recovery analysis or benchmarking against Basel Internal Ratings-Based (IRB) parameters. EAD extraction detailed how product-specific exposures are determined, highlighting the use of utilization rates and Credit Conversion Factors (CCF) for revolving and off-balance sheet items.

To identify a SICR, the procedures code for both quantitative backstops and qualitative management judgments. Quantitatively, the study documented Days Past Due (DPD) thresholds, noting variations between the common 30-day benchmark and more conservative 15-day thresholds. The coding also covered the use of internal Credit Risk Ratings (CRR), where specific notch downgrades serve as primary indicators for staging. Qualitative triggers identified include loan restructuring (forbearance), evidence of bankruptcy, modified auditor opinions, or significant financial difficulty of the borrower.

The integration of FLI focused on how banks align historical default data with future economic prospects using MEVs. Common Cambodian MEVs coded include Gross Domestic Product (GDP) growth, inflation, foreign reserves, and domestic credit to the private sector. Banks typically formulate three economic scenarios—Base, Upside, and Downside—assigning them judgmental

probability weightings. The coding procedure determined if a statistical relationship was established between these MEVs and default rates; in instances where no correlation was found, the analysis noted the application of management overlays or expert-derived forward-looking scalars.

Finally, the analytic strategy extracted sensitivity analysis data to enhance the faithful representation of each bank's risk profile. This involved documenting the reported impact of shifts in key MEVs or scenario weightings on the total ECL allowance. The quality of these disclosures varies across the sector, with some institutions providing granular technical notes while others remain more opaque regarding their internal models. This comprehensive coding framework allows for a Level Two inference regarding how banks in an emerging market navigate technical complexities through a blend of quantitative modeling and qualitative management overlays.

4. Results

4.1. Market Leaders and Systemically Important Banks

4.1.1. ABA Bank

Note 32.1.2(a) describes ABA Bank's implementation of the IFRS 9 three-stage approach for measuring ECL, which categorizes financial assets into Stage 1 (performing) for 12-month ECL, Stage 2 (underperforming) for lifetime ECL due to a SICR, and Stage 3 (non-performing) for credit-impaired instruments. Pursuant to Note 2.6, interest revenue is recognized via the effective interest method on the gross carrying amount for Stage 1 and Stage 2 assets, while shifting to the net carrying amount (amortized cost net of the ECL allowance) once an asset becomes credit-impaired in Stage 3. Furthermore, the bank accounts for POCI assets, which are consistently measured on a lifetime basis using a credit-adjusted effective interest rate established at the time of initial recognition.

As delineated in Note 32.1.2(a)(i), the bank's criteria for identifying a SICR utilize a multifactor approach involving both quantitative backstops and qualitative indicators. Quantitatively, the bank identifies a SICR no later than 30 DPD for long-term facilities and 15 DPD for short-term facilities. Note 32.1.2(a) further defines the bank's internal CRR scale of 1–10, where a rating of 9 (watch list) serves as a primary driver for a move to Stage 2. Additionally, the bank utilizes qualitative triggers for SICR and default status, including loan restructuring (forbearance), evidence of bankruptcy, and the significant financial difficulty of the borrower.

In accordance with Note 32.1.2(a)(iv), ECL is measured as the discounted product of the PD, LGD, and EAD. Note 32.1.2(a) states that PD is estimated utilizing Cohort Analysis (Gamma), which models historical default trends to reflect forward-looking, point-in-time expectations. LGD is derived through a period workout analysis of active accounts, incorporating recovery cash flows and contemporary collateral valuations. EAD is defined as the gross carrying amount; Note 3.1 clarifies that for revolving credit facilities, such as cards and overdrafts, the exposure incorporates both the drawn balance and the anticipated portion of the undrawn commitment expected to be utilized before a default event.

Note 32.1.2(a)(ii) specifies that FLI is integrated into the ECL model via MEVs, including Cambodia's GDP growth rate, the Cambodia Securities Exchange (CSX) Index, Crude Oil Brent prices, and USD/KHR exchange rates. The bank employs three judgmental economic scenarios with established probability weightings: Base (50%), Upside (20%), and Downside (30%). For sectors where statistical relationships between MEVs and default rates are not fully captured, or to address broader economic uncertainties, the bank applies management overlays (post-model adjustments). As highlighted in Note 32.1.3, these overlays amounted to an additional USD 58 million in the 2024 ECL allowance for customer loans.

As shown in Note 32.1.2(a)(ii), the bank's ECL disclosure quality is enhanced by a detailed sensitivity analysis, which evaluates the impact of applying a 100% weighting to each economic scenario on the Stage 1 and Stage 2 loss allowances. For the 2024 period, the probability-weighted allowance of USD 41.4 million would increase to USD 45.4 million under a 100% Downside scenario.

Finally, the comprehensive reconciliations of movements in both the gross carrying amount and the loss allowance by stage, found in Note 32.1.3, provide granular transparency into the drivers of credit risk migration and impairment trends.

4.1.2. ACLEDA Bank

Note 39.1(f) describes ACLEDA Bank's implementation of the IFRS 9 three-stage approach to categorize financial instruments into Stage 1 (performing) for 12-month ECL, Stage 2 (underperforming) for assets exhibiting a SICR, and Stage 3 (non-performing) for credit-impaired assets. Pursuant to Note 2(q), interest revenue is recognized via the effective interest method on the gross carrying amount for Stage 1 and Stage 2 assets, while it shifts to the net carrying amount (amortized cost) once an asset reaches Stage 3. Furthermore, the bank accounts for POCI assets by applying a credit-adjusted effective interest rate to the amortized cost from initial recognition, ensuring loss allowances are consistently measured on a lifetime basis.

Note 2(e)(vii) emphasizes that the bank's ECL measurement methodology (Credit Loss = PD × LGD × EAD) utilizes a migration approach or an external credit rating approach to estimate the PD based on historical data. The LGD is estimated based on recovery expectations and specific collateral types; notably, as detailed in Note 4, the bank applies an LGD floor of 10% in cases of over-collateralization, particularly for concentrations in land and building assets. EAD is calculated according to product nature: the current contractual amount for amortizing facilities, utilization rates for revolving facilities, and CCF for off-balance sheet items.

As outlined in Note 39.1(g), the criteria for identifying a SICR include quantitative backstops where assets migrate to Stage 2 no later than 30 DPD for long-term facilities or 15 DPD for short-term facilities. Note 39.1(f) further specifies that ACLEDA employs an internal CRR scale of 1–10, where a rating of 7 (special mention) serves as a trigger for Stage 2, and ratings of 8–10 (substandard, doubtful, and loss) represent Stage 3 status. According to Note 39.1(g), qualitative indicators for SICR and default include significant financial difficulty, breach of contract, bankruptcy filings, and manual management classification based on credit profile deterioration.

As detailed in Note 39.1(g), FLI is integrated into the ECL model via MEVs tailored to the Cambodian context, such as Nominal and Constant GDP, Foreign Reserves, Domestic Credit to the Private Sector (as a percentage of GDP), and USD/KHR exchange rates. The bank utilizes three probability-weighted economic scenarios—Base, Upside, and Downside—with weightings adjusted in 2024 to reflect sector-specific risk profiles. For example, while the Base scenario is generally weighted at 60%, the Downside weighting varies between 15% and 25% depending on whether a specific sub-sector is anticipating recovery or stagnation. Statistical alignment is maintained by analyzing seven years of historical data to establish the relationship between these MEVs and default rates.

As shown in Note 39.1(h), ACLEDA's ECL disclosure quality is bolstered by a comprehensive sensitivity analysis that evaluates the impact of MEV fluctuations across diverse economic sectors. For 2024, the bank reported that a downside scenario in the Retail Trade sector alone would impact the ECL allowance by approximately USD 11.46 million. Finally, in Note 39.1(g), the bank provides detailed reconciliations of movements in the loss allowance by stage, ensuring granular transparency regarding credit risk migration, new originations, and the impact of write-offs.

