Basel

Methodology Implementation

White Paper

AXTRIA
INGENIOUS INSIGHTS

Introduction

Basel will have significant impact on the banking sector. One recent study[1] estimated that as the Basel rules are written today; by 2019 the US banks will need about $870 billion of additional Tier 1 capital, $800 billion of short-term liquidity, and about $3.2 trillion of long-term funding, absent any mitigating actions.

Closing these gaps will have a substantial impact on profitability. Just the implementation of Basel program in a mid-sized bank is likely to cost $65 to $100 Mn, mainly driven by IT. Bulk of this cost (65-70%) is to be spent in ensuring data consistency and availability, developing applications and designing new IT landscape. As a result, getting the Basel implementation right, the first time itself, is super critical.

One key component of the implementation is getting Basel models methodology right – methodology that is not only compliant with the regulatory guidelines but also aligned to business needs. This paper covers three critical aspects of the methodology where the devil is in the details and which warrants great attention. These three aspects are:

1. What is the right segmentation approach for Basel models?
2. How should the impact of 'stressed market' (downturn) scenarios be estimated?
3. For assessing Probability of Default (PD), which approach is appropriate - Point in Time approach or Through-The-Cycle?

The paper attempts to highlight the nuances (both theoretical and practical) involved in these aspects and shares Axtria's empirical approaches and insights into their implementation. We hope the proposed approaches in the paper will be helpful for modelers and risk managers in implementing Basel programs within their organizations.

[1] *Basel III and European Banking – Its impact, how banks might respond, and the challenges of implementation, Nov 2010.*

Segmentation Approach

While Basel has left room for banks to manoeuvre as to how they can devise the segmentation as per the business strategies for managing their portfolios, the following guidelines are critical in clustering the accounts into pools:

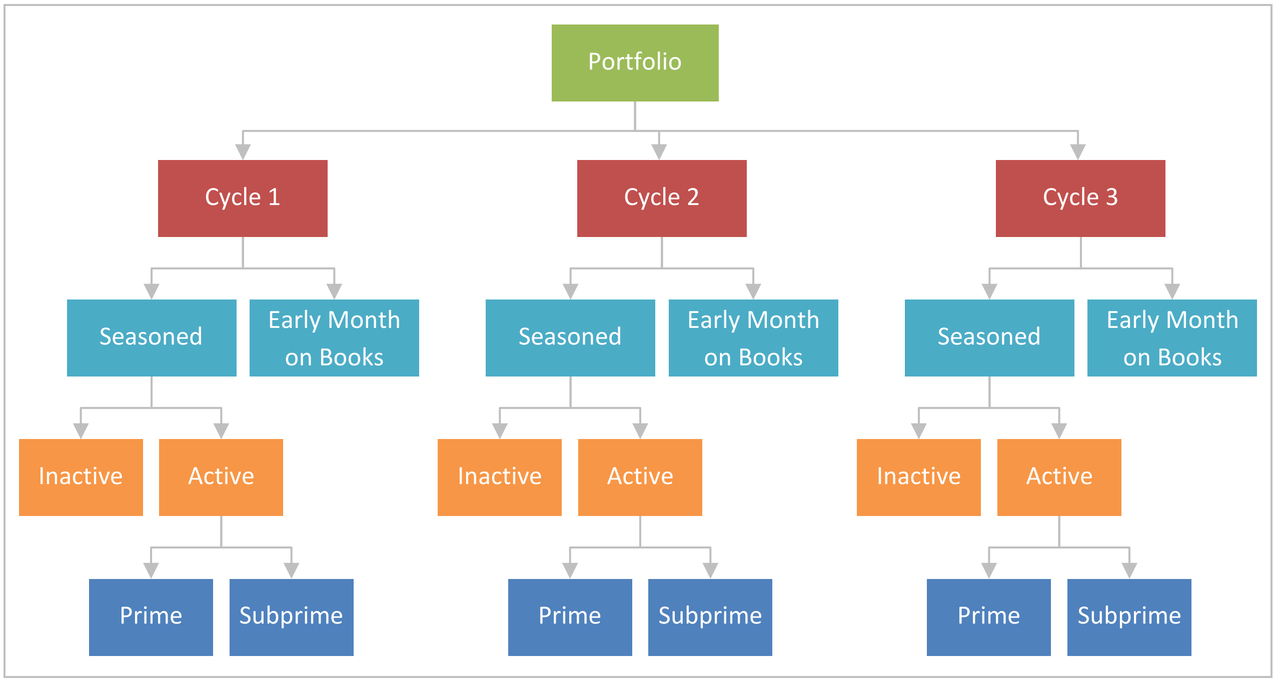
- Segments should be based on homogenous risk pools (uniform risk rates) to accurately measure the tail of the loss distribution and the resulting capital requirement for the portfolio.
- Segments should be used / usable by the business (and not just assessed for regulatory reporting purposes).
- The aim of the segmentation should be to achieve high predictive power as well as stable accuracy over time

Thus, at Axtria, we first evaluate behavioral score based segments (currently used for account management); to see if they can be used for Probability of Default (PD) calculations. However there are a few questions that need to be addressed:

a. Definition of default: Is the bank's business definition of default compliant to Basel guidelines on default identification.

b. Risk Separation: Are the existing segments having fundamentally differing default rates across segments and homogenous rates within the segments? It needs extensive engagement with business users to identify and evaluate existing business rules and align on intuitive indicators that make business sense (e.g. separating inactive accounts, early month on books accounts, Prime versus Subprime etc.).

