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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, whereas 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 consistent with a signaling interpretation regarding institutional safety. These results suggest that ECL compliance in data-limited environments may be interpreted as 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 (ICL) 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).

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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).

Academically, this research addresses a notable gap by positioning its contribution within the growing international literature on IFRS 9. While a global study of 666 banks suggests that IFRS 9 implementation facilitates a reduction in bank risk through increased transparency (Kyiu & Tawiah, 2025), other research highlights the strategic use of reporting discretion inherent in the standard's principle-based nature (Bischof et al., 2022; Ulfah & Diyanty, 2024). In Germany, Bischof et al. (2022) found that banks assign better internal ratings to identical borrowers to avoid the higher provisioning required by Stage 2, while Shubita et al. (2025) documented a structural shift in capital management in Jordan as banks strengthened capital buffers to absorb anticipated credit risks. Despite these quantitative insights, there is a profound lack of qualitative research explaining how and why banks in data-limited emerging markets define and operationalize these complex technical parameters during periods of economic uncertainty.

This study is theoretically grounded in the IFRS *Conceptual Framework*, specifically examining the tension between relevance (predictive value through FLI) and faithful representation (neutrality and completeness). In emerging market contexts like Cambodia, this balance is tested by data limitations and unique regulatory settings. The Cambodian financial system is currently 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 environment provides a compelling case study to investigate how banks operationalize SICR triggers and technical parameters when statistical links to historical defaults may be weak—a phenomenon this study identifies as the "macro-correlation paradox."

The analysis reveals that ECL compliance strategies are not uniform but are shaped by specific drivers of variation, including bank size, internal technical capacity, ownership structure, and domestic data legacies. Market leaders with high-volume domestic data legacies demonstrate high technical sophistication by developing advanced internal statistical methods, such as cohort analysis. In contrast, major international subsidiaries leverage top-down proxy models and parent-group influence to bridge local data gaps and ensure consistency with global standards.

Based on the documentary evidence, this paper 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 an 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?

It is a plausible inference that highly transparent institutions use granular technical disclosures to function as strategic signaling tools, reducing information asymmetry and signaling institutional safety to international investors.

The objective of this research is to perform a rigorous qualitative content analysis of 2024 audited financial statements from 13 representative institutions. By applying

replication logic, the study aims to identify sector-wide patterns and technical divides, providing vital information for supervisory authorities like the National Bank of Cambodia (NBC) regarding the impact of IFRS 9 on financial stability. The findings support the need for the regulatory standardization of certain modeling assumptions to improve inter-bank comparability without undermining the standard's principle-based nature.

The remainder of this paper is organized as follows: Section 2 establishes the institutional and theoretical context while reviewing international perspectives on IFRS 9 implementation; Section 3 details the materials and methods, including the multiple-case study design; Section 4 presents the results by institutional cluster; Section 5 discusses the underlying drivers of variation and the macro-correlation paradox; and Section 6 concludes the study by outlining limitations and policy recommendations.

2. Literature Review

2.1. 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, 2024b, Conceptual Framework, para. 2.5). Information is deemed relevant if it possesses predictive or confirmatory value (IFRS Foundation, 2024b, 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, 2024b, 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, 2024b, 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 strate-

gic 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, 2018b). 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, 2024c, IFRS 9, para. 5.5.5). Stage 2 includes assets showing an SICR, requiring the recognition of lifetime ECL (IFRS Foundation, 2024c, IFRS 9, para. 5.5.3). Stage 3 consists of credit-impaired or non-performing assets (IFRS Foundation, 2024c, 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, 2024c, 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, 2024a, para. BC5.84). Defining what constitutes an SICR is inherently judgmental (IFRS Foundation, 2024a, paras. BC5.154–BC5.158), relying on qualitative triggers such as loan restructuring (forbearance), bankruptcy filings, or specific industry headwinds (IFRS Foundation, 2024c, IFRS 9, para. B5.5.17). Management must also make critical assumptions when modeling technical parameters, including PD, LGD, and EAD.

2.2. International Perspectives on IFRS 9 Implementation and Bank Transparency

The shift from the "too little, too late" ICL model of IAS 39 to the forward-looking ECL model under IFRS 9 represents a paradigm shift in financial instrument accounting (Azhar, 2022; Ricapito, 2024). Internationally, this transition has been characterized by significant implementation complexity, particularly in emerging markets where data limitations are prevalent (Ricapito, 2024). Evidence from European banks suggests that rather than developing entirely new systems, the majority of institutions adapted existing Basel II regulatory models (EAD, PD, and LGD) to meet IFRS 9 requirements (Beerbaum, 2024). While this approach provided a practical transition path, it necessitated substantial model adjustments to remove embedded prudential conservatism, such as regulatory floors, and to incorporate point-in-time macroeconomic predictions (Beerbaum, 2024). In other emerging economies like Jordan, the implementation has been linked to a structural shift in capital management, with banks strengthening capital buffers while simultaneously seeing declines in equity-to-asset and loan-to-asset ratios (Shubita et al., 2025).

A central theme in international literature is the strategic use of reporting discretion inherent in the principle-based nature of IFRS 9 (Bischof et al., 2022; Ulfah & Diyanty, 2024). While the standard intends to enhance transparency, the subjectivity involved in assessing future credit events provides incentives for opportunistic reporting behavior (Beerbaum, 2024; Bischof et al., 2022). In Germany, an identification strategy centered on internal ratings found that banks assign better ratings to identical borrowers compared to non-adopters, specifically around the investment-grade cutoff (Bischof et al., 2022). This pattern is consistent with managers exploiting discretion to avoid the "cliff effect" of Stage 2 classifications, which require significantly higher provisioning (Bischof et al., 2022). Similarly, in Indonesia, the adoption of IFRS 9 was found to increase bank managerial discretion, failing to limit earnings management practices during the economic volatility of the pandemic (Ulfah & Diyanty, 2024). This indicates that simultaneous changes in

standards and economic conditions may heighten the "moral hazard" in professional judgment (Ulfah & Diyanty, 2024).