4.1.3. Canadia Bank

Canadia Bank implements the IFRS 9 three-stage approach for measuring ECL, as delineated in Note 2.6.1(iv) and Note 39.1(c). Financial instruments are categorized into Stage 1 (performing) for assets without a SICR, Stage 2 (underperforming) for assets exhibiting an SICR but not yet credit-impaired, and Stage 3 (non-performing) for credit-impaired exposures. Pursuant to Note 2.15, interest revenue is recognized via the effective interest method on the gross carrying amount for Stage 1 and Stage 2 assets, while shifting to the net carrying amount (amortized cost net of the loss allowance) once an asset becomes credit-impaired in Stage 3. Furthermore, the bank accounts for POCI assets,

which are consistently measured on a lifetime basis using a credit-adjusted effective interest rate established at the time of initial recognition.

As specified in Note 39.1(c)(i), the bank's criteria for identifying a SICR involve a holistic, multifactor analysis of both quantitative and qualitative indicators. Quantitatively, the bank utilizes a backstop where a SICR is triggered if contractual payments are 30 DPD or more. Regarding the definition of default (Stage 3), Note 39.1(c)(ii) stipulates a threshold of 30 DPD for short-term facilities and 90 DPD or more for long-term facilities. Qualitative indicators for SICR and default status include the significant financial difficulty of the borrower, evidence of bankruptcy, loan restructuring or rescheduling (forbearance) due to increased credit risk, and force impaired status approved by management regardless of the past-due status.

In accordance with Note 39.1(c)(iii), ECL is calculated as the discounted product of the PD, LGD, and EAD. PD represents the likelihood of default over either a 12-month or lifetime horizon, with the latter developed by applying a maturity profile to the current 12-month PD. LGD estimates the severity of loss on a defaulted exposure and varies based on counterparty type, claim seniority, and the mitigating effect of collateral, such as residential and business mortgages. EAD for amortizing products is derived from contractual repayments, whereas for revolving products, it incorporates a utilization rate at default to project future outstanding balances by considering undrawn credit limits.

Regarding the integration of FLI, Note 39.1(c)(iv) explains that the bank conducted statistical regression analysis on MEVs sourced from an external research house to identify correlations with historical default rates. However, the bank reported that no direct statistical relationship was established, concluding that unadjusted historical information remains the most reasonable and supportable basis for its estimates. Consequently, FLI was not incorporated into the bank's ECL models for either the 2023 or 2024 reporting periods.

Due to the absence of a statistically validated link between MEVs and default rates, the bank did not provide a standard sensitivity analysis showing the impact of $\pm 1\%$ shifts in key MEVs on the total ECL allowance. Instead, as noted in Note 39.1(c)(iv), the bank emphasizes that it periodically performs statistical assessments and monitors portfolio circumstances to determine if management overlays or adjustments are required to reflect evolving economic conditions. Transparency regarding risk concentration is maintained in Note 39.1(d), which reports that 95.7% of the bank's total maximum credit risk exposure is derived from customer loans and advances and placements with other banks.

4.1.4. Cross-Case Synthesis: Market Leaders and Systemically Important Banks

As outlined in Table 1, the cross-case synthesis of Cambodia's market leaders and systemically important banks—ABA Bank, ACLEDA Bank, and Canadia Bank—reveals a complex interplay of literal replication and theoretical divergence in their IFRS 9 compliance strategies. Quantitatively, these institutions demonstrate a pattern of literal replication regarding their primary backstops for identifying a SICR. All three banks adopt a universal 30-DPD threshold for Stage 2 migration on long-term facilities. This objective benchmark is augmented by qualitative triggers, such as loan restructuring (forbearance) and bankruptcy indicators, ensuring a multifactor approach to staging. ABA and ACLEDA further bolster this framework by mapping these triggers to formal internal CRR scales (1–10), which ensures that credit risk migration is systematically tracked through both objective delinquency data and subjective management classification.

In terms of modeling, a clear distinction emerges between institutions utilizing advanced internal statistical methods and those relying on historical benchmarks. ABA Bank demonstrates high technical sophistication by employing Cohort Analysis (Gamma) to generate point-in-time PD estimates, whereas ACLEDA utilizes a migration approach based on seven years of historical data. Conversely, Canadia Bank highlights the inherent challenges of modeling in an emerging market; by reporting a lack of statistical correlation between MEVs and default rates, the institution chose to rely on unadjusted historical information as the most faithful representation of its risk profile.

The integration of FLI represents the most pronounced area of divergence. ABA and ACLEDA both utilize probability-weighted economic scenarios—Base, Upside, and Downside—incorporating MEVs such as GDP growth and USD/KHR exchange rates to ensure provisions are anticipatory. However, Canadia’s exclusion of FLI due to regression inconsistencies reflects a strategic choice to prioritize faithful representation over model-driven relevance when management believes the underlying data does not support a reliable predictive relationship.

Ultimately, this synthesis moves the analysis to a higher conceptual plane, suggesting that ECL compliance among market leaders is not merely a technical exercise but a strategic communication choice. As specified in the IFRS *Conceptual Framework*, the balance between relevance and faithful representation is critical for primary users to assess future cash flows. This variation underscores that while parent company influence or institutional legacy may drive technical sophistication, the level of ECL disclosure quality remains subject to management’s willingness to expose the granular assumptions behind their ECL models.

Table 1. ECL Compliance Strategies of Cambodian Market Leaders

Bank Name	SICR Triggers	PD/LGD/EAD Modeling	FLI Scenarios & MEVs
ABA Bank	Quantitative: 30 DPD (LT), 15 DPD (ST); Rating 9 (Watch List).	PD: Cohort Analysis (Gamma) for point-in-time estimates. LGD: Period workout analysis including collateral.	Scenarios: Base (50%), Upside (20%), Downside (30%). MEVs: Cambodia GDP growth, CSX Index, Crude Oil Brent, USD/KHR.
	Qualitative: Restructuring, bankruptcy, financial difficulty.	EAD: Gross carrying amount including undrawn limits.	
ACLEDA Bank	Quantitative: 30 DPD (LT), 15 DPD (ST); Rating 7 (Special Mention).	PD: Migration approach or external credit rating. LGD: Based on collateral type with 10% floor.	Scenarios: Base (60%), Upside (15–25%), Downside (15–25%) based on sector. MEVs: Nominal/Constant GDP, Foreign Reserves, Domestic Credit to Private Sector, USD/KHR.
	Qualitative: Breach of contract, bankruptcy, manual classification.	EAD: Contractual amount or CCF for off-balance sheet.	
Canadia Bank	Quantitative: 30-DPD backstop.	PD: Likelihood of default (12m/lifetime). LGD: Varies by counterparty, seniority, and mortgage collateral.	No FLI incorporated in 2024; regression analysis found no statistical link between MEVs and default rates. Reliance on unadjusted historical information.
	Qualitative: Significant financial difficulty, restructuring, force impaired by management.	EAD: Contractual repayments or utilization rates.	

4.2. Major International Subsidiaries

4.2.1. Maybank (Cambodia)

Maybank explicitly adopts the IFRS 9 three-stage approach for measuring ECL, as detailed in Note 2.3.1(d)(i). Financial instruments are categorized into Stage 1 (performing) for 12-month ECL, Stage 2 (underperforming) for lifetime ECL following a SICR, and Stage 3 (non-performing) for credit-impaired assets. Pursuant to Note 2.3.15, interest income is calculated using the effective interest method on the gross carrying amount for Stage 1 and Stage 2 assets, whereas it shifts to the net carrying amount (amortized cost net of the ECL provision) once an asset becomes credit-impaired in Stage 3. Furthermore, the bank accounts for POCI assets, which are consistently measured on a lifetime basis using a credit-adjusted effective interest rate.