The aim is to ensure the segments developed for PD calculations are defined by proxy borrower risk characteristics (reflecting borrowers' ability and intent to make payments) and are coherent with how the business looks at the portfolio. The following diagram highlights a typical segmentation schema for PD calculations:



Separating out inactive and Early MoB accounts helps achieve the following objectives:

a. Inactive segment is required since typically a sizeable proportion of a portfolio is inactive; Creating a separate segment helps in more accurate prediction for both inactive and active segments.

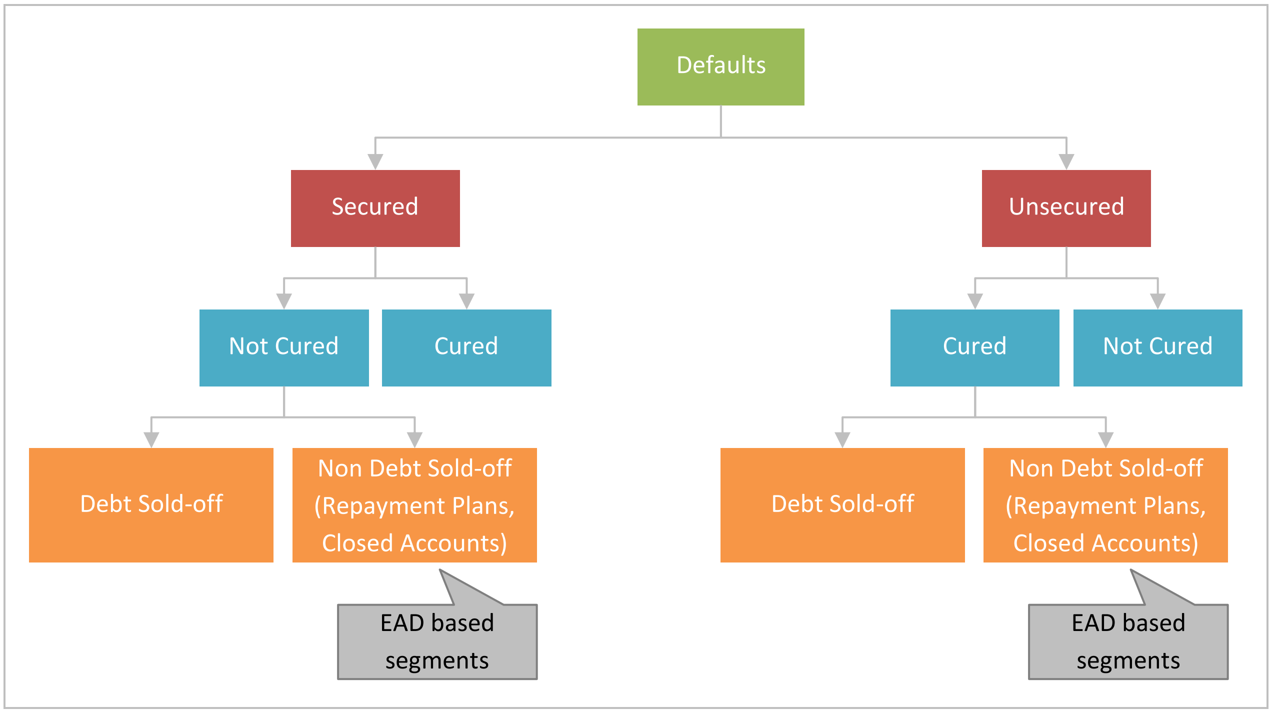
b. Similarly Early MoBs reflect more the acquisition strategies of a bank and not exactly the performance, therefore separating these from accounts where banks have observed sufficient internal history helps achieve higher accuracy in prediction of defaults.

c. Any change to banks acquisition or inactive accounts management strategy will not impact the performance of the other segments of the model and the models for these segments can be re-calibrated in isolation.

The methodology of segmentation for Loss Given Default (LGD) is even more evolved. LGD by its very nature computes post event (default) loss. Therefore it is important to fully decipher the curvature of recovery curves over time in default. These curvatures are mostly driven by the underlying collections and recovery policies of the bank. Since banks often have post default programs (forbearance, repayment plans, litigation, debt sale etc) a thorough end state analysis needs to be done to determine the possible end states to which an account can belong.