The impact of IFRS 9 on bank transparency is often framed as a "double-edged sword" (Kyiu & Tawiah, 2025). On one hand, forward-looking provisions can enhance market discipline by providing earlier warnings to capital providers regarding a bank's risk-taking behavior (Kyiu & Tawiah, 2025). A global study of 666 banks across 61 countries documented a significant decrease in bank risk following implementation, arguing that the standard's detailed disclosures on loan quality and creditworthiness reduce information asymmetry (Kyiu & Tawiah, 2025). On the other hand, the complexity and discretionary nature of ECL estimation can create opacity, allowing managers to present information that aligns with stakeholder interests while potentially obscuring underlying model deficiencies (Kyiu & Tawiah, 2025).

The role of accounting judgment is further illuminated by experimental research on managerial conservatism (Goh et al., 2021). Studies show that high supervisor conservatism is positively associated with higher levels of loan loss provisions specifically under the ECL model, a relationship not found under the more rigid ICL framework (Goh et al., 2021). Furthermore, bank managers often demonstrate unconditional conservatism in their forecasts, showing a reluctance to incorporate "good news" when historical data indicates high default risk (Du et al., 2023).

While international literature often provides quantitative evidence of IFRS 9's impact on bank risk or performance, there is a profound lack of qualitative research explaining how banks in developing economies actually define and operationalize technical parameters like PD, LGD, and EAD. Existing studies often utilize broad cross-country datasets or focus on data-rich markets like Germany, where banks adapt sophisticated Basel II models. This study fills this gap by utilizing replication logic to demonstrate how institutions in a data-limited emerging market navigate technical complexity through a blend of quantitative modeling and qualitative management overlays.

Theoretical and experimental research generally assumes that incorporating FLI through MEVs enhances the predictive value of ECL provisions. However, this study identifies a specific gap in this logic: the "macro-correlation paradox." This paradox occurs when institutions prioritize the faithful representation of their risk profile by excluding MEVs when statistical links to historical defaults remain weak. By documenting this, the study challenges the international assumption that forward-looking modeling is always statistically superior to historical benchmarks in emerging markets.

Additionally, international studies often frame IFRS 9 implementation as a technical transition. This study fills a gap in the literature regarding bank transparency and strategic reporting discretion. It positions ECL compliance as a strategic management choice rather than a standardized exercise. The findings reveal a transparency gap where highly transparent institutions use granular technical notes and sensitivity analyses specifically as signaling tools to reduce information asymmetry and signal institutional safety to global investors. This provides a Level Two inference that technical transparency is a discretionary choice driven by management's strategic intent.

Furthermore, the study addresses the need to explain the drivers of variation in ECL practices by showing how institutional data legacies and parent-group influence create a pronounced technical divide. It fills a gap by explaining why international subsidiaries utilize top-down proxy models to bridge local data gaps, while market leaders develop advanced internal statistical methods like cohort analysis. This moves the study beyond a simple comparison of banks to an analysis of how institutional capacity and ownership structure dictate compliance strategies during periods of credit stress.

Finally, while some international research has examined IFRS 9 during the global pandemic, there is little evidence regarding how banks in small emerging markets operationalize SICR triggers during localized economic headwinds, such as an NPL ratio of 8.6%. The study fills this gap by providing an empirical examination of how banks use management overlays and qualitative triggers (such as restructuring and bankruptcy indicators) to bridge the gap between mechanistic statistical outputs and the qualitative realities of a stagnant market.

3. Materials and Methods

3.1. Multiple-Case Study Design and Replication Logic

This research utilizes a multiple-case study design to investigate the heterogeneous IFRS 9 ECL compliance strategies within the Cambodian banking sector. Following the methodological framework established by Yin (2018b), evidence derived from multiple cases is considered more robust and compelling than single-case evidence.

The study strictly adheres to replication logic rather than the sampling logic characteristic of survey-based research. Following the guidelines from Yin (2018b), cases were selected to facilitate either literal replication (predicting analogous results within clusters) or theoretical replication (producing contrasting results for anticipatable reasons, such as varying technical capacities or parent-group influence). This embedded design allows for a multi-layered analysis: the primary unit of analysis is the institutional compliance strategy, while embedded subunits include the granular technical parameters of ECL models, such as PD, LGD, and EAD.

3.2. Sampling Rationale and Representativeness

The study's sample comprises 13 representative institutions selected from the total population of 59 commercial banks operating in Cambodia. To ensure a comprehensive and faithful representation of the sector, a stratified purposive sampling approach was employed, focusing on three critical dimensions: market share, systemic importance, and ownership structure. This methodology allows for a nuanced analysis of IFRS 9 ECL compliance strategies across diverse institutional profiles, ranging from large market leaders to international subsidiaries and specialized domestic banks.

Quantitative evidence from the NBC Annual Supervision Report 2025 confirms that the selected sample represents a significant cross-section of systemically important financial institutions, collectively accounting for approximately 61.2% of total commercial banking assets as of 31 December 2025 and 60.8% as of 31 December 2024. Additionally, these institutions represent approximately 64.7% of the commercial banking sector's total credit activity as of 31 December 2025. The sample includes the nation's two largest commercial banks, ABA and ACLEDA Bank, which together accounted for approximately 28.7% and 27.3% of the sector's total assets in 2025 and 2024, respectively. By including these benchmarks alongside other major players—such as Canadia Bank (asset shares of 9.4% in 2025 and 9.7% in 2024) and KB Prasac Bank (asset shares of 6.0% in 2025 and 6.4% in 2024)—the study ensures that the qualitative findings regarding technical modeling and disclosure granularity reflect the core drivers of financial stability within the Cambodian banking industry.

3.3. Rationale for Institutional Clustering

To systematically analyze the drivers of variation in ECL practices, the study classifies institutions into three distinct clusters based on their institutional data legacies and parent-group influence. The first group, Market Leaders and Systemically Important Banks, includes ABA, ACLEDA Bank, and Canadia Bank, which serve as the primary industry

benchmarks. These institutions are clustered to examine how their high-volume domestic data legacies and systemic responsibility influence their internal statistical modeling and institutional reporting strategies.