The bank's criteria for identifying a SICR rely on quantitative backstops and qualitative indicators as outlined in Note 31.2(e). Quantitatively, a transition to Stage 2 is triggered no later than 30 DPD, with the Stage 3 default threshold set at more than 90 DPD. The bank aligns these stages with regulatory classifications, mapping standard accounts (0–29 DPD) to Stage 1 and Special Mention accounts (30–89 DPD) to Stage 2, as shown in Note 2.3.14(iii). Qualitative triggers for Stage 2 or 3 status include loan restructuring or rescheduling due to financial difficulty, forced default indicators, and related default obligations where an obligor's default on one facility triggers a reassessment of their entire portfolio.

In accordance with Note 2.3.1(d)(ii), ECL is measured as the product of the PD, LGD, and EAD. These components leverage Basel II models with necessary adjustments for IFRS 9 compliance. As specified in Note 3.2.1, PD and LGD are point-in-time estimates that incorporate forward-looking adjustments based on data from the bank's research arm, Maybank Investment Banking Group. LGD values are determined by recovery expectations and the mitigating effect of collateral, while EAD represents the anticipated gross carrying amount at the time of default.

FLI is integrated into the ECL model by evaluating a range of possible outcomes under future economic conditions, as described in Note 2.3.1(d)(v). The bank utilizes MEVs such as GDP growth, unemployment rates, and house price indices, sourced from governmental bodies, monetary authorities, and supranational organizations like the International Monetary Fund (IMF) (Note 31.2(e)). Three probability-weighted economic scenarios are applied to reflect potential outcomes: Base (reflecting prevailing conditions), Upside, and Downside.

Maybank's ECL disclosure quality is supported by comprehensive reconciliations of movements in the loss allowance and gross carrying amounts by stage, providing granular transparency into credit risk migration and impairment drivers (Note 9). The bank employs sensitivity analysis to evaluate market risks, such as a $\pm 1\%$ shift in foreign currency exchange rates (Note 31.3.1) and identifies the selection of MEVs and scenario weightings as significant accounting estimates (Note 3.2.1). Transparency regarding exposure concentration is maintained in Note 9(ii), which reports that Wholesale/Retail remains the largest sector in the loan portfolio at USD 519.8 million, while the bank's total assets reached USD 1.78 billion in 2024.

4.2.2. CIMB Bank

Note 2.5(vii) describes CIMB Bank's adoption of the IFRS 9 three-stage approach for measuring ECL, which categorizes financial assets into Stage 1 (performing) for 12-month ECL, Stage 2 (underperforming) for lifetime ECL due to a SICR, and Stage 3 (non-performing) for credit-impaired assets. Pursuant to Note 2.18, interest revenue is recognized via the effective interest method on the gross carrying amount for Stage 1 and Stage 2 assets, while shifting to the net carrying amount (amortized cost net of the ECL allowance) once an asset becomes credit-impaired in Stage 3. Furthermore, the bank accounts for POCI assets, which are consistently measured on a lifetime basis using a credit-adjusted effective interest rate established at initial recognition.

As delineated in Note 35.1(c)(i), the bank's criteria for identifying a SICR utilize a multifactor and holistic analysis of both quantitative and qualitative information. Quantitatively, the bank utilizes special monitoring thresholds found in Note 35.1(e): assets migrate to Stage 2 if they are between 30 and 89 DPD for long-term facilities or 15 to 30 DPD for short-term facilities. Qualitative triggers for SICR and default status include loan restructuring or rescheduling (forbearance) due to financial difficulty, breaches of contract, and cross-default obligations. The definition of default is generally applied to obligors assessed as impaired or those reaching credit-impaired status.

In accordance with Note 35.1(c)(iii), ECL is measured as the product of the PD, LGD, and EAD, discounted to the reporting date using the original effective interest rate. The bank utilizes a point-in-time PD reflecting conditions at the reporting date and future economic forecasts. LGD estimates the severity of loss and varies based on counterparty type, claim seniority, and the mitigating effect of collateral. EAD for amortizing products is based on contractual repayments, whereas for revolving

products, Note 35.1(c)(ix) specifies the use of internal CCF, such as 20% for the unused portion of credit cards and overdrafts.

Note 35.1(c)(iv) specifies that FLI is integrated into the model through statistical regression analysis to determine the relationship between MEVs and default rates. In 2024, the bank's statistical tests identified the CPI as the key variable, whereas the 2023 model utilized GDP. The bank applies three probability-weighted economic scenarios: Base (70%), Best (10%), and Worst (20%). To capture risks not fully reflected in the model, such as those impacting specific industries or restructured loans, the bank applies management overlays (post-model adjustments) as detailed in Note 35.1(c)(v).

As shown in Note 35.1(i), the bank's ECL disclosure quality is supported by a detailed sensitivity analysis evaluating the impact of MEV fluctuations on the total loss allowance. For the 2024 period, the bank reported that a $\pm 1\%$ change in the CPI would result in an ECL impact of USD 304,910. Transparency is further enhanced by comprehensive reconciliations of movements in the loss allowance and gross carrying amounts by stage, found in Note 35.1(f), which provide insight into credit risk migration and write-offs. Finally, Note 35.1(d) reports that 60% of the bank's total maximum credit risk exposure is derived from customer loans and advances.

4.2.3. Shinhan Bank (Cambodia)

Note 36(a)(iii) describes Shinhan Bank's implementation of the IFRS 9 three-stage approach for measuring ECL, which categorizes financial instruments into Stage 1 (performing) for 12-month ECL, Stage 2 (underperforming) for lifetime ECL following a SICR, and Stage 3 (non-performing) for credit-impaired assets. Pursuant to Note 36(a)(v) and Note 5(t)(iii), interest revenue is recognized via the effective interest method on the gross carrying amount for Stage 1 and Stage 2 assets, while shifting to the net carrying amount (amortized cost net of the ECL allowance) once an asset becomes credit-impaired in Stage 3. Furthermore, the bank accounts for POCI assets, which are consistently measured on a lifetime basis using a credit-adjusted effective interest rate that does not revert to a gross basis even if credit risk subsequently improves.

As delineated in Note 36(a)(iii), the bank's criteria for identifying a SICR involve a multifactor and holistic analysis of quantitative and qualitative information. Quantitatively, the bank utilizes a backstop where a transition to Stage 2 is triggered no later than 30 DPD. Qualitative indicators for SICR include significant downgrades in internal credit ratings and adverse changes in business or economic conditions. The definition of default (Stage 3) is triggered at 90 DPD or earlier if qualitative factors exist, such as forced impaired status due to bankruptcy, loan restructuring (forbearance), or cross-default obligations.

In accordance with Note 36(a)(i) and Note 36(a)(iii), ECL is measured as the product of the PD, LGD, and EAD, discounted using the original effective interest rate. As specified in Note 5(c)(vii), the bank utilizes proxy models provided by its Head Office to estimate PD, which reflect point-in-time expectations and incorporate forward-looking adjustments. LGD estimates the severity of loss and considers claim seniority and the mitigating effect of collateral, primarily residential and commercial mortgages. EAD for amortizing products is based on contractual repayments, while Note 36(a)(iii) specifies that off-balance sheet exposures utilize internal CCF of 75% for unused credit facilities and 100% for bank guarantees.

Note 36(a)(iii) clarifies that FLI is integrated into the ECL models by evaluating economic data and forecasts from governmental and academic sources. For portfolios where historical default data is insufficient, such as non-retail segments, the bank employs proxy PDs and LGDs adjusted at the Head Office level to absorb future credit risk. The bank emphasizes that these assumptions and estimation techniques are monitored and refreshed periodically to ensure they remain reasonable and supportable.

As shown in Note 36(a)(iii), the bank's ECL disclosure quality is supported by a detailed sensitivity analysis evaluating the impact of a $\pm 1\%$ change in the ECL rate on the total loss allowance. For the 2024 period, a +1% change in the ECL rate would result in an ECL decrease of USD 181,731. Transparency is further enhanced by comprehensive reconciliations of movements in the loss

allowance by stage, found in Note 36(a)(vi), which provide granular insight into credit risk migration, new originations, and write-offs. Finally, Note 36(a)(iv) reports that 90% of the bank's total maximum credit risk exposure is derived from customer loans and advances, almost all of which are collateralized with loan-to-collateral values ranging from 50% to 90%.

