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# Transitioning to IFRS 9

## Practical Challenges with Implementing IFRS 9 Requirements for Expected Credit Losses in the Caribbean

***A Discussion Paper by First Citizens Research & Analytics***[1]

**To be presented at the 50th Annual Monetary Studies Conference**

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**Abstract**

The International Accounting Standards Board (IASB) has developed and published the new International Financial Reporting Standard (IFRS) 9 for Financial Instruments, which will have material implications for financial institutions around the world, including for those operating in the Caribbean. The new IFRS 9 Standard became effective 1 January 2018, with early adoption permitted. The new standard replaces the International Accounting Standard (IAS) 39: Financial Instruments, which was criticized as being late in recognizing credit losses. According to the IASB, IFRS 9 specifies how an entity should classify and measure financial assets and liabilities. One of the fundamental changes introduced is the move towards impairment modelling based on *expected* credit losses. This paper will deal specifically with the impairment step in the implementation of IFRS 9 and will outline the practical challenges observed in developing a model to calculate expected credit losses given the data limitations in the Caribbean. We will compare the transition issues observed in moving towards an expected credit loss model in the Caribbean with some of the experiences in the more advanced countries.

## I. Introduction

Credit risk is generally defined as the risk arising from the possibility that the borrower will default or fail to meet his contractual obligations. For financial institutions, this is one of the most important concepts, giving rise to a credit-scoring model, which helps to quantify the probability of default. This essentially will give a financial institution an idea of the credit worthiness of a borrower. The introduction of Basel II capital requirements in 2004 placed greater emphasis on the banking sector's ability to predict probability of default. According to the Basel II requirements, the internal rating based approach (IRBA) comprises the probability of Default (PD) as well as the loss given default (LGD), exposure at default (EAD) and maturity. Accordingly, banks are required under Basel II, to maintain adequate capital levels to cover potential unexpected losses.

Under IFRS 9, the concept of credit risk analysis and management will be under even more scrutiny. The new standard suggests that recognition of impairment of a financial asset no longer solely depends on a reporting entity identifying a credit loss event, which was the main criticism of its predecessor IAS 39. IAS 39 was more 'rules-based' and was heavily criticized for being too late in recognition of a credit event. Instead, IFRS 9 uses forward-looking indicators to recognize *expected* credit losses (ECL) for all debt-type financial instruments that are not measured at fair value through profit or loss. One of the most critical principles under the new standard is the impairment methodology, which constitutes a framework for the calculation of the ECL, which would ultimately determine the loss provisions for the reporting entity.

Based on the new accounting standard, credit losses and allowances should be recognized based on expectations, which entails it has to be *before* any adverse potential credit event. According to IFRS 9, impairment of financial assets is measured as the 12-month expected credit losses or lifetime expected credit losses, depending on whether there has been a *significant increase in credit risk* associated with the asset since initial recognition. The assessment of a *significant increase in credit risk* will therefore play a critical role in the calculation of the ECL. Accordingly, all relevant historical and forward-looking information, including economic forecasts have to be incorporated into measurement of the ECL.

This discussion paper will be presented as follows: we will briefly explore the principles of IFRS 9 for Financial Instruments, including the specific requirements. We will conduct a literature review on the practical challenges in constructing and implementing the IFRS 9 requirements for expected credit losses as well the experiences of large financial institutions in some advanced economies. We will then look specifically at the practical challenges with the determination of an expected credit loss model for the Caribbean. Finally, we will conclude and discuss a way forward that can aid in the construction of a more robust and sustainable expected credit loss model.

While we will briefly explore the classification and measurement of financial assets, this paper will deal more comprehensively and specifically with some of the practical challenges observed in developing a model to determine expected credit losses given the data limitations in the Caribbean. A separate principle in the implementation of IFRS 9 deals with the concept of hedging, which is beyond the scope of this paper.

## II. Principles of IFRS 9

The IFRS 9 accounting standard was published by the International Accounting Standards Board (IASB) in July 2014, and is effective for annual periods beginning on or after 1 January 2018. IAS 39, which it superseded, was criticized as being too late in recognizing events in a credit cycle, particularly in the wake of the 2008/ 2009 global financial crisis. Even in the Caribbean region, under IAS 39, entities could not have provided for an impending debt restructuring in Barbados, although it was widely expected. Indeed, IAS 39 was based on an 'incurred losses' model – where the recognition of credit losses was delayed until there was independent and verifiable evidence of a credit event. Loss allowances were only recognized after a credit event, usually after a default. For example, entities holding Barbados debt had to wait for an actual default (missed interest or principal payment) or a downgrade to 'default' credit rating in order to recognize a credit event, and only then make a provision.

The new accounting standard was developed in three phases, dealing with:

a. Classification and measurement of financial assets
b. Impairment
c. Hedging[2]

The principles-based IFRS 9 standard requires careful use of judgement as opposed to the more rules-based approach of IAS 39. While the new IFRS 9 model may be simpler than IAS 39, analysis from PwC suggests that implementation will have several consequences, including the addition of more volatility in the income statement, earlier recognition of impairment losses on receivables and loans, as well as significant new disclosure requirements[3].