The second cluster consists of Major International Subsidiaries, such as Maybank, CIMB, Shinhan Bank, Woori Bank, and Campu Bank, to investigate the top-down influence of global parent company standards on local implementation. These banks often bridge local data gaps by leveraging sophisticated Basel II or III models adapted from their global head offices for IFRS 9 compliance, a strategy that highlights a significant technical divide across the sector.

Finally, the study analyzes Key Locally Incorporated and Specialized Institutions, comprising Foreign Trade Bank (FTB), Sathapana Bank, KB Prasac Bank, Chip Mong Commercial Bank (CMCB), and Vattanac Bank. This group focuses on institutions with deep local roots or specific market orientations, such as a retail or Small and Medium Enterprise (SME) focus and was clustered to reveal how domestic banks navigate technical complexity without the support of international parent-group proxy models.

3.4. Data Collection and Sources

The primary data source consists of audited financial statements and annual reports for the fiscal year ending 31 December 2024. Documentary evidence was selected as the centerpiece of this inquiry because it is stable, unobtrusive, and provides the precise technical nomenclature required to evaluate ECL modeling (Yin, 2018a). These documents were manually accessed from official bank websites between January and April 2026 to ensure a complete audit trail.

3.5. Coding Protocol and Analytic Strategy

The study utilizes qualitative content analysis through a hybrid deductive-inductive coding approach to investigate institutional compliance strategies. Initially, a coding framework was deductively derived from the technical mandates of IFRS 9, focusing on the core requirements for staging and impairment. However, as data extraction from the 13 representative 2024 financial statements progressed, inductive codes were developed to capture emergent phenomena, specifically the macro-correlation paradox regarding the exclusion of weak macroeconomic data and the strategic use of technical transparency as a "signaling tool" for institutional safety.

The core of the coding protocol focuses on SICR triggers and model inputs. For SICR, the analysis codes both quantitative backstops—such as the standard 30-DPD and more conservative 15-DPD thresholds—and qualitative indicators including loan restructuring, evidence of bankruptcy, and modified auditor opinions. Model inputs are meticulously extracted by examining the specific methodologies used for PD, LGD, and EAD.

Furthermore, the analytic strategy addresses FLI, management overlays, and disclosure quality. FLI coding examines the integration of macroeconomic variables (such as GDP and inflation), scenario weightings, and the critical distinction between establishing a statistical link versus applying expert scalars. This is complemented by documenting explicit management overlays, or post-model adjustments, used to account for uncertainties not captured by mechanistic statistical outputs. To evaluate the effectiveness of communication with stakeholders, the study codes for disclosure quality, specifically checking for the presence of technical sensitivity analyses, stage reconciliation tables, and the mapping of regulatory grades to IFRS 9 stages.

3.6. Interpretive Consistency and Reliability

To ensure interpretive consistency and minimize researcher bias, a formal case study database was maintained throughout the analysis, a critical principle for increasing the

reliability of qualitative findings. While the internal database includes raw financial statements and a comprehensive coding matrix of excerpts, Table 1 (the Supplementary Data Extraction Matrix) serves as the primary audit trail for the documentary evidence presented in this study. This matrix provides external readers with a transparent link between specific institutional findings and the primary source documents, detailing the stable URLs, exact page numbers, and the specific Technical Notes analyzed for each of the 13 banks.

Table 1. Supplementary Data Extraction Matrix and Audit Trail.

Bank Name	Primary Source Document Analyzed	URL	Key Notes for ECL Disclosures	Page Numbers
ABA	Annual report 2024 (Advanced Bank of Asia Ltd., 2025)	https://www.ababank.com/fileadmin/user_upload/Annual_Reports/ABA_Bank_Annual_Report_2024-EN.pdf (accessed on 4 April 2026)	Note 2.6 Note 3.1 Note 32.1.2(a) Note 32.1.2(a)(i) Note 32.1.2(a)(ii) Note 32.1.2(a)(iv) Note 32.1.3	42–46 50–51 72–74 74 74–75 76 77–85
ACLEDA Bank	2024 Annual Report (ACLEDA Bank Plc., 2025)	https://www.acledabank.com.kh/kh/assets/pdf_zip/ACLEDA-Annual-Report-2024-High.pdf (accessed on 4 April 2026)	Note 2(e)(vii) Note 2(q) Note 4 Note 39.1(f) Note 39.1(g) Note 39.1(h)	31–35 42–43 47–48 126–137 138–152 153
Canadia Bank	Annual report 2024 (Canadia Bank Plc., 2025)	https://cdn.prod.website-files.com/5ee6fcad61bab357cf10c8fa/68550f64679ed35cfab2e483_ANNUAL%20REPORT%202024_FA_V003_for%20Views.pdf (accessed on 5 April 2026)	Note 2.6.1(iv) Note 2.15 Note 39.1(c) Note 39.1(d)	78–79 83 143–146 147–149
Maybank	Annual report 2024 (Maybank (Cambodia) Plc. (2025))	https://www.maybank2u.com.kh/iwov-resources/kh/pdf/annual_report/AR-2024-ENG.pdf (accessed on 11 April 2026)	Note 2.3.1(d)(i), (ii), and (v) Note 2.3.14(iii) Note 2.3.15 Note 3.2.1 Note 9 and 9(ii) Note 31.2(e) Note 31.3.1	76–77 81 81–82 83 88–90 119 120–121
CIMB	Annual report 2024 (CIMB Bank PLC, 2025)	https://www.cimbbank.com.kh/content/dam/cimbkh/personal/annual-reports/20231/2024_CIMB_AR_EN_Digital.pdf (accessed on 11 April 2026)	Note 2.5(vii) Note 2.18 Note 35.1(c) Note 35.1(d) Note 35.1(e) Note 35.1(f) Note 35.1(i)	100 103 124–126 126–127 127–128 129–131 133–134
Shinhan Bank	Annual report 2024 (Shinhan Bank (Cambodia) Plc. (2025))	https://shinhan.com.kh/uploads/2025/Annual%20report/Annual%20Report%20EN%E2%80%8B%202024%20for%20mail01.pdf (accessed on 12 April 2026)	Note 5(c)(vii) Note 5(t)(iii) Note 36(a)(i) Note 36(a)(iii) Note 36(a)(iv) Note 36(a)(v) Note 36(a)(vi)	57–63 71–72 105 106–111 112–113 113–119 119–121