4.2.4. Woori Bank (Cambodia)

The 2024 annual report of Woori Bank does not contain a complete *Notes to Financial Statements*; thus, the study used the audited financial statements available on the bank's website. Woori Bank (Cambodia) Plc.'s (2025b) Note 31B(iv) describes the bank's implementation of the IFRS 9 three-stage approach for measuring ECL, which categorizes financial assets into Stage 1 (performing) for 12-month ECL, Stage 2 (underperforming) for lifetime ECL due to a SICR, and Stage 3 (non-performing) for credit-impaired assets. Pursuant to Note 33S, interest revenue is recognized via the effective interest method on the gross carrying amount for Stage 1 and Stage 2 assets, while shifting to the net carrying amount (amortized cost net of the ECL allowance) once an asset becomes credit-impaired in Stage 3. Furthermore, the bank accounts for POCI assets, which are consistently measured on a lifetime basis using a credit-adjusted effective interest rate established at initial recognition.

As detailed in Note 31B(i) and Note 31B(iv), the bank's criteria for identifying a SICR utilize both quantitative backstops and qualitative indicators. Quantitatively, the bank identifies a SICR no later than 30 DPD for long-term facilities and 15 DPD for short-term facilities. The definition of default (Stage 3) is generally triggered at 90 DPD for long-term loans and 31 DPD for short-term loans. Qualitative triggers for SICR and default status, as specified in Note 33C(vii), include the significant financial difficulty of the borrower, breach of contract, and loan restructuring (forbearance) due to credit deterioration.

In accordance with Note 33C(vii), ECL is measured as the product of the PD, LGD, and EAD, discounted using the original effective interest rate. PD is estimated utilizing a migration approach based on historical data to reflect point-in-time expectations. LGD estimates the severity of loss upon default and incorporates parameters derived from historical recovery rates and the mitigating effect of collateral, primarily land and buildings. EAD represents the anticipated gross carrying amount at default, taking into account expected changes in exposure such as amortization profiles and drawdowns on committed facilities.

Note 31B(i) specifies that FLI is integrated into the ECL model through statistical regression analysis to determine the relationship between MEVs and default rates. The bank utilizes three probability-weighted economic scenarios: Base (68%), Good (16%), and Bad (16%). Notably, FLI is currently applied only to PD estimates, as default counts were deemed insufficient for reliable forward-looking statistical analysis of LGD. To address risks not fully reflected in the model, such as those impacting restructured loans or vulnerable sectors, the bank applies management overlays (post-model adjustments).

The bank's ECL disclosure quality is supported by comprehensive reconciliations of movements in both the loss allowance and gross carrying amounts by stage, providing granular transparency into credit risk migration and new originations (Note 31B(v)). While the bank provides sensitivity analysis for market risks like interest rate fluctuations (Note 31C(i)), the bank does not explicitly tabulate the $\pm 1\%$ impact of specific MEVs on the total loss allowance. Transparency is further maintained through a credit quality analysis that maps regulatory credit grades—Normal, Special Mention, Substandard, Doubtful, and Loss—to the IFRS 9 staging framework (Note 31B(iv)).

4.2.5. Cambodian Public Bank

Note 2.7.1(vi)(b) describes Campu Bank's implementation of the IFRS 9 three-stage approach for measuring ECL, which categorizes financial assets into Stage 1 (performing) for 12-month ECL, Stage 2 (underperforming) for lifetime ECL where a SICR has occurred, and Stage 3 (non-performing) for credit-impaired assets. Pursuant to the bank's accounting policies, interest revenue is recognized via the effective interest method on the gross carrying amount for Stage 1 and Stage 2 assets, while

shifting to the net carrying amount (amortized cost net of the ECL allowance) once an asset becomes credit-impaired in Stage 3.

As delineated in Note 27.2(f), the bank's criteria for identifying a SICR involve a multifactor analysis of both quantitative backstops and qualitative indicators. Quantitatively, the bank identifies a SICR no later than 30 DPD for long-term facilities and 15 DPD for short-term facilities. Qualitative triggers for SICR and default status include loan restructuring and rescheduling (R&R) due to credit deterioration, evidence of forced default where a credit profile shows significant weakness despite being less than 90 DPD, and related default obligations where an obligor's cross-default on one facility triggers a reassessment of their entire portfolio. The definition of default is generally set at 90 DPD for long-term loans and 31 DPD for short-term products.

In accordance with Note 2.7.1(vi)(b), ECL is measured as the product of the PD, LGD, and EAD, discounted to the reporting date using the original effective interest rate. The bank utilizes point-in-time PDs that reflect conditions at the reporting date as well as future economic forecasts. LGD estimates the severity of loss upon default and incorporates the mitigating effect of collateral, its expected value when realized, and the time value of money. EAD represents the anticipated gross carrying amount at the time of default, accounting for expected drawdowns on committed facilities and contractual repayment profiles.

FLI is integrated into the ECL model through the application of MEVs, as specified in Note 2.7.1(vi)(b). These variables, which include economic indicators and industry statistics, are sourced from governmental bodies, monetary authorities, and supranational organizations such as the IMF. The bank utilizes a statistical scalar to model the correlation between these MEVs and historical default and recovery rates, ensuring the final ECL allowance reflects an unbiased, probability-weighted assessment of future economic conditions.

The bank's ECL disclosure quality is supported by comprehensive reconciliations of movements in the loss allowance and gross carrying amounts by stage, providing granular transparency into credit risk migration and impairment drivers (Note 6(i)). Transparency regarding risk concentration is maintained in Note 27.2(e), which reports that Wholesale and Retail remains the largest sector in the loan portfolio at USD 385.3 million, followed by Household and personal essentials at USD 312.0 million. Finally, Note 27.2(d) reports that the bank's total maximum credit risk exposure reached approximately USD 2.23 billion as of 31 December 2024.

4.2.6. Cross-Case Synthesis: Major International Subsidiaries

As summarized in Table 2, the ECL compliance strategies of Cambodia's major international subsidiaries—Maybank, CIMB Bank, Shinhan Bank, Woori Bank, and Campu Bank—exhibit a high degree of literal replication in their structural adoption of the IFRS 9 ECL framework. All five institutions strictly operationalize the three-stage impairment model, utilizing a universal 30-DPD backstop as the primary quantitative trigger for identifying a SICR for long-term facilities. This quantitative benchmark is consistently augmented by qualitative overlays, such as loan restructuring (forbearance), cross-default obligations, and bankruptcy indicators, ensuring that credit risk migration is not merely a function of delinquency but a holistic assessment of borrower viability.

A defining technical characteristic of this cluster is the heavy reliance on global parent-group expertise to bridge local data limitations. Maybank and CIMB, for instance, leverage sophisticated Basel II models adapted for IFRS 9, while Shinhan Bank utilizes proxy models developed by its Head Office to estimate parameters for portfolios with insufficient internal historical data. This top-down modeling approach ensures technical consistency across regional operations but also creates a technical divide between these subsidiaries and locally incorporated banks that must build frameworks from the ground up. For technical parameters, these banks generally employ point-in-time estimates for PD, while LGD is typically modeled through a combination of historical recovery analysis and the mitigating effects of collateral.

The integration of FLI further illustrates the strategic influence of parent companies. As detailed in Table 2, the MEVs used to calibrate ECL models are frequently sourced from centralized research

arms, such as the Maybank Investment Banking Group or parent-level economics teams. While variables like GDP growth and USD/KHR exchange rates are standard across the cluster, specific institutions prioritize different localized indicators; for example, CIMB emphasized the CPI in its 2024 modeling, whereas Campu Bank focused on the correlation between investment and default rates. All five banks utilize three probability-weighted economic scenarios—Base, Upside, and Downside—to derive a range of possible future outcomes.