[2] Hedging will not be dealt with in this discussion paper
[3] IFRS 9, Financial Instruments – Understanding the Basics (pwc) (www.pwc.com/ifrs9)

### *i. Classification and measurement of financial assets*

The classification of financial assets is determined at initial recognition and it determines how they are categorized in the financial statements and thus, forms the foundation of how the financial instruments are accounted for, according to EY. There are three categories by which financial assets can be classified:

a. Amortized cost (AC)
b. Fair value through profit and loss (FVTPL)
c. Fair value through other comprehensive income (FVOCI)

Financial assets valued at *amortized costs* must meet specified criteria; including the condition that the asset is held within an entity whose business model allows it to hold assets in order to collect contractual cash flows. Further, the contractual terms of the financial asset should give rise on specified dates to cash flows that are solely payments of principal and interest (SPPI). This classification essentially captures what was previously referred to as 'held to maturity'.

If financial assets are held in by an entity whose business model allows both the collecting of contractual cash flows as well as the selling of financial assets, then the assets should be measured at fair value through other comprehensive income (FVOCI). Changes in fair value of FVOCI debt instruments are recognized in the income statement as other comprehensive income (OCI). This classification can be considered what was known as the 'available for sale' portfolio. Finally, any financial assets that are not held in one of the two preceding business models are measured at fair value through profit and loss (FVTPL)[4]. FVTPL essentially captures instruments that are held for trading – not holding the asset for contractual cash flows. It is the 'residual' or default category if assets do not meet the criteria to be classified as AC or FVOCI.

Only in certain circumstances can an entity reclassify a financial asset. If changes in the business model result in changes to the way the entity manages financial assets, only then can reclassification occur. It will be a significant change to the operations of the entity and is not expected to be a frequent occurrence.

[4] https://www.ifrs.org/issued-standards/list-of-standards/ifrs-9-financial-instruments/

### *ii. Impairment*

Unlike under IAS 39, which only considers impairment as a result of incurred loss events, IFRS 9 introduces several new concepts, including the expected credit loss model (ECL), which is applied using two approaches – the *general approach* which looks at significant increase in credit risk and 12 month- and lifetime- ECL. The second approach is the *simplified approach*, which would be applied to trade receivables, contract assets and lease receivables.

Credit losses are defined as the difference between all the contractual cash flows that are due to an entity and the cash flows that it actually expects to receive (cash shortfalls). Further, ECL is a probability-weighted estimate of credit losses over the expected life of a financial instrument. (Grant Thornton, 2016). The standard defines ECL as "the weighted average of credit losses with the respective risks of a default occurring as the weights".

Indeed, under the new accounting standard, reporting entities do not have to wait for a credit event in order to recognize an impairment. Instead, IFRS 9 requires that for all financial assets that are not classified as fair value through profit and loss, forward-looking macroeconomic indicators must be used to determine ECLs. Previously, under IAS 39, the incurred loss model delayed the recognition of a loss allowance until objective evidence of a credit event was available. One important implication of this change is the incurrence of a 'day-one loss' for the reporting entity – recognition of impairment no longer depends on the company first identifying a credit loss event. Specifically, under IFRS 9, entities will have to record a day-one loss on initial recognition for financial assets that are not credit impaired.

The standard generally dictates that in a reporting entity's estimation of expected credit losses, it must consider all relevant historical and forward-looking information. Indeed, entities must now introduce macroeconomic forecasts into its ECL modelling. Accordingly, *one of the fundamental challenges associated with the implementation of the IFRS 9 requirements for the expected credit loss model is how to select appropriate economic variables and how to integrate them into the ECL model.*

Under IFRS 9, an expected loss allowance has to be estimated for each type of asset or exposure and the standard specifies three different approaches depending on the type of asset or exposure. Principally, credit losses and the resultant loss allowance should be recognized based on expectations of some credit event likely to occur in the future. Based on the requirements of the standard, the expected credit loss model must be applied to debt instruments measured at amortized cost or FVOCI, examples of which are trade receivables, loans and debt securities.

IFSR 9 distinguishes between financial assets that have not deteriorated significantly in credit risk and those that have. According to the standard, a three-stage approach to recognize impairment is used and the stage is determined by the level of credit risk associated with the financial instrument.

For financial assets, stage 1 indicates that credit risk has not significantly increased since initial recognition and the 12-month ECL will be recognized. Further, interest income will be recognized on a gross basis. At stage 2, financial assets are determined to have significantly increased in credit risk and therefore, are required to recognize lifetime ECL, however, interest income will continue to be recognized on a gross basis. At the end of the credit risk spectrum are assets that are in stage 3, which indicate that the financial assets are non-performing or are credit impaired, based on an actual event occurring. Under IAS 39, this would have been classified as incurred loss event. At this stage, reporting entities are required to recognize lifetime ECL but interest income will be recognized on a net basis.