Table 1. *Cont.*

Bank Name	Primary Source Document Analyzed	URL	Key Notes for ECL Disclosures	Page Numbers
Woori Bank	Financial statements for the year ended 31 December 2024 and report of the independent auditors (Woori Bank (Cambodia) Plc. (2025))	https://www.wooribank.com.kh/wp-content/uploads/2025/06/Woori-31-Dec-2024-FS-EN-Signed.pdf (accessed on 12 April 2026)	Note 31B(i) Note 31B(iv) Note 31B(v) Note 31C(i) Note 33C(vii) Note 33S	49–54 62–67 67–69 69–72 90–94 103–104
Campu Bank	Annual report 2024 (Cambodian Public Bank Plc., 2025)	https://www.cpbebank.com/media/dgzhl4ae/campu-bank-annual-2024-eng.pdf (accessed on 14 April 2026)	Note 2.7.1(vi)(b) Note 2.7.13 Note 6(i) Note 27.2(d) Note 27.2(e) Note 27.2(f)	71–74 81–82 92–93 127 128–131 132–135
FTB	Annual report 2024 (Foreign Trade Bank of Cambodia, 2025)	https://ftb.com.kh/uploads/2025/06/Final-FTB-AR-2024-EN.pdf (accessed on 14 April 2026)	Note 2.5(e) Note 2.18 Note 3 Note 36.1(c) Note 36.1(d) Note 36.1(e) Note 36.1(f)	61–62 71–72 72–73 111–116 116–117 118–122 123–126
Sathapana Bank	Annual report 2024 (Sathapana Bank Plc., 2025)	https://www.sathapana.com.kh/storage/annual_report/Sathapana_Bank_Annual_Report_2024_English.pdf (accessed on 15 April 2026)	Note 2.5.1(g) Note 2.5.15 Note 2.6.2 Note 6(i) Note 17(iv) Note 30.2	70–72 77 80–81 86 101–102 115–120
KB Prasac	Annual report 2024 (KB Prasac Bank Plc., 2025)	https://www.kbprasacbank.com.kh/wp-content/uploads/2025/06/KB-PRASAC-Annual-Report-2024_EN.pdf (accessed on 14 April 2026)	Note 2.6.1(iv) Note 2.12 Note 34.1(b) Note 34.1(c) Note 34.1(f) Note 34.1(g)(i)	15 18 54 54–58 63–64 65
CMCB	Annual report 2024 (Chip Mong Commercial Bank Plc., 2025)	https://www.chipmongbank.com/en/files/annual_report_2024_en.pdf (accessed on 15 April 2026)	Note 2.5(e) Note 2.17 Note 35.1(b) Note 35.1(c) Note 35.1(d) Note 35.1(f)	50 53 76 76–79 79–80 83–87
Vattanac Bank	Annual report 2024 (Vattanac Bank, 2025)	https://drive.google.com/file/d/1JN0vm_g-KtuPYnaiolZCFID5OBQ0R83h/view (accessed on 16 April 2026)	Note 33B(v) Note 33B(vi) Note 33C(i) Note 33C(ii) Note 35C(vii) Note 35Q	140–147 148–155 155–158 158–160 171–176 183–184

By providing these direct references, the study maintains a rigorous chain of evidence, allowing for the derivation of findings to be traced from the initial research questions back to the original technical disclosures. This structure adheres to the methodological standards established by Yin (2018a), ensuring that the evidence is sufficient for independent verification. Finally, construct validity was further strengthened through data triangulation

within each case, cross-referencing technical ECL notes with management commentary and independent auditor reports to ensure a faithful representation of each institution's compliance strategy.

Finally, the study strengthened construct validity through data triangulation within each institutional case. By comparing technical notes with management commentary and independent auditor reports, the researcher ensured a faithful representation of each bank's ECL strategy. This triangulating fashion minimizes the subjective judgments often criticized in qualitative research and ensures that the operational measures accurately reflect the technical parameters being studied.

4. Results

4.1. Market Leaders and Systemically Important Banks

This institutional cluster comprising ABA, ACLEDA Bank, and Canadia Bank serves as the primary industry benchmark for ECL compliance in Cambodia. Their strategies are predominantly driven by high-volume domestic data legacies and their systemic responsibility to signal financial stability to international investors and regulators. As summarized in Table 2, the analysis reveals a significant technical divide in how these leaders interpret the IFRS *Conceptual Framework*'s tension between relevance and faithful representation.

Table 2. ECL Compliance Strategies of Cambodian Market Leaders.

Bank Name	ECL Model	PD/LGD/EAD Methodology	FLI Integration and Methodology	Management Overlays	MEV Sensitivity Analysis	Assessment of Disclosure Quality	Possible Signaling Interpretation
ABA	Local advanced model	PD: Cohort Analysis (Gamma) point-in-time. LGD: Period workout analysis. EAD: Gross carrying amount including undrawn limits.	Methodology: Statistical regression linking defaults to MEVs. Scenarios: Base (50%), Upside (20%), Downside (30%).	Yes: Explicit USD 58 million post-model adjustment applied to customer loans for economic uncertainties.	Yes: Detailed analysis showing the impact of applying a 100% weighting shift to individual economic scenarios.	High: Explicit reconciliation of post-model overlays and comprehensive staging details.	Signals institutional resilience and high internal model sophistication.
ACLEDA Bank	Local model	PD: Migration approach or external credit rating. LGD: Collateral-based with 10% floor. EAD: Contractual amount or CCF.	Methodology: Statistical alignment via 7-year historical data. Scenarios: Base (60%), Upside (15–25%), Downside (15–25%).	Not explicitly reconciled: Adjustments noted in narrative but not quantified or itemized in the ECL notes.	Yes: Comprehensive sectoral analysis, such as the reported USD 11.46 million impact for the Retail Trade sector.	High: Detailed reporting on sectoral sensitivities and granular stage movements.	Signals financial stability and creditworthiness to international investors.
Canadia Bank	Local model	PD: Likelihood of default (12 m/lifetime). LGD: Varies by counterparty and seniority. EAD: Contractual repayments or utilization.	Methodology: Regression showed no statistical link; FLI excluded in 2024. Scenarios: None incorporated.	Not explicitly reconciled: Adjustments performed based on periodic assessments without formal reconciliation.	No: Standard sensitivity analysis omitted due to the lack of a statistically validated relationship with MEVs.	Low/Moderate: Focus on broad alignment with primary regulatory requirements.	Signals prioritization of neutrality and faithful representation over complex modeling.