Ultimately, this cross-case synthesis moves the analysis to a higher conceptual plane, suggesting that for international subsidiaries, IFRS 9 compliance is a strategic balancing act between localized credit realities and global institutional standards. By utilizing group-wide proxy models and centralized economic forecasting, these banks signal institutional safety and technical sophistry to primary users. However, the variation in ECL disclosure quality—ranging from Maybank’s and CIMB’s granular reconciliations of loss allowances to more opaque regulatory-focused notes in other cases—underscores that technical transparency remains a discretionary choice driven by management’s willingness to expose internal predictive assumptions.

Table 2. ECL Compliance Strategies of Major International Subsidiaries

Bank Name	SICR Triggers	PD/LGD/EAD Modeling	FLI Scenarios & MEVs
Maybank (Cambodia)	Quantitative: 30–89 DPD (LT); 31 DPD default for trade finance. Qualitative: Restructuring (R&R), forced default status.	PD/LGD: Based on parent Basel II models adjusted for IFRS 9. EAD: Expected drawdowns for revolving facilities.	Scenarios: 3 (Base, Upside, Downside). MEVs: GDP, unemployment, and house price indices sourced from Maybank IBG.
CIMB Bank	Quantitative: 30–89 DPD (LT); 15–30 DPD (ST). Qualitative: R&R (forbearance), cross-default.	PD: Point-in-time; uses forward-looking proxy PDs for low-data portfolios. EAD: Higher of balance or CCF-adjusted limit.	Scenarios: Base (70%), Upside (10%), Downside (20%). MEVs: CPI (2024) and GDP (2023) from parent economics team.
Shinhan Bank (Cambodia)	Quantitative: 30-DPD backstop. Qualitative: Internal rating downgrades, modified auditor opinions.	PD/LGD: Estimated via proxy models from Head Office. EAD: CCF of 75% for unused credit and 100% for guarantees.	Scenarios: PD models incorporate FLI adjusted at Head Office level. MEVs: Data from governmental and academic sources.
Woori Bank (Cambodia)	Quantitative: 30 DPD (LT), 15 DPD (ST). Qualitative: Breach of covenants, bankruptcy restructuring, management overlays.	PD: Migration approach. LGD: History of recovery rates with applied floors. EAD: Repayments and expected drawdowns.	Scenarios: Base (68%), Good (16%), Bad (16%). FLI used for PD only; LGD relies on historical counts.
Cambodian Public Bank	Quantitative: 30 DPD (LT); 15 DPD (ST). Qualitative: Forced default, cross-defaults, and R&R status.	PD: Point-in-time estimates. LGD: Considers collateral mitigating effects. EAD: Principal and interest plus expected drawdown.	Scenarios: 3 probability-weighted (Base, Upside, Downside). MEVs: GDP growth and investment correlated to default rates.

4.3. Key Locally Incorporated and Specialized Institutions

4.3.1. Foreign Trade Bank of Cambodia

FTB explicitly adopts the IFRS 9 three-stage approach for ECL, as outlined in Note 2.5(e). Assets are categorized as Stage 1 (performing), Stage 2 (under-performing/SICR), and Stage 3 (non-performing/credit-impaired). Note 2.18 on details the interest revenue calculation: Stage 1 and 2 assets use the effective interest method on the gross carrying amount, while Stage 3 assets shift to the net carrying amount (amortized cost net of ECL provision). This same note accounts for POCI assets, which are measured on a lifetime basis using a credit-adjusted effective interest rate.

The bank's criteria for SICR are defined in Note 36.1(c)(i), which specifies that a move to Stage 2 is triggered no later than 30 DPD. Internal credit quality monitoring via standard monitoring (<30 DPD) and special monitoring (30 DPD) is detailed in Note 36.1(e). Qualitative triggers for SICR and Stage 3 (default), such as forbearance (restructuring), forced impaired status, and cross-default obligations, are listed in Note 36.1(c)(ii). This note also defines default as 90 DPD for long-term facilities and 30 DPD for short-term facilities.

The methodology for measuring ECL on a collective or individual basis as the product of PD, LGD, and EAD is described in Note 36.1(c)(iii). Within this note, PD is identified as a point-in-time estimate, with 12-month PDs used to generate lifetime curves. LGD is based on recovery expectations and includes the application of LGD floors for secured loans. EAD calculation differs by product: amortizing products use contractual repayments, while revolving products use the credit limit multiplied by a utilization rate. Note 36.1(c)(viii) explains that off-balance sheet items utilize CCF.

The integration of FLI, including the annual refreshing of MEVs and the use of external research forecasts, is noted in Note 3. Note 36.1(c)(iv) describes the use of statistical regression analysis to determine the relationship between MEVs and default rates, the formulation of three economic scenarios (baseline, upside, and downside), and the application of a probability-weighted outcome.

FTB's transparency is supported by detailed reconciliations of the loss allowance and gross carrying amount by stage in Note 36.1(f). Note 3 confirms that the bank tests key variables for sensitivity, while Note 36.1(c)(iv) emphasizes that the weightings assigned to economic scenarios are the most significant assumptions. Finally, Note 36.1(d) reports that 77% of total maximum credit exposure is derived from customer loans and advances, noting that almost all are collateralized with Loan-to-Value ratios between 60% and 80%.

4.3.2. Sathapana Bank

Sathapana Bank's implementation of the IFRS 9 three-stage approach is described in Note 30.2. The methodology for interest income calculation—using the gross carrying amount for Stage 1 and 2 assets and the amortized cost (net amount) for Stage 3 assets—is detailed in Note 2.5.15. This same note specifies that for POCI assets, interest is calculated on the amortized cost using a credit-adjusted effective interest rate and never reverts to a gross basis.

The bank's ECL formula ($\text{Credit Loss} = \text{PD} \times \text{LGD} \times \text{EAD} \times \text{EFA} \times \text{DF}$) and its components are defined in Note 2.5.1(g). This note explains that PD is estimated using a delinquency-based transition matrix, historical loss rates, and proxy models. LGD is calculated using a workout style method based on historical recovery cash flows discounted by the effective interest rate. EAD is defined as the gross carrying amount at default, and for lending commitments, it incorporates potential future drawdowns.

The quantitative 30 DPD backstop for identifying a SICR is established in Note 2.5.1(g). The use of an internal rating tool for counterparty PD assessment is mentioned in Note 30.2. Qualitative indicators for Stage 2 or 3, including debt restructuring, forced accounts (deterioration despite delinquency < 30 DPD), and related default (cross-defaults), are listed in Note 2.5.1(g) and Note 30.2. The general definition of default at 90 DPD and the more conservative 31 DPD for trade finance are found in Note 30.2 and Note 2.5.1(g).

The integration of FLI via the Economic Factor Adjustment (EFA) scalar is noted in Note 2.5.1(g). Note 30.2 describes how the bank identifies key credit risk drivers by analyzing historical data and MEVs sourced from organizations like the IMF. The evaluation of exposure outcomes using scenario and statistical techniques is detailed in Note 2.5.1(g).

A comprehensive reconciliation of movements in the ECL allowance is provided in Note 6(i). For 2024, this table reports that the impact from exposures transferred between stages was USD 14,522,811 and loans written off totaled USD 9,810,329. While Note 17(iv) contains sensitivity analyses for defined benefit obligations, a granular table showing the sensitivity of the total ECL allowance to $\pm 1\%$ MEV changes is not included in these excerpts, although Note 2.6.2 acknowledges FLI as a significant estimate.

4.3.3. KB Prasac Bank

KB Prasac's adoption of the IFRS 9 three-stage approach for ECL is described in Note 2.6.1(iv). Note 2.12 details the interest revenue calculation: Stage 1 and 2 assets use the effective interest method on the gross carrying amount, while Stage 3 assets shift to the net carrying amount (amortized cost net of provision). This same note, alongside Note 34.1(c), accounts for POCI assets, which are measured on a lifetime basis using a credit-adjusted effective interest rate established at initial recognition.