Grant Thornton (March 2016) summarizes the three-stage process under the general approach prescribed by the standard in the following chart:

**TABLE 2: Three-Stage Impairment Approach**

| | ***Stage 1 Performing*** | ***Stage 2 Under-Performing*** | ***Stage 3 Non-performing*** |
|---|---|---|---|
| **Credit Quality** | Financial instruments that have not deteriorated significantly in credit quality since initial recognition or that have low credit risk at the reporting date | Financial instruments that have deteriorated significantly in credit quality since initial recognition but that do not have objective evidence of a credit loss event | Financial assets that have objective evidence of impairment at the reporting date |
| **Recognition of expected credit losses** | 12-month expected credit losses are recognized | Lifetime expected credit losses are recognized | Lifetime expected credit losses are recognized |
| **Recognition of interest** | Interest revenue is calculated on the gross carrying amount of the asset | Interest revenue is still calculated on the asset's gross carrying amount | Interest revenue is calculated on the net carrying amount (reduced for expected credit losses) |
| **Practical expedient** | Low Credit Risk | Credit Risk > Low | |

*Source: Grant Thornton (March, 2016)*

Under the new impairment requirements of IFRS 9, if there has been a significant increase in credit risk of a financial asset, lifetime expected credit losses are recognized rather than the 12 month expected credit losses. Effectively, the 12-month credit loss is a portion of the lifetime expected credit loss and is calculated by multiplying the probability of default in the next 12 months by the total or lifetime ECL that would result from that default. Importantly, the 12-month ECL is NOT the credit loss on financial instruments that are forecast to actually default in the next 12 months.

While the standard does not prescribe a specific method for measuring the ECL, it does indicate that the measurement may vary based on the type of financial instrument as well as the information that is available. Nevertheless, IFRS 9 requires that credit risk be well assessed and should reflect the following information, which is both quantitative and qualitative:

- An unbiased and probability weighted amount that is determined by evaluating a range of possible outcomes.
- The time value of money
- Reasonable and supportable information about past events, current conditions and forecasts of future economic events at the reporting date.

Accordingly, the most simplified measurement of the ECL is a *probability-weighted loss default (PLD) model.* The PLD model represents a probability-weighted estimate of credit losses. The ECL is calculated as follows:

$$ECL = EAD * PD * LGD * DF$$

*Where:*

- *ECL* = expected credit loss
- *EAD* = exposure at default, which is the total value that one entity is exposed to when a counter-party defaults. Simply, the EAD is the total value that a reporting entity is exposed to at the time of a default.
- *PD* = probability of default, which is the likelihood of a counter-party defaults during a particular period
- *LGD* = loss given default, which is the percentage of contractual claims that would be lost if the counter-party defaults. It is the share of an asset that is lost if a borrower defaults.[5]
- *DF* = discount factor, which is the factor which needs to be multiplied in order to convert future cash flows into the present value at the measurement date.

Of critical importance is the identification of a significant increase in credit risk, as this determines the way in which the allowance for the ECL is calculated. It is possible for a financial instrument to switch from lifetime ECL to 12-month based on an improvement in credit risk. According to Grant Thornton (2016), to make this assessment, an entity compares the risk of a default occurring on the financial instrument as at the reporting

[5] The recovery rate (RR) is calculated as 1-LGD

date with the same risk as at the date of initial recognition, considering reasonable and supportable information that is indicative of significant increases in credit risk since initial recognition.

The standard does not provide a definition of ‘default’; however, entities must determine what constitutes a default. IFSR 9 suggests that an entity shall apply a default definition, which is consistent with internal credit risk definitions and should consider relevant qualitative factors.

## III. Literature Review

Since IFRS 9 was issued in 2014, there has been a dearth of academic literature on the topic of interpretation of the standard as well as the challenges associated with the transition to the new requirements. This section of the paper highlights some of the findings from existing literature and the recommendations for implementation.

According to a study done by Vanek and Hampel (2017), the calculation of the ECL should be based on a weighted average of credit losses that can occur within various scenarios with an associated probability. The authors used Markov models, an estimated economic adjustment coefficient and official economic forecasts from the Czech National Bank in order to devise a framework for the multi-period probability of default (PD) estimation. The multiple PD estimation was performed using the Markov model, and economic forecasts were incorporated via the decomposition of the economic adjustment coefficient, which was estimated by linear regression using official data. The computational framework involved three steps. First, the authors estimated the one-year PD and then the economic adjustment coefficient, which captures the impact of the expected future economic developments on the PD, is calculated. Finally, the original one-year PD was adjusted for future periods by the decomposition of the effect quantified in the second step, and calculation of the multi-period PDs within the concept of the Markov model.