Note: The first six columns of this table summarize observed documentary evidence extracted directly from the 2024 audited financial statements. The final two columns represent the author's qualitative interpretation of institutional disclosure patterns, framed as plausible inferences in accordance with the replication logic detailed in Section 3.

Regarding the identification of SICR, these institutions demonstrate literal replication of objective quantitative backstops. All three banks utilize a universal 30-DPD threshold for Stage 2 migration on long-term facilities, aligning with the rebuttable presumption in

IFRS 9. However, technical sophistication is evident in the adoption of more conservative triggers for short-term products; ABA and ACLEDA utilize a 15-DPD backstop, reflecting a stricter internal risk appetite and a commitment to earlier impairment recognition.

To ensure credit risk migration is not merely a function of delinquency, ABA and ACLEDA systematically map these triggers to internal Credit Risk Rating (CRR) scales (1–10). For example, a downgrade to ABA's Rating 9 (Watch List) functions as a primary driver for staging, facilitating a holistic assessment of borrower viability. These qualitative triggers, which include loan restructuring and bankruptcy indicators, ensure a multifactor approach to credit monitoring.

A profound modeling divide exists within this cluster, driven by varying institutional capacities and the maturity of internal statistical systems. ABA demonstrates the highest level of complexity by utilizing Cohort Analysis (Gamma) to generate point-in-time PD estimates. In contrast, ACLEDA Bank employs a more pragmatic migration approach based on seven years of historical data to estimate risk. Canadia Bank utilizes a straightforward likelihood of default model, assessing 12-month and lifetime horizons based on historical benchmarking.

The integration of FLI reveals a strategic divergence identified as the macro-correlation paradox. While ABA and ACLEDA prioritize the relevance of their models by integrating probability-weighted scenarios (Base, Upside, and Downside), Canadia Bank excluded FLI in 2024. Canadia's regression analysis found no statistically reliable relationship between MEVs and historical defaults, leading management to prioritize faithful representation through unadjusted data rather than forcing a weak predictive link.

As detailed in Table 2, ABA and ACLEDA successfully link defaults to Cambodian-specific MEVs, including GDP growth and USD/KHR exchange rates. ACLEDA further enhances technical transparency by disclosing a 10% LGD floor for over-collateralized real estate loans, a prudential adjustment designed to account for local market illiquidity. These modeling choices reflect how institutional capacity dictates the operationalization of technical parameters.

Ultimately, the variation in disclosure quality across these leaders is consistent with a signaling interpretation regarding IFRS 9 compliance. Granular disclosures, such as ABA's explicit reconciliation of a USD 58 million management overlay, are leveraged to reduce information asymmetry and signal institutional resilience to global investors. Conversely, a reliance on unadjusted data in other cases may signal a prioritization of neutrality over complex, statistically weak modeling. Detailed ECL disclosure practices and technical note references for each bank are provided in Appendix A.

4.2. Major International Subsidiaries

This institutional cluster comprising Maybank, CIMB, Shinhan Bank, Woori Bank, and Campu Bank is primarily defined by its ownership structure and the resulting parent-group influence on local implementation. As summarized in Table 3, these institutions exhibit a high degree of literal replication in their structural adoption of the IFRS 9 ECL framework. Their strategies are driven by a need to maintain technical consistency across regional operations, ensuring that Cambodian reporting aligns with the global standards of their respective parent entities.

Regarding the identification of SICR, these institutions demonstrate a near-universal adoption of the 30-DPD backstop as the primary quantitative trigger for Stage 2 migration on long-term facilities. This quantitative benchmark is systematically augmented by qualitative overlays, such as loan restructuring (forbearance), cross-default obligations, and evidence of bankruptcy. This multifactor approach ensures that credit risk migration is

not merely a function of objective delinquency data, but a holistic assessment of borrower viability monitored through parent-group risk management protocols.

Table 3. ECL Compliance Strategies of Major International Subsidiaries.