The bank's criteria for SICR, involving a multifactor analysis of quantitative and qualitative information, are defined in Note 34.1(c)(i). This note specifies a quantitative backstop of 30 DPD. The definition of default (Stage 3) triggered no later than 90 DPD, and its qualitative indicators—such as forbearance (restructuring), bankruptcy, and cross-default obligations—are detailed in Note 34.1(c)(ii).

The methodology for measuring ECL as the discounted product of PD, LGD, and EAD is described in Note 34.1(c)(iii). Within this note, PD is defined over a 12-month or lifetime horizon, with the latter developed by applying a maturity profile. LGD estimates the severity of loss upon default and accounts for the mitigating effect of collateral like mortgages, as detailed in Note 34.1(b). EAD for amortizing products is based on contractual repayments adjusted for overpayments, as explained in Note 34.1(c)(iii).

The integration of FLI and the sourcing of MEVs from the NBC, IMF, and World Bank are noted in Note 34.1(c)(iv). This note explains that because statistical regression showed no direct relationship between these variables and historical defaults, the bank applied a forward-looking scalar estimate to historical PD and LGD. The bank applies three probability-weighted scenarios—Baseline (20%), Upside (20%), and Downside (60%)—which remained unchanged between 2023 and 2024.

KB Prasac's transparency is supported by detailed stage reconciliations of the loss allowance and gross carrying amount in Note 34.1(f). Note 34.1(c)(iv) identifies that while scenario weightings are the most significant assumption, a granular $\pm 1\%$ sensitivity table for individual MEVs is not provided. Finally, Note 34.1(g)(i) provides a breakdown of the loan portfolio by industry, showing the largest concentrations in Trade and Commerce (USD 1.27 billion) and Home Improvement (USD 863 million).

4.3.4. Chip Mong Commercial Bank

CMCB's adoption of the IFRS 9 three-stage approach for ECL is detailed in Note 2.5(e). This framework categorizes assets into Stage 1 (performing), Stage 2 (underperforming), and Stage 3 (non-performing). Note 2.17 explains the interest income calculation: interest is calculated on the gross carrying amount for Stage 1 and 2 assets, while it shifts to the amortized cost (net of ECL provision) for Stage 3 assets. This note also accounts for POCI assets, which are measured on a lifetime basis using a credit-adjusted effective interest rate established at initial recognition.

The criteria for identifying a SICR using a multifactor and holistic analysis are defined in Note 35.1(c)(i). Quantitatively, a move to Stage 2 is triggered no later than 15 DPD for short-term facilities and 30 DPD for long-term facilities. Note 35.1(c)(ii) defines default (Stage 3) as generally 90 DPD. Qualitative indicators for SICR and default, including cross-default obligations, significant internal risk grading downgrades, and loan restructuring or modification due to financial difficulty, are detailed in Note 35.1(c)(ii) and the bank's modification policy in Note 35.1(c)(vii).

The methodology for measuring ECL as the product of PD, LGD, and EAD, discounted using the original effective interest rate, is described in Note 35.1(c)(iii). PD is a point-in-time estimate; for portfolios with insufficient data, the bank utilizes market default data from the Credit Bureau Cambodia (CBC). LGD varies based on counterparty type and the presence of collateral (primarily residential mortgages), as noted in Note 35.1(c)(iii) and Note 35.1(b). EAD calculation differs by product: amortizing products use contractual repayments, while revolving products use the higher of the outstanding balance or the limit multiplied by a CCF. Note 35.1(c)(viii) specifies internal CCFs at 40% for unused loans, 50% for unused overdrafts, and 100% for financial guarantees.

The integration of FLI into the ECL model through statistical regression analysis of MEVs is detailed in Note 35.1(c)(iv). For 2024, the bank's tests identified Inflation GDP as the key variable, while the 2023 model utilized the CPI. The bank applies three probability-weighted scenarios: Base (68%), Best (16%), and Worst (16%). Management's use of expert judgment to adjust weightings, giving a heavier weight to the worst-case scenario in 2024 to reflect economic uncertainties, is noted in Note 35.1(c)(iv).

Transparency is supported by a detailed sensitivity analysis in Note 35.1(c)(iv), which reports that a $\pm 19.15\%$ change in Inflation GDP would result in an ECL increase of USD 184,634 or a decrease of USD 136,069. Comprehensive stage reconciliations of the loss allowance and gross carrying amount are provided in Note 35.1(f). Finally, Note 35.1(d) reports that 63% of the bank's total maximum credit risk exposure is derived from loans and advances, with nearly all exposures collateralized at a loan-to-collateral value of 80%.

4.3.5. Vattanac Bank

Vattanac Bank's adoption of the IFRS 9 three-stage ECL approach is described in Note 33B(v) and Note 35C(vii), which categorize assets into Stage 1 (performing), Stage 2 (underperforming/SICR), and Stage 3 (nonperforming/credit-impaired). The methodology for interest revenue calculation—using the gross carrying amount for Stage 1 and 2 assets and the net carrying amount (amortized cost) for Stage 3 assets—is detailed in Note 33B(v) and Note 35Q. Note 35Q also specifies that for POCI assets, interest is calculated using a credit-adjusted effective interest rate on the amortized cost and never reverts to a gross basis.

The criteria for identifying a SICR are defined in Note 33B(v), which specifies quantitative backstops of 30 DPD for long-term facilities and 15 DPD for short-term facilities. The same note defines default (Stage 3) as 90 DPD for long-term and 31 DPD for short-term facilities. Qualitative triggers for SICR and default, such as borrower financial difficulty, breach of contract, or restructuring, are listed in Note 35C(vii). Furthermore, Note 33B(v) explains that for restructured loans, if a customer is offered a grace period but remains able to service payments regularly, no SICR is deemed to exist.

The bank's ECL formula ($\text{Credit Loss} = \text{PD} \times \text{LGD} \times \text{EAD}$) and the use of statistical models are described in Note 35C(vii). Within this note, PD is identified as a point-in-time estimate of remaining lifetime PD, and LGD is estimated by benchmarking against Basel IRB parameters (45% and 30%) for corporate, sovereign, and bank claims. EAD is defined as the gross carrying amount at default; for lending commitments, it incorporates potential future drawdowns based on historical data and forward-looking forecasts.

The integration of FLI, including the regression of Observed Default Rates (ODRs) against MEVs sourced from the World Bank, is detailed in Note 33B(v). This note describes the calculation of a forward-looking scalar as a ratio of ODRs and the formulation of three economic scenarios: Baseline (40%), Best (35%), and Worst (25%). These scenarios are generated by shocking base MEVs by ± 1 standard deviation of historical values.

Vattanac Bank's transparency is supported by detailed stage reconciliations of the loss allowance and gross carrying amount by instrument class (e.g., Term Loans, Overdrafts, Credit Cards) in Note 33B(vi). Note 33C(ii) provides a sensitivity analysis for foreign currency risk, while Note 33C(i) explicitly states that no sensitivity analysis was prepared for interest rate risk because financial

instruments are not carried at fair value. Finally, Note 33B(v) includes a credit quality analysis mapping internal risk grades—Normal, Special Mention, Substandard, Doubtful, Loss—to the IFRS 9 stages.

4.3.6. Cross-Case Synthesis: Key Locally Incorporated and Specialized Institutions

As presented in Table 3, the cross-case synthesis of Cambodia’s key locally incorporated and specialized institutions—FTB, Sathapana Bank, KB Prasac Bank, CMCB, and Vattanac Bank—reveals a strategy of theoretical replication driven by diverse institutional data legacies. Unlike international subsidiaries that rely on parent-group proxies, these institutions must balance internal historical data with external benchmarks to define their ECL frameworks. Quantitatively, these institutions demonstrate literal replication regarding the 30-DPD backstop for SICR on long-term facilities. However, a significant divergence occurs in the treatment of short-term products, where CMCB and Vattanac Bank apply a more conservative 15-DPD trigger for Stage 2 migration. Qualitatively, the operationalization of a SICR is augmented by triggers such as loan restructuring (forbearance), evidence of bankruptcy, and forced default indicators, which institutions like Sathapana and FTB map to internal monitoring categories such as special monitoring or watch list.