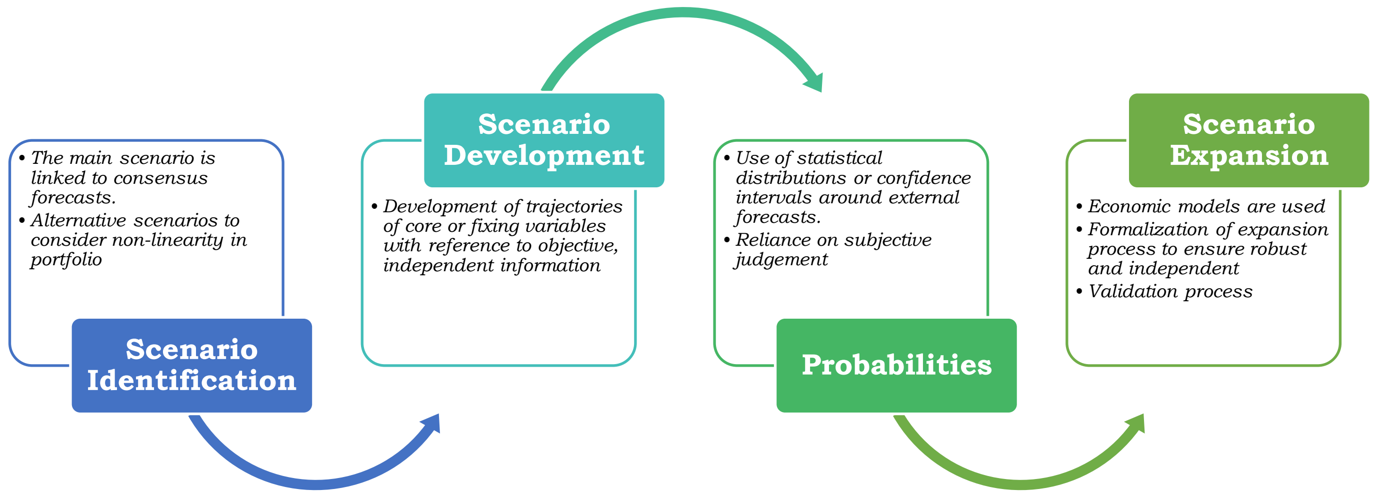
One of the shortfalls of the methodology employed by the authors was the unavailability of official forecasts. It was noted that the official forecasts extended only a few years out and one of the concerns highlighted is that for mortgages, which has maturities exceeding the economic forecasts available. However, simplification of the model can assist, such as abstracting from the economic adjustment for longer horizons or by using long-run averages of economic variables.

A study done by KPMG (2016) highlighted the practical aspects of implementation of IFRS 9 requirements fir expected credit losses in Iceland. The study discussed the main concerns for banks in implementation as the following:

- Model misspecification and the generation of spurious correlations and regressions. The quality and appropriateness of data has to be considered when constructing models incorporating the standard's requirements.
- While there is an understanding that scenario analysis must be used, how many scenarios should reporting entities consider?
- How should banks link macroeconomics to staging?

According the author underscores the cornerstones of generating scenarios and identifies the process for generating discrete economic scenarios as:

**FIGURE 2: Generating Economic Scenarios**




*Source: Adapted from:* ***Iceland: Practical Aspects Of Implementing IFRS 9 Requirements Fir Expected Credit Losses*** *- KPMG, October 2016*

For commercial portfolios, KPMG has suggested the Markov Chain-based approaches, which is also regarded as the most common method since sufficient number of defaults often are not available.

Miu and Ozdemir (2017) have made the case for banks to build on their internal models under the advanced internal-ratings-based (A-IRB) and leverage their well-established credit risk stress testing models since there are several similarities between IFRS 9's credit risk measure and those required to satisfy the Basel Committee on Banking Supervision's regulatory requirements. Accordingly, the authors have proposed an adapted A-IRB probability of default, loss given default and exposure at default models for IFRS 9 and have shown how the expected loss measure can be derived by integrating the PD, LGD and EAD. Further, to fulfil the requirements of IFRS 9, the model was developed to be dynamically driven by key macroeconomic variables.

In the authors' model, the PD and the expectations are assessed based on the current forecast of the credit environment (CFCE) and the CFCE is articulated in terms of a probability measure. In order to assign probabilities to future scenarios in evaluating the expected PD in scenario analysis, the authors used a convexity adjustment approach to deal with the non-linear relationship between conditional PD's and the underlying macroeconomic drivers. This modified version of the A-IRB lessens the banks' modelling efforts in fulfilling the new standard's requirements.

Deloitte (2017) examined the Merton-Vasicek Model which decomposes default risks into systematic and obligor specific factors. This approach models default risks as an unobserved latent asset return index that is positively correlated with a given obligor's asset value on book. Intuitively, a lower expected future return is expected to increase default risks. Further, when the index falls below a given threshold, which is the default boundary, the obligor is expected to default. However, Deloitte also noted several challenges with this methodology, including the absence of cyclical behaviour. The model assumes that systematic risk is cyclical or stationary. However, based on empirical data, this is not the case. Another challenge with this model is what Deloitte termed as *good-time optimism bias*. According to Deloitte, predictions made based on the data from the Great Moderation period (between 1992 and 2007) in the UK showed 63 consecutive quarters of economic growth and a persistent decline in mortgage default risk. However, this trend ended abruptly and dramatically. As a result, it is easy to establish that the forecast errors post the 2008-2009 global financial crisis assuming the same trend will by very large and significant. The Merton-Vasicek Model also poses the issue of paradigm shifts detection. While visually, one can potentially identify different states in the economic cycle, the dividing line can be arbitrary. The conventional approach to paradigm shifts prescribes the use of a dummy variable to model the instability of time series in hindsight (assuming two paradigms – stressed and baseline). The major issues with this approach is that it is only useful in hindsight and it does not assign probabilistic weight to possible future paradigms. Further IFRS 9 requires scenario forecasts and information on future paradigms, which this not covered in the conventional approach to paradigm shifts.