Bank Name	ECL Model	PD/LGD/EAD Methodology	FLI Integration and Methodology	Management Overlays	MEV Sensitivity Analysis	Assessment of Disclosure Quality	Possible Signaling Interpretation
Maybank	Parent-group models	PD/LGD: Point-in-time based on group Basel II models. EAD: Expected drawdowns for revolving facilities.	Methodology: Evaluations of outcomes using Maybank IBG forecasts. Scenarios: Base, Upside, Downside.	Yes: Qualitative provisions increased in response to observed rises in NPL.	Yes: Focused on market risk sensitivities, specifically a ±1% shift in FX rates.	High: Granular stage reconciliations and transparent reporting of sector concentrations.	Signals global institutional safety and regional model resilience.
CIMB Bank	Parent-group models	PD: Point-in-time; uses group proxy PDs for low-data portfolios. EAD: Higher of balance or CCF-adjusted limit.	Methodology: Statistical regression linking CPI in 2024 or GDP in 2023 to defaults. Scenarios: Base (70%), Upside (10%), Downside (20%).	Yes: Specific post-model adjustments applied to selected industry portfolios and restructured loans.	Yes: Explicit quantification of impact for key variables, such as a ±1% CPI change (USD 304,910).	High: Itemized MEV sensitivity impacts and highly granular technical notes.	Signals technical sophistication and a strategic commitment to transparency.
Shinhan Bank	Parent-group models	PD/LGD: Estimated via proxy models provided by Head Office. EAD: Internal CCFs (75% credit; 100% guarantees).	Methodology: Incorporates FLI adjusted at Head Office level. Scenarios: Integrated into group-level proxy modeling.	Yes: Qualitative assessments utilized to absorb anticipated future credit risk not captured by proxy models.	Yes: Detailed tabulated impact showing a ±1% change in the overall ECL rate (USD 181,731).	Moderate/High: Comprehensive reconciliations of stages and detailed collateral mapping.	Signals strong parent-group support and conservative risk management.
Woori Bank	Local framework (with parent alignment)	PD: Migration approach based on historical data. LGD: Historical recovery analysis with applied floors. EAD: Amortization profiles and drawdowns.	Methodology: Statistical regression linking MEVs to PD only. Scenarios: Base (68%), Upside (16%), Downside (16%).	Yes: Additional ECL set aside for restructured loans and identified vulnerable economic sectors.	No: Sensitivity provided for market risks (e.g., interest rates); no explicit ±1% MEV impact table.	Moderate: Focus on mapping regulatory credit grades to the IFRS 9 staging framework.	Signals prioritization of regulatory alignment over communicative depth.
Campu Bank	Parent-group influence	PD: Point-in-time estimates. LGD: Workout style with collateral mitigation. EAD: Principal and interest plus drawdowns.	Methodology: Statistical scalar correlating GDP and investment to defaults. Scenarios: Base, Upside, Downside.	Yes: Forward-looking adjustments integrated via single probability-weighted scalars.	No: MEV sensitivity analysis for FX omitted based on a lack of materiality.	Low/Moderate: Emphasis on broad regulatory reporting and alignment with NBC standards.	Signals prioritization of faithful representation through basic compliance.

Note: The first six columns of this table summarize observed documentary evidence extracted directly from the 2024 audited financial statements. The final two columns represent the author's qualitative interpretation of institutional disclosure patterns, framed as plausible inferences in accordance with the replication logic detailed in Section 3.

A defining characteristic of this cluster is its technical sophistication, manifested through the heavy reliance on global parent-group expertise to bridge domestic data limitations. Rather than building frameworks from the ground up, these subsidiaries leverage top-down proxy models and sophisticated Basel II or III frameworks adapted from their head offices for IFRS 9 compliance. This approach creates a pronounced technical divide across the sector, as these institutions utilize point-in-time estimates for PD and LGD that are often more statistically mature than those used by local banks.

The integration of FLI further illustrates the strategic influence of parent entities, with MEVs frequently sourced from centralized research arms, such as the Maybank Investment Banking Group or parent-level economics teams. While standard indicators like GDP growth and USD/KHR exchange rates are utilized across the cluster, specific institutions prioritize different localized indicators to calibrate their models. For example, CIMB emphasized the Consumer Price Index (CPI) in its 2024 modeling, whereas Campu Bank focused on the statistical correlation between investment rates and defaults.

Despite a shared reliance on parent frameworks, a significant transparency gap exists within this cluster regarding ECL disclosure quality. Institutions like Maybank and CIMB provide granular reconciliations of movements in loss allowances and gross carrying amounts by stage, assisting primary users in evaluating the drivers of credit risk migration. Conversely, other subsidiaries remain more technically opaque, focusing their disclosures on broad regulatory alignment with the NBC. This variation underscores that technical transparency functions as a strategic signaling tool, leveraged by management to signal institutional safety and model resilience to international capital providers. Detailed ECL disclosure practices and technical note references for each financial institution are provided in Appendix B.

4.3. Key Locally Incorporated and Specialized Institutions

The institutional cluster comprising FTB, Sathapana Bank, KB Prasac Bank, CMCB, and Vattanac Bank focuses on institutions with deep local roots or specific market orientations, such as a retail or SME focus. As summarized in Table 4, these institutions exhibit a strategy of theoretical replication, where compliance choices are driven by diverse institutional data legacies rather than the top-down parent-group influence seen in international subsidiaries. Academically, this cluster reveals how domestic banks navigate technical complexity by balancing internal historical data with external benchmarks.

Regarding the identification of SICR, these institutions demonstrate literal replication concerning the 30-DPD backstop for Stage 2 migration on long-term facilities. However, a significant divergence in technical sophistication occurs in the treatment of short-term products; CMCB and Vattanac Bank apply a more conservative 15-DPD trigger for migration, reflecting a stricter internal risk appetite during periods of credit stress. This quantitative framework is systematically augmented by qualitative triggers, such as loan restructuring (forbearance) and evidence of bankruptcy, which institutions like Sathapana and FTB map to internal monitoring categories like “Special Monitoring” or “Watch List” to ensure a holistic assessment.

The modeling of PD, LGD, and EAD parameters within this cluster exhibits a pragmatic divide based on internal institutional capacity and data availability. For instance, CMCB distinguishes itself by utilizing Credit Bureau Cambodia (CBC) market default data to supplement portfolios where internal historical data is insufficient. In contrast, Vattanac Bank relies on Basel IRB benchmarks (such as 45% for senior claims) to estimate its LGD, while Sathapana Bank utilizes a workout-style method based on historical recovery cash flows. These diverse strategies underscore that the operationalization of technical parameters is a discretionary choice shaped by the maturity of each bank’s statistical systems.

The integration of FLI further highlights the macro-correlation paradox in data-limited environments. While institutions like FTB and CMCB successfully utilize statistical regression to link default rates to MEVs, KB Prasac Bank reported no direct statistical relationship. Consequently, KB Prasac management opted to apply a forward-looking scalar to historical risk parameters, a choice that prioritizes faithful representation over statistically forced relevance. Across the cluster, scenarios have been standardized to Base, Upside,

and Downside for comparative purposes, with weightings adjusted to reflect prevailing economic uncertainties.

Table 4. ECL Compliance Strategies of Key Locally Incorporated and Specialized Institutions.