Technical modeling strategies within this cluster exhibit a pragmatic divide based on data availability. CMCB distinguishes itself by utilizing CBC market default data to supplement portfolios with insufficient internal history, while Vattanac Bank relies on Basel IRB benchmarks (45% for senior claims) to estimate its LGD. In contrast, Sathapana Bank utilizes a workout style method based on historical recovery cash flows, and FTB generates lifetime PD curves derived from 12-month point-in-time estimates.

The integration of FLI highlights a phenomenon termed the “macro-correlation paradox”. While FTB and Vattanac utilize statistical regression to link ODRs to MEVs sourced from the World Bank and IMF, KB Prasac reported no direct statistical relationship between standard MEVs and historical defaults. Consequently, KB Prasac utilizes an expert-derived forward-looking scalar to absorb future credit risk—a strategy that prioritizes faithful representation over statistically forced relevance.

Finally, the ECL disclosure quality of this group reflects a strategic communication choice regarding technical transparency. CMCB and Vattanac Bank provide granular sensitivity analyses, with CMCB reporting the specific ECL impact of an $\pm 19.15\%$ shift in Inflation GDP. Conversely, Sathapana and KB Prasac remain more technically opaque, focusing disclosures on regulatory alignment rather than detailing the $\pm 1\%$ impact of individual MEV shifts. This variation underscores that while IFRS 9 provides a technical “box,” the decision to disclose the internal “arrows” of the model remains subject to management’s comfort with the reliability of their internal predictive systems.

Table 3. ECL Compliance Strategies of Key Locally Incorporated and Specialized Institutions

Bank Name	SICR Triggers	PD/LGD/EAD Modeling	FLI Scenarios & MEVs
FTB	Quantitative: 30 DPD. Qualitative: R&R (forbearance), forced impaired (bankruptcy), cross-default.	PD: Point-in-time; 12m PDs used for lifetime curves. LGD: Recovery expectations with applied floors. EAD: Contractual (amortizing) vs. credit limit x utilization (revolving).	Scenarios: baseline, upside, downside (probability-weighted). MEVs: Refreshed annually via regression against ODR; sourced from external research houses.
Sathapana Bank	Quantitative: >30 DPD. Qualitative: R&R status, forced accounts (deterioration <30 DPD), related cross-defaults.	PD: Delinquency-based transition matrix and proxy models. LGD: Workout style based on historical recovery cash flows.	Scenarios: Range of outcomes via scenario/statistical techniques.

		EAD: Gross carrying amount plus future drawdowns.	MEVs: Integrated via EFA scalar; sourced from IMF/Gov.
KB Prasac Bank	Quantitative: 30 DPD. Qualitative: Loan R&R (forbearance), financial difficulty, bankruptcy, cross-default.	PD: 12m PD adjusted by maturity profile for lifetime. LGD: Varies by counterparty/seniority and collateral. EAD: Contractual repayments adjusted for overpayments.	Scenarios: Baseline (20%), Upside (20%), Downside (60%). MEVs: Forward-looking scalar used because regression showed no direct link to historical defaults.
CMCB	Quantitative: 15 DPD (ST); 30 DPD (LT). Qualitative: Internal risk rating downgrades, cross-default, modification due to difficulty.	PD: Point-in-time; utilizes CBC data for low-data portfolios. LGD: Severity varies by presence of residential mortgages. EAD: Higher of balance or limit x CCF.	Scenarios: Base (68%), Best (16%), Worst (16%). MEVs: Regression using Inflation GDP (2024) or CPI (2023). Weightings adjusted for economic uncertainty.
Vattanac Bank	Quantitative: 30 DPD (LT); 15 DPD (ST). Qualitative: Breach of contract, restructuring on non-standard terms.	PD: Statistical model for remaining lifetime PD estimates. LGD: Basel IRB benchmarks (45%/30%). EAD: Gross carrying amount including expected undrawn drawdowns.	Scenarios: Baseline (40%), Best (35%), Worst (25%). MEVs: Regression of ODR against World Bank data; uses a forward-looking scalar based on ODR ratios.

4.4. Sector-Wide Comparative Analysis

The sector-wide synthesis of Cambodia's banking industry reveals a complex landscape where the literal replication of regulatory backstops coexists with significant technical divergence in modeling execution. Across all analyzed clusters—market leaders, international subsidiaries, and local institutions—there is a near-universal adoption of the 30-DPD threshold as the primary quantitative trigger for Stage 2 migration on long-term facilities. This pattern of replication ensures a baseline level of comparability for the NBC; however, nuances emerge in the treatment of short-term products, where institutions like ABA Bank, ACLEDA Bank, CMCB, and Vattanac Bank apply more conservative 15-DPD triggers, reflecting a stricter internal risk appetite.

In addressing RQ1, the results show a profound technical divide in the modeling of PD, LGD, and EAD parameters, driven largely by institutional data legacies and parent-group influence. Major international subsidiaries demonstrate a top-down strategy, leveraging sophisticated Basel II frameworks and proxy models from their global head offices to bridge local data limitations. In contrast, market leaders like ABA and ACLEDA utilize advanced internal statistical methods, such as cohort analysis or migration matrices based on multi-year historical data. Locally incorporated banks, lacking both parent proxies and extensive internal histories, adopt pragmatic, bottom-up approaches, ranging from workout style recovery analysis to the use of external CBC market default data to supplement their models.

The integration of FLI represents the most pronounced area of divergence and introduces what this study terms the macro-correlation paradox. While most subsidiaries and market leaders utilize probability-weighted economic scenarios (Base, Upside, Downside) incorporating standard MEVs like GDP growth, a segment of the market intentionally excludes these inputs when statistical relationships fail to hold. For instance, Canadia Bank and KB Prasac Bank reported regression inconsistencies between MEVs and historical defaults, choosing instead to rely on unadjusted

historical data or expert-derived scalars. These choices reflect a strategic prioritization of faithful representation over statistically forced relevance when underlying data does not support a reliable predictive relationship.

Regarding RQ2, the variation in ECL disclosure quality across the sector indicates that IFRS 9 compliance is utilized as a strategic communication tool rather than a purely technical exercise. Institutions with granular ECL disclosures and detailed sensitivity analyses, such as CIMB Bank or Vattanac Bank, use technical transparency to signal institutional safety and model sophistication to primary users. These banks often provide detailed reconciliations of loss allowances and gross carrying amounts by stage, which assists investors in assessing future cash flows. Conversely, other institutions remain technically opaque, focusing their disclosures on broad regulatory alignment and providing minimal insight into the internal arrows of their predictive systems.

This variation in transparency is further explained by the management choice to expose or mask internal modeling assumptions based on institutional maturity. Market leaders like ABA Bank enhance their ECL disclosure quality by providing explicit reconciliations of management overlays, such as the USD 58 million applied in 2024 to account for broader economic uncertainties not captured by mechanistic models. International subsidiaries, such as Maybank and CIMB, align their local disclosures with global standards, signaling a commitment to high-quality financial reporting that may potentially lower their long-term cost of capital. In contrast, institutions that provide only minimal notes often signal a prioritization of regulatory compliance over the communicative potential of the standard.

The synthesis also highlights the tension between regulatory requirements and accounting objectives in the Cambodian context. Banks must reconcile the principle-based impairment requirements of IFRS 9 with the prescribed credit grading rates issued by the NBC, often leading to the creation of regulatory reserves when accounting provisions fall below prudential floors. This dual-reporting environment influences how institutions operationalize SICR triggers, as seen in the mapping of regulatory grades like Special Mention directly to Stage 2 migration. Ultimately, this alignment ensures that while modeling techniques diverge, the prudential baseline for credit risk classification remains relatively consistent across the industry.