Because of the shortfalls of the Merton-Vasicek Model, Deloitte has proposed a *Markov-Switching (MS) framework* which is similar to the Vanek and Hampel approach. The MS model is developed such that the dynamics of the credit cycle index are modelled as a state-dependent process where the state (stressed or baseline) is unobserved. The difference between the MS model and the dummy-variable regression model is that the state-switching mechanism is a random process. The MS framework also allows probabilities to be calculated on the particular states identified. Using the model, forecasts can be made using the key outputs and the scenario analysis can then be conducted.

## IV. Transition to and Implications of IFRS 9

Major international banks have already reported under the new standard, and have done transition reports to show the impact of IFRS 9, compared to IAS 39. We have observed that the methodologies employed were more or less in line with each other, using significant amount of subjectivity and management overlays but the implications varied across some of the banks.

In an IFRS 9 Transition report published by Deutsche Bank (DB) published in April 2018, it was stated that implementation of the new standard as of 1 January 2018 led to a 1.1% decline in the Bank's shareholders' equity and a 0.8% decline in regulatory capital. Total impairment would have increased by around 16% due to the incorporation of the ECL model and reclassification of financial instruments. In terms of the staged approach to the determination of expected credit losses, DB recognizes a credit loss allowance at an amount equal to 12-month expected credit losses at stage 1. At stage 2, in line with the IFRS 9 standards, the Group recognizes a credit loss allowance at an amount equal to the lifetime expected credit losses for financial assets considered to have experience a significant increase in credit risk. For financial assets in stage 3 as guided by the standard, the PD is 100%. DB's definition of default is in line with the regulatory definition.

In analysing the concept of 'significant increase in credit risk', DB considers reasonable and supportable information that is relevant and available without undue cost or effort, which includes for Deutsche Bank, both qualitative and quantitative information, based on the Group's historical experience, credit risk assessment and forward looking information, which also includes macroeconomic forecasts. The framework for analysis credit risk aligns with the Group's internal credit risk management processes.

Since IFRS 9 requires the incorporation of forward-looking information into allowance for credit losses, the Deutsche Bank Group uses two key elements:

1. A base scenario, which utilizes macroeconomic forecasts, provided by its research department, such as GDP, unemployment rates, interest rates. These forecasts reflect the Group's outlook typically over a two-year period and is updated quarterly. The Group uses through-the-cycle rating migration matrices in the absence of reliable economic forecasts.
2. Once the base scenario is established, a multiple scenario analysis is done using the Group's Group-wide stress test environment. This environment generates the impact of a multitude of economic scenarios and is used as the basis for deriving multi-year PD curves for different ratings and counterparty classes. This is then applied to the calculation of the ECL and to identify any deterioration in credit quality.

In its measurement of the ECL, DB is leveraging the existing parameters used under the Basel Internal Ratings Based Approach as well as internal risk management practices, with adjustments where necessary to comply with IFRS 9. Future economic conditions will affect the allowance for credit losses and to calculate the lifetime expected credit loss, DB derives corresponding lifetime PD's from transition matrices which reflect economic forecasts.

The one year PD used is derived from the Group's internal rating systems. The methods used to rate counterparties range from statistical scoring models to expert-based models taking into account the relevant available quantitative and qualitative information. For counterparties in the exposure classes 'central government and central banks', institutions' and 'corporates', expert-scoring models. For those segments which lack data for statistical modelling, including the retail segment, hybrid models are applied. Quantitative rating methodologies are developed based on statistical modelling techniques such as logistic regression. In order to incorporate the economic forecasts, one-year PD's are extended to multi-year PD curves using transition matrices. The 'through the cycle' (TTC) matrices are estimated, which are derived from a multi-year rating history. The two-year forecasts are then used to transform the TTC matrices into 'point in time' (PIT) rating migration matrices. The calculation of the PIT matrices is performed in Deutsche Bank's stress testing environment, which is based on the Group's credit portfolio model, where macroeconomic variables are linked to the default and rating behaviour of counterparties. Simulated scenarios are selected using statistical techniques and are randomly scattered around the macroeconomic forecast.

Barclays Plc adopted IFRS 9 on 1 January 2018. The impact of implementation of the new standard was a significant 58% increase in total impairment allowance and provisions for Barclay's. Shareholders' equity also declined by 3.5%. The impact on the company's common equity tier 1 (CET1) capital is a reduction of approximately 34 basis points from 13.3% as at 31 December 2017 to 12.9% as a 1 January 2018. According to Barclays, the majority of the increase in the incremental impact of lifetime impairment allowance due to the PD deterioration notably from unsecured portfolios which now has to be assessed with a lifetime PD, most significantly, UK cards and US cards. The remaining increase in allowance was due to differences in the way ECL and incurred loss provisions are calculated for delinquent accounts, classified as collectively impaired under IAS 39 and yet to reach the trigger for stage 3. Assets that are credit impaired and are in stage 3, the increase in impairment was due to the differences in the way ECL and incurred loss provisions are calculated, including the integration of probability weighted economic scenarios as opposed to an expected outcome. For the Barclays retail portfolio, this included allowances for identified impairment for accounts greater than 90 days past due, accounts in forbearance and assets in recovery.