Bank Name	ECL Model	PD/LGD/EAD Methodology	FLI Integration and Methodology	Management Overlays	MEV Sensitivity Analysis	Assessment of Disclosure Quality	Possible Signaling Interpretation
FTB	Local model	PD: Point-in-time; 12m PDs used for lifetime curves. LGD: Recovery expectations with applied floors. EAD: Contractual vs. utilized credit limit.	Methodology: Statistical regression linking defaults to ODRs. Scenarios: Base, Upside, Downside.	Not explicitly reconciled: Overlay methodology mentioned but not itemized or quantified in the 2024 notes.	Yes: Testing of major variables with a primary focus on the sensitivity of economic scenario weightings.	Moderate/High: Detailed reconciliations of loss allowances and gross carrying amounts.	Signals institutional reliability and emerging technical maturity.
Sathapana Bank	Local model	PD: Delinquency-based transition matrix and proxy models. LGD: Workout style based on historical recovery. EAD: Gross carrying amount plus future drawdowns.	Methodology: Integrated via Economic Factor Adjustment (EFA) scalar. Scenarios: Range of exposure outcomes via scenario techniques.	Not explicitly reconciled: Reconciliation focused on stage movement impacts rather than formal overlays.	No: Granular impact table for ±1% changes in specific MEVs were not included.	Low/Moderate: Focus on broad regulatory reporting and alignment with NBC standards.	Signals prioritization of faithful representation through basic compliance.
KB Prasac Bank	Local model	PD: 12m PD adjusted by maturity profile. LGD: Varies by counterparty and collateral. EAD: Contractual repayments (adjusted).	Methodology: Regression showed no direct link; used expert-derived forward-looking scalar. Scenarios: Base (20%), Upside (20%), Downside (60%).	Yes: Applied as expert-derived forward-looking scalars to historical PD and LGD parameters.	No: Scenario weightings identified as significant, but individual MEV sensitivity was not tabulated.	Low/Moderate: Technical notes restricted to broad alignment with regulatory presumptions.	Signals limitations in model transparency caused by the macro-correlation paradox.
CMCB	Local model	PD: Point-in-time; utilizes CBC market default data for gaps. LGD: Severity by mortgage presence. EAD: Higher of balance or limit × CCF.	Methodology: Statistical regression (Inflation GDP). Scenarios: Base (68%), Upside (16%), Downside (16%).	Yes: Management expert judgment used to adjust scenario weightings to reflect economic uncertainty.	Yes: Detailed sensitivity reported for Inflation GDP, including the impact of a ±19.15% shift.	High: Detailed sensitivity analysis and comprehensive movement reconciliations.	Signals technical sophistication and a strategic commitment to transparency.
Vattanac Bank	Local model	PD: Statistical model for remaining lifetime PD. LGD: Basel IRB benchmarks (45%/30%). EAD: Gross amount including future drawdowns.	Methodology: Regression of ODRs; uses forward-looking scalar based on ODR ratios. Scenarios: Base (40%), Upside (35%), Downside (25%).	Not explicitly reconciled: Manual adjustments performed to ensure adjusted PDs remain within valid statistical ranges.	Yes: Qualitative reporting on sectoral concentrations and the impact of foreign currency risk.	High: Granular movement reconciliations provided specifically by instrument class.	Signals prudent risk management and advanced model sophistication.

Note: The first six columns of this table summarize observed documentary evidence extracted directly from the 2024 audited financial statements. The final two columns represent the author's qualitative interpretation of institutional disclosure patterns, framed as plausible inferences in accordance with the replication logic detailed in Section 3.

Ultimately, the variation in disclosure quality among these institutions is consistent with a signaling interpretation regarding IFRS 9 compliance. CMCB and Vattanac Bank provide high technical transparency through granular sensitivity analyses, such as CMCB reporting the specific ECL impact of a ±19.15% shift in Inflation GDP. Conversely, Sathapana and KB Prasac remain more technically opaque, focusing their disclosures on broad

regulatory alignment with the NBC. This bifurcation indicates that while the standard provides a uniform framework, the decision to disclose internal modeling "arrows" remains a management choice. Detailed ECL disclosure practices and technical note references for each institution are provided in Appendix C.

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, 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 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.

Overall, 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, ownership structure, and management's strategic intent. The Cambodian banking industry appears bifurcated between highly transparent institutions whose adoption of model complexity is consistent with a signaling interpretation regarding institutional safety and resilience, and technically opaque banks providing disclosures that appear more focused on regulatory compliance than on detailed technical communication. This observed variation emphasizes that the faithful representation of a bank's risk profile in a data-limited environment may be interpreted as an act of management judgment rather than a standardized statistical exercise.

5. Discussion

The qualitative content analysis reveals a significant transparency gap across the Cambodian banking sector, where the observed variation in IFRS 9 compliance is consistent with a signaling interpretation rather than representing a purely standardized technical exercise. A primary driver for the divergence in modeling sophistication is bank size and internal technical capacity. Large, systemically important banks, such as ABA, demonstrate a high level of technical sophistication by utilizing complex internal statistical systems, such as Cohort Analysis (Gamma), to generate point-in-time PD estimates. The use of the gamma function to model the evolution of PD over time requires significant technical resources and historical data volume to perform maximum likelihood estimations across various loan segments. In contrast, smaller local banks with more limited technical infrastructure often adopt more pragmatic, simplified approaches, such as likelihood-of-default models based on unadjusted historical benchmarking, which require less intensive statistical validation.

The ownership structure of an institution significantly dictates its compliance strategy, particularly through parent-group influence. Major international subsidiaries, such as Maybank, CIMB, and Shinhan Bank, leverage top-down proxy models and sophisticated Basel II or III frameworks adapted from their global head offices. This reliance on centralized expertise allows these subsidiaries to bridge domestic data limitations and maintain technical consistency across regional operations. For instance, Shinhan Bank utilizes proxy PD models with multiple parameters provided by its head office, which already incorporate FLI adjusted at the group level. This strategy highlights a technical divide where subsidiaries utilize statistically mature estimates that may not be available to independent domestic banks.