In a nutshell, the sector-wide comparative analysis underscores that while IFRS 9 provides a uniform technical framework, the operationalization of ECL (RQ1) and the depth of resulting disclosures (RQ2) are shaped by the interplay of data availability, parentage, and management's strategic intent. The industry is bifurcated between highly transparent institutions that embrace model complexity to signal resilience and technically opaque banks that treat IFRS 9 as a regulatory box to be checked. This divergence emphasizes that the faithful representation of a bank's risk profile in an emerging market remains as much an act of management judgment as a statistical calculation.

5. Discussion

The qualitative content analysis reveals a significant transparency gap across the Cambodian banking sector, where IFRS 9 compliance often serves as a strategic communication tool rather than a purely standardized technical exercise. This technical divide is most apparent between market leaders, who leverage granular ECL disclosures to signal model sophistication, and other institutions that remain technically opaque by providing only minimal notes on broad regulatory alignment. For instance, while institutions like CIMB Bank and Vattanac Bank provide detailed sensitivity analyses and reconciliations of loss allowances, others omit the specific impact of shifts in MEVs, making it difficult for investors to evaluate institutional resilience.

This variation suggests that ECL disclosure quality in an emerging market is a strategic choice driven by management's willingness to expose internal predictive assumptions. Institutions utilizing advanced internal statistical methods, such as ABA Bank's Cohort Analysis (Gamma), often use technical transparency to signal institutional safety and model sophistry to primary users. Conversely, institutions that provide technically opaque disclosures may be prioritizing basic

regulatory compliance over the communicative potential of the standard, potentially obscuring underlying model deficiencies.

Management overlays, or post-model adjustments, have emerged as a critical mechanism for bridging the gap between mechanistic statistical outputs and the qualitative realities of the Cambodian market. Under IFRS 9, these qualitative adjustments allow banks to incorporate FLI regarding risks that are not fully captured by objective delinquency data or historical models. In the context of Cambodia's current economic headwinds, including a stagnant real estate sector and high capital funding costs, these overlays serve as a vital buffer for institutional stability.

A prime example is found in ABA Bank, which explicitly reconciled a USD 58 million management overlay in 2024 to account for economic uncertainties not captured by its mechanistic models. Similarly, the incorporation of overlays by Woori Bank to address bankruptcy restructuring risks demonstrates how qualitative triggers are essential for a holistic assessment of borrower viability. This reliance on subjective judgment underscores that ECL compliance during periods of credit stress is as much an act of management assessment as it is a statistical calculation.

The integration of FLI into ECL models introduces a fundamental tension between relevance and faithful representation, as outlined in the IFRS *Conceptual Framework*. While IFRS 9 aims to enhance relevance by making provisions anticipatory, the study identifies a macro-correlation paradox where institutions struggle to link external MEVs to internal default rates. This complexity is particularly pronounced for locally incorporated banks that lack the top-down proxy models provided by international parent groups.

Strategic divergence occurs when banks, such as Canadia Bank and KB Prasac Bank, find no statistical correlation between standard MEVs and historical default rates. In these cases, management may choose to prioritize faithful representation by relying on unadjusted historical data or expert-derived scalars rather than forcing a statistically unreliable predictive relationship. This highlights that in data-limited emerging markets, a simpler modeling approach may sometimes provide more neutral and useful information than a highly complex but statistically weak model.

For the NBC, these findings highlight an urgent need for the standardization of modeling assumptions and MEVs to improve inter-bank comparability. While the NBC has modernized its supervisory framework with 51 reporting templates and automated data verification via the NBC Portal, the diverse ways institutions operationalize SICR triggers remain a challenge for system-wide analysis. Regulatory updates in 2025 have already moved toward tightening oversight through early intervention measures and revised capital buffer requirements.

6. Conclusions

This study has provided a comprehensive qualitative analysis of the heterogeneous IFRS 9 compliance strategies adopted within the Cambodian banking sector during a period of heightened credit stress. The findings reveal a significant technical divide shaped by institutional data legacies and parent-group influence. While there is a near-universal adoption of the 30-DPD threshold as a primary quantitative backstop for identifying a SICR, the modeling of core parameters such as PD and LGD varies significantly across institutional clusters. Market leaders like ABA Bank and ACLEDA Bank utilize advanced internal statistical methods, such as cohort analysis or multi-year migration matrices, whereas international subsidiaries rely heavily on top-down proxy models provided by their global head offices.

The FLI has introduced a pronounced macro-correlation paradox within the sector. While many institutions utilize probability-weighted economic scenarios, others—specifically Canadia Bank and KB Prasac Bank—have intentionally excluded external MEVs after finding no reliable statistical link between these variables and internal default rates. In these instances, management prioritizes faithful representation by relying on unadjusted historical data or expert-derived scalars rather than forcing statistically weak predictive relationships.

Furthermore, the study identifies a significant transparency gap where technical disclosures are leveraged as a strategic communication tool. Highly transparent institutions use granular technical

notes and sensitivity analyses to signal institutional safety and model resilience to investors and regulators. Conversely, technically opaque institutions provide only minimal notes focused on broad regulatory alignment, potentially obscuring underlying model deficiencies. Finally, the reliance on management overlays, such as the USD 58 million buffer applied by ABA Bank, underscores that ECL compliance remains as much an act of subjective management judgment as a mechanistic statistical calculation.

Despite the rigor of the qualitative content analysis, this study is subject to several limitations. First, the data were drawn solely from commercial and specialized banks in one emerging market—Cambodia—which may limit the immediate generalizability of the findings to other developing economies with different regulatory settings. Second, the analysis is based primarily on documentary evidence from published audited financial statements. While these reports provide stable and precise technical nomenclature, they may not capture the full nuance of internal risk-ownership dynamics or the informal management discussions that drive staging decisions.

Third, the sample size of 13 representative institutions, while providing deep insights through replication logic, represents only a portion of the total population of 59 commercial banks in Cambodia. Consequently, the technical practices of smaller or more niche institutions may not be fully represented. Additionally, as a qualitative study, this research does not attempt to quantify the exact magnitude of the impact of IFRS 9 on bank performance indicators like return on assets and return on equity, a task addressed by prior quantitative studies. Finally, while the study considers the 2024 reporting period, the long-term stability of these models across multiple economic cycles remains an area for further investigation.

Building on these findings, several pathways for future research are identified. To enhance comparability, future studies should consider cross-country examinations of IFRS 9 implementation in emerging markets with varying levels of dollarization and data availability. Longitudinal research is also needed to track the evolution of ECL models as Cambodian institutions accumulate more historical data and refine their internal CRR systems. Further research could also investigate the efficacy of management overlays in predicting actual losses during economic downturns, exploring whether these post-model adjustments serve as genuine safety buffers or tools for earnings management. Additionally, analyzing the impact of IFRS 9 on the quality of earnings and the value relevance of accounting information for primary users in developing stock markets like the CSX would provide vital practical insights. Finally, as the digital economy expands, the role of artificial intelligence and machine learning in enhancing the predictive power of ECL models for MSME and retail portfolios warrants significant academic attention.

Funding: This research received no external funding. CamEd Business School funded the APC.

Institutional Review Board Statement: Not applicable, as this study does not involve human or animal subjects and is based solely on the qualitative analysis of published audited financial statements.

Informed Consent Statement: Not applicable, as this research did not involve human participants.

Data Availability Statement: The original contributions presented in this study are contained within the article, specifically through the qualitative content analysis of the 2024 audited financial statements of the 13 analyzed Cambodian banks. These primary documents are publicly available on the respective official websites of these financial institutions.

Conflicts of Interest: The author declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

CBC	Credit Bureau Cambodia
CCF	Cash Conversion Factors
CIFRS	Cambodian International Financial Reporting Standards

CRR	Credit Risk Rating
DPD	Days Past Due
EAD	Exposure at Default
ECL	Expected Credit Loss
FLI	Forward-Looking Information
IFRS 9	International Financial Reporting Standard 9
LGD	Loss Given Default
MEV	Macroeconomic Variable
NBC	National Bank of Cambodia
NPL	Non-Performing Loan
ODR	Observed Default Rate
PD	Probability of Default
POCI	Purchased or Originated Credit-Impaired
SICR	Significant Increase in Credit Risk

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