Significant amount of management judgement, estimates and assumptions were applied to facilitate the new impairment requirements. Barclays assesses a significant increase in credit risk using both quantitative and qualitative means. Financial instruments are moved to stage 2 when the annualized cumulative weighted average lifetime PD has increased by more than the agreed threshold relative to the equivalent at origination (quantitative) and/ or when the accounts that meet the portfolio's 'high risk' criteria and are subject to closer credit monitoring (qualitative). Barclays also looks at backstop criteria, which is guided by the standard, where accounts that are 30 calendar days or more past due are moved into stage 2. The backstop criteria is not the primary driver of classifying exposures as under-performing.

In incorporating forward looking information, once there is a non-linear relationship between forward looking economic scenarios and their corresponding expected credit losses, Barclays establishes five scenarios to ensure an unbiased representative sample. The Group's current stress testing methodologies are applied in forecasting these economic scenarios to fulfil the requirements of IFRS 9.

The standard calculation of the ECL is done, by multiplying the PD, LGD and the EAD, discounted at the original effective interest rate. Like Deutsche Bank, which leveraged the Basel ECL calculations, Barclays adjusts the model to satisfy the requirements of IFRS 9. While Basel required 12-month through the economic cycle losses, IFRS 9 requires 12 months or lifetime point-in-time losses based on conditions at the reporting date and forecasted economic scenarios over the expected lives

Management overlays are made to the modelled output to account for situations where known or expected risk factors and information have not been considered into the modelling process, such as political events.

**Practical Challenges in Developing an ECL Model in the Caribbean**

The literature on the implementation of IFRS 9 in the Caribbean is very limited. Specifically, there has not been any documented research into the development of a model to calculate expected credit losses.

In an article published by the Central Bank of Barbados (CBB) in August 2018, the Bank highlighted some of the challenges which the domestic financial institutions will face in implementation, considering the requirements of the new standard. The first was the availability of data and the quality of the data. Reporting entities, as is required by the standard, have to incorporate forward-looking information into their expected credit loss models. The CBB highlighted that at a granular level, institutions may lack historical data on credit risk at the time of origination, particularly as it relates to longer dated credits like mortgages. This may hinder the reporting entities' ability to accurately categorize the assets. Further, the Bank has noted that where the financial institution cannot determine the level of credit risk that existed at the time of origination lifetime credit losses are to be estimated. As a result, this may result in significantly higher credit loss provisions, which will have implications for capital adequacy. Another challenge, which the CBB identified, is the use of macroeconomic variables, which are expected to have an *a priori* relationship with the credit quality for institutions. However, the CBB is suggesting that the current forecasting frameworks of these entities may be inadequate for developing models to support the ECL provisioning process under IFRS 9.

Some of the other challenges emphasized by the Bank is the potential costs of implementation, where entities may be required to adopt more robust data management systems as well as periodic analysis as the business cycle evolves, as well as the access/ availability of skilled resources. This speaks to the quantitative aspect of modelling the requirements of IFRS 9, integrating internal credit risk rating models with forward looking information and building multiple scenarios.

## V. Methodology and Data

The accounting standard requires that forward looking information is used and losses be accounted for based on what may happen in the macroeconomic environment. Further, a single scenario would be insufficient. The IASB has suggested that the expectation is that the IFRS 9 impairment allowance will be a *probability weighted summation of a range of scenarios*.

For the investment portfolio, therefore, we construct a 'macroeconomic overlay' for inclusion in the ECL calculation. The macroeconomic overlay seeks to provide the internal economic outlook for all sovereign exposure as well as the associated probabilities for three possible scenarios – baseline, worst and best case. One of the serious drawbacks is that most macroeconomic analysis applies probabilities in a very subjective manner; however, the methodology will have to provide a less arbitrary means of assigning probabilities. Economic theory, mostly will be the basis of macroeconomic variable selection process, however they must have a statistically significant relationship with the incidence of a default.

The steps involved in the estimation of the macroeconomic overlay for the calculation of the ECL for the investment exposures based on the requirements of IFRS 9 are:

1. Establishing a base case
2. Determining alterative scenarios
3. Assigning probabilities

### *Establishing the 'BASECASE' Scenario*

The macroeconomic overlay is largely based on the Standard and Poor's (S&P) sovereign rating model. Our objective to forecast a foreign currency credit rating for three years out, using forecasts provided by official and other reliable sources. The S&P sovereign rating model addresses the factors that affects sovereign government's willingness and ability to service its debt on time and in full. The five key factors that form the foundation of the sovereign credit analysis are:

- Institutional and governance effectiveness and security risks (institutional assessment)
- Economic structure and growth prospects (economic assessment)
- External liquidity and international investment position (external assessment)
- Fiscal performance and flexibility as well as debt burden (fiscal assessment)
- Monetary flexibility (monetary assessment)

### ***Determining Alternative Scenarios***

*Determining the Relationship Between Rating and Macroeconomic Indicator*

To simplify the macroeconomic overlay, we determine through simple regression analysis, the main macroeconomic indicator *($Y_k$)* that will affect the sovereign $k$'s credit rating. Y will vary based on each sovereign and will be determined by an in-depth knowledge of the sovereign as well as the main driver of the particular economy.[6] The rating will be proxied by credit default swaps (CDS) levels associated with the sovereigns, and where CDS data is not available, government benchmark bond yields will be used *(CR)*. CDS is a type of insurance against default by a particular sovereign. Because these are financial instruments that are traded on the market, they reflect the risk of default as perceived by investors and are more real-time and indicative of a possible sovereign credit event. As such, we use CDS levels as the dependent variable, where available. Simple regression analysis will determine the relationship between $Y$ and *CR*, such that:

$$CR_k = \alpha + \beta(Y_k)$$

The null hypothesis $H_0$ tests that the coefficient of $Y_k$ ($\beta$) is equal to zero, which implies that there is no effect on the endogenous or dependent variable ($CR_k$) from changes in explanatory variable ($Y_k$).