Variation in modeling is further driven by institutional data legacies. Market leaders with long-standing operations in Cambodia benefit from high-volume domestic data legacies, enabling them to build robust internal models like multi-year migration matrices. Conversely, locally incorporated institutions without extensive internal histories must rely

on external benchmarks. CMCB serves as a key example, distinguishing itself by utilizing CBC market default data to supplement portfolios where internal data is insufficient. This reliance on external data underscores that the operationalization of technical parameters is a discretionary choice shaped by the maturity and depth of a bank's historical database.

This study introduces the term macro-correlation paradox as an empirical label to describe cases where institutions find no statistically reliable relationship between standard MEVs and historical default rates despite IFRS 9's mandate to include FLI. This phenomenon highlights a fundamental tension in the IFRS *Conceptual Framework* between relevance and faithful representation. In data-limited environments like Cambodia, banks such as Canadia and KB Prasac prioritized faithful representation by intentionally excluding MEVs from their 2024 ECL models. Rather than forcing a statistically weak predictive link, management chose to rely on unadjusted historical data or expert-derived scalars, suggesting that in emerging markets, a simpler model may provide more useful and neutral information than a highly complex but statistically unvalidated one.

The variation in ECL disclosure quality across the sector suggests that compliance functions as a signaling tool for stakeholders. It is a plausible inference that highly transparent institutions, such as CIMB and Vattanac Bank, use granular technical notes and detailed sensitivity analyses to signal institutional safety and model sophistication to primary users, including global investors and regulators. These granular disclosures, including explicit reconciliations of management overlays (e.g., ABA's USD 58 million adjustment), may serve to reduce information asymmetry regarding a bank's resilience. However, these differences in transparency may also reflect external factors such as the requirements of different auditors, the use of standardized group reporting templates, or varying regulatory expectations rather than purely deliberate management intent. This bifurcation emphasizes that the depth of disclosure remains a management choice that balances basic regulatory compliance against the standard's potential for strategic communication.

6. Conclusions

This study 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 an SICR, the operationalization of core parameters such as PD and LGD varies significantly across institutional clusters. Market leaders like ABA and ACLEDA Bank utilize advanced internal statistical methods, such as cohort analysis or multi-year migration matrices, whereas major international subsidiaries rely heavily on top-down proxy models provided by their global head offices.

The integration of 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—intentionally excluded external MEVs after finding no reliable statistical link between these variables and internal default rates. In these instances, the evidence suggests that management prioritizes faithful representation by relying on unadjusted historical data or expert-derived scalars rather than forcing statistically weak predictive relationships that may lack predictive value in a data-limited environment.

Furthermore, the study identifies a significant transparency gap where technical disclosures appear to function as institutional signaling devices. Based on the documentary evidence, it is a plausible inference that highly transparent institutions use granular technical notes and detailed 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, which may be interpreted as a prioritization of basic compliance over strategic communication. These findings are inferences derived from the IFRS *Conceptual Framework* and the observed data patterns. While these variations in disclosure quality suggest strategic behavior, they should be viewed as interpretations of the published reports rather than proven internal motivations, as they may also reflect differences in auditor requirements or the use of standardized group reporting templates.

From a policy perspective, these findings suggest a role for the regulatory standardization of certain modeling assumptions and macroeconomic variables to improve inter-bank comparability. However, such a recommendation must be carefully balanced against the principle-based nature of IFRS 9. While increased standardization would reduce the observed technical divide, it might also undermine the standard's core objective of allowing banks the flexibility to exercise professional judgment to faithfully represent the specific risk profiles of their unique portfolios. Regulators should therefore aim for a framework that enhances the comparability of how risks are reported without mandating a one-size-fits-all model that ignores institutional nuances.

Despite the rigor of the qualitative content analysis, this study is subject to several critical limitations regarding observable data, as the analysis relied primarily on documentary evidence from published audited financial statements and could not account for internal risk management processes, internal credit committee deliberations, or the results of internal model validation procedures and independent technical reviews. Furthermore, the research did not observe auditor-client discussions or the specific negotiations regarding the depth of disclosure, nor did it capture the informal management deliberations that drive credit staging decisions and the application of management overlays. Consequently, findings related to managerial intent and strategic signaling must be interpreted as plausible inferences derived from public reports rather than directly observed internal motivations.

Building on these findings, future research should consider longitudinal studies to track the evolution of these ECL models as more historical data becomes available. Further investigation is also warranted into 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 in emerging markets.

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Abbreviations

The following abbreviations are used in this manuscript:

CBC	Credit Bureau Cambodia
CCF	Credit Conversion Factor
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

Appendix A. ECL Disclosure Practices of Market Leaders and Systemically Important Banks

Appendix A.1. ABA

Note 32.1.2(a) describes ABA'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 an 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 an SICR utilize a multifactor approach involving both quantitative backstops and qualitative indicators. Quantitatively, the bank identifies an 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.

Appendix A.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 an 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 $\times$ LGD $\times$ 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 Credit Conversion Factor (CCF) for off-balance sheet items.

As outlined in Note 39.1(g), the criteria for identifying an 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.

Appendix A.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 an 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 an SICR involve a holistic, multifactor analysis of both quantitative and qualitative indicators. Quantitatively, the bank utilizes a backstop where an 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.

Appendix B. ECL Disclosure Practices of Major International Subsidiaries

Appendix B.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 an 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 an 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.

Appendix B.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 an 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 an 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.

Appendix B.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 an 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 an 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%.

Appendix B.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. 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 an 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 an SICR utilize both quantitative backstops and qualitative indicators. Quantitatively, the bank identifies an 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 ±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)).

Appendix B.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 an 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 an SICR involve a multifactor analysis of both quantitative backstops and qualitative indicators. Quantitatively, the bank identifies an 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.

Appendix C. ECL Disclosure Practices of Key Locally Incorporated and Specialized Institutions

Appendix C.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%.

Appendix C.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 (Credit Loss = PD $\times$ LGD $\times$ EAD $\times$ EFA $\times$ 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 an 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 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 ±1% MEV changes is not included in these excerpts, although Note 2.6.2 acknowledges FLI as a significant estimate.

Appendix C.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 ±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).

Appendix C.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 an 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 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%.

Appendix C.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 an 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 (Credit Loss = PD × LGD × 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.

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