We use the p-value to determine whether we reject the null hypothesis. If $H_0$ is rejected, it means that there is a statistically significant relationship between the endogenous and explanatory variables. The p–value shows the lowest level of significance at which the null would be rejected. For example, if the p-value is 0.07, then it suggests that the null hypothesis must be rejected at levels of significance 7% and higher, but not at 5% or 1%. Essentially, the lower the p-value, the better, as it suggest that the predictor values are indeed related to changes in the response variable.

Once we establish a statistically significant relationship between $Y_k$ and $CR_k$, we compute the correlation matrix with the most appropriate rating indicators (taken from the S&P rating model) against $Y_k$ .

Very critical is that the sign of the coefficients will have to meet *a priori* economic expectations and should be intuitive with theoretical basis. Once we establish the relationships between the rating (credit risk) indicator and the macroeconomic indicator, we then choose the most significant three rating indicators, *($V_1$, $V_2$, $V_3$)* based on strength and sign of the coefficients. Following this, we quantify the impact of $Y_k$ on each of the three rating indicators, *($V_1$, $V_2$, $V_3$)*, such that:

[6] See appendix 1

$$V_1 = \alpha + \beta_1(Y_k)$$

$$V_2 = \alpha_2 + \beta_2(Y_k)$$

$$V_3 = \alpha_3 + \beta_3(Y_k)$$

Further, since we have to determine alternative scenarios, we obtain official forecasts for all $Y_k$in years *t+1, t+2* and *t+3*. In order to determine the impact of changes on $Y_k$ in the various scenarios, we calculate the standard deviation of each $Y_k$ and apply a two standard deviation shock[7] to the forecasted values for $Y_k$. We then input this into the equations: $V_1$, $V_2$,and $V_3$ to come up with their new values.

Usual tests of significance and goodness of fit will be undertaken and the $\beta$ coefficients are obtained. We then calculate the standard deviations of the historical data of $Y_k$ to obtain the alternative scenarios. Therefore, for $Y_k$, we calculate the standard deviation of the historical dataset and apply a two standard deviations to forecasted $Y_k$ in years *t+1, t+2 and t+3* for the best case and worst case scenarios. Once the different scenarios of $Y_k$ are determined, the value of the three rating indicators, ($V_1$, $V_2$, $V_3$) are calculated. These new values of $V_1$, $V_2$, $V_3$ are then used in the S&P sovereign rating model to determine the revised ratings under the different scenarios of $Y_k$.

### *Assigning probabilities*

Using specific criteria defined by S&P and following its methodology, we use forecasted data to determine what the credit rating will be for each sovereign three years out. Once the credit rating is determined in years - *t+1, t+2 and t+3,* we then use the S&P's transition matrix[8] to establish the probability of the credit rating moving to the forecasted rating from the current period's credit rating. S&P computes the transition rates by comparing the issuer ratings at the beginning of a period with the ratings at the end of the period. The one-year transition rating (by rating category) is calculated by comparing the rating on each entity at the end of a particular year with the rating at the beginning of the same year. Multiyear transitions are also calculated for periods of two to 15 years, where the rating at the beginning of the multiyear period is compared to the rating at the end. For example, the three-year transition matrices were the result of comparing ratings at the beginning of the years 1975 – 2015 with the ratings at the end of the years 1977 – 2017. The ratios in the average transition matrices represent the historical incidence of the ratings changing over a multiyear period.

[7] The number of standard deviations vary, to ensure that the scenarios are realistic in the specified period.
[8] See appendix 2

In attempting to utilise the sovereign overlay at the loan portfolio level it was recognised that a statistically significant relationship could not be identified between non-performing data and the indicators used for the sovereign overlay. For the loan portfolio, a *scorecard* methodology was employed to incorporate forward-looking indicators in calculating the ECL. The scorecard model requires a significant amount of management decisions. The Scorecard model attempts to quantify the impact of changes in key economic variables on the loan portfolio via the use of multiplier factors. The multiplier factors are subjectively determined based on Management's judgement. Scenarios are then developed by looking at a base case, upside scenario and downside scenario and getting the weighted average impact of these scenarios on the loan portfolio by calculating an adjustment factor. The resultant weighted average adjustment factor is then used to calculate the macroeconomic impact on the ECL for the loan portfolio.

In assigning the probabilities, it was determined that the base case carries the heaviest weight as this is the most likely to occur. The upside and downside scenarios represent the more optimistic and pessimistic scenarios.

This model is best designed to cater for situations where markets are thin and the availability of industry or sector data is limited which makes more quantitative approaches difficult to achieve. While this methodology is heavily based on management's judgment, it was adopted due to various issues regarding model misspecification and incomplete data sets, among other challenges. A pseudo logistic regression was attempted, but the results were not statistically significant and there were not a sufficient number of macroeconomic variables datasets.

**Data and Key Assumptions**

One of the major issues is the availability of large and comprehensive datasets to complete the analysis for the macroeconomic overlay for the calculation of the impairment as prescribed under IFRS 9.

Particularly, the Caribbean there are many weaknesses in terms of official statistics. Official statistics are usually not timely and/ or often published with a considerable lag. Further, statistics are sometimes inconsistent given the frequent revisions and in most cases, the Caribbean's statistical repositories often provide insufficient coverage for key areas which are necessary to support decision making particularly in the private sector. While in other jurisdictions, data collection may be easier, there still exists issues with specific macroeconomic data, which are not readily available and are critical in determining the vulnerabilities which the sovereigns and/ or financial institutions face. Moreover, several of the Caribbean countries are not rated by any international/ regional rating agencies.

Naturally, one of the most important limitation with which we are faced is the limited number of data points available for the analysis and in some cases, we are not able to achieve the necessary sample size. To address this shortcoming, we will use a significance level (alpha) of 5% -10%. An alpha of 0.05 refers to a 5% chance that a significant result is a false positive. The lower the alpha, the more rigorous the model and less the probability of a 'Type I' error, which means you are incorrectly rejecting the true null hypothesis (false positive). Further, since we required only one lead indicator per sovereign, the regression may show some level of autocorrelation.

For the most part, our major data sources are S&P, Business Monitor International, Bloomberg and various central banks and IMF reports. We proxy sovereign risk of default for credit spreads and/ or government bond yields. Our analysis is hindered by the lack of forecasted data as well, which is required to run the regressions to ascertain the impact of the lead indicator on the macroeconomic variables which affect the sovereign credit rating. Another limitation was the derivation of the actual yield curves. Many of our markets do not have a standard yield curve because they are severely underdeveloped and there is little benchmark securities, which are actively traded.

One of the other limitations is that some regressions did not meet economic expectations because of erratic movement in government bond yields (which were used as a proxy for sovereign credit risk). For example, in SLU, SVG and other Caribbean economies– even though tourism is the economic driver, the regression was not statistically significant.

The challenges encountered in developing the expected credit loss model for the retail and corporate portfolios have been even more acute. The Central Bank of Barbados indeed had an accurate assessment of the issue sin implementing the new standard in the region. The data sets required to calculate the probabilities of default was not complete and robust and the data that was available did not satisfy *a priori* relationships that were expected between some key macroeconomic variables and asset quality. For example, some of the Caribbean economies has historically been affected with structurally high unemployment rates, even though throughout the economic cycle banks' asset quality may have been improving. Therefore, the statistical relationships were not evident from the sample data collected.

## VI. Conclusion and Way Forward

The requirements of the new IFRS 9 accounting standard will have significant implications for financial institutions of the region. One of the fundamental changes introduced is the move towards impairment modelling based on *expected* credit losses compared to the previous IAS 39 incurred losses model, which was based on objective and verifiable credit events. This paper looked specifically at the impairment step in the implementation of IFRS 9 and has outlined some of the practical challenges observed in developing a model to calculate expected credit losses given the data limitations in the Caribbean. We also looked at the transition experiences in the more advanced countries as well as the general methodology used to develop a 'macroeconomic overlay', which incorporates the scenario analysis and the forward-looking information as required by the standard.

Under IFRS 9, impairment calculation hinges largely on forward looking information, including for key macroeconomic indicators, as well as reliable forecasts. We have established that in the Caribbean, the data infrastructure is lacking and as a result, heavily quantitative approaches to developing robust and dynamic expected credit loss models is severely limited. IFRS 9 allows for more subjectivity than its predecessor IAS 39 does, however, there is a lot of work to be done to improve the quality and frequency of data, both from a macroeconomic perspective as well as from a micro or industry level.

Official statistics often provide insufficient coverage in some areas, which are critical for decision making at an institutional level. With the adoption of the new IFRS 9 for Financial Instruments, all reporting entities now have to consider reasonable and supportable information about past events, current conditions and reasonable and supportable forecasts of future economic conditions when measuring expected credit loss. The availability of statistics from both a macro level and micro level have become a critical element in estimating ECL.

The introduction of IFRS 9 has indeed expanded the need for more technologically driven analytics as transition will be much smoother if risk analytics are aligned with the finance functions. The new standard requires continuous monitoring of financial assets, not only at initial recognition, but throughout its life to determine if credit quality has deteriorated. The data inefficiencies, including the lack of historical data and consistent forecasts make it difficult to assess and monitor credit quality and to model expected credit losses. Aligning IFRS 9 impairment requirements with existing credit risk systems can assist in the transition and reduce implementation costs.

The underdeveloped capital markets of the region also needs to be addressed. This has affected the implementation process since it dampens efficiency and transparency of both the estimation of yield curves and ultimately the valuation of financial assets.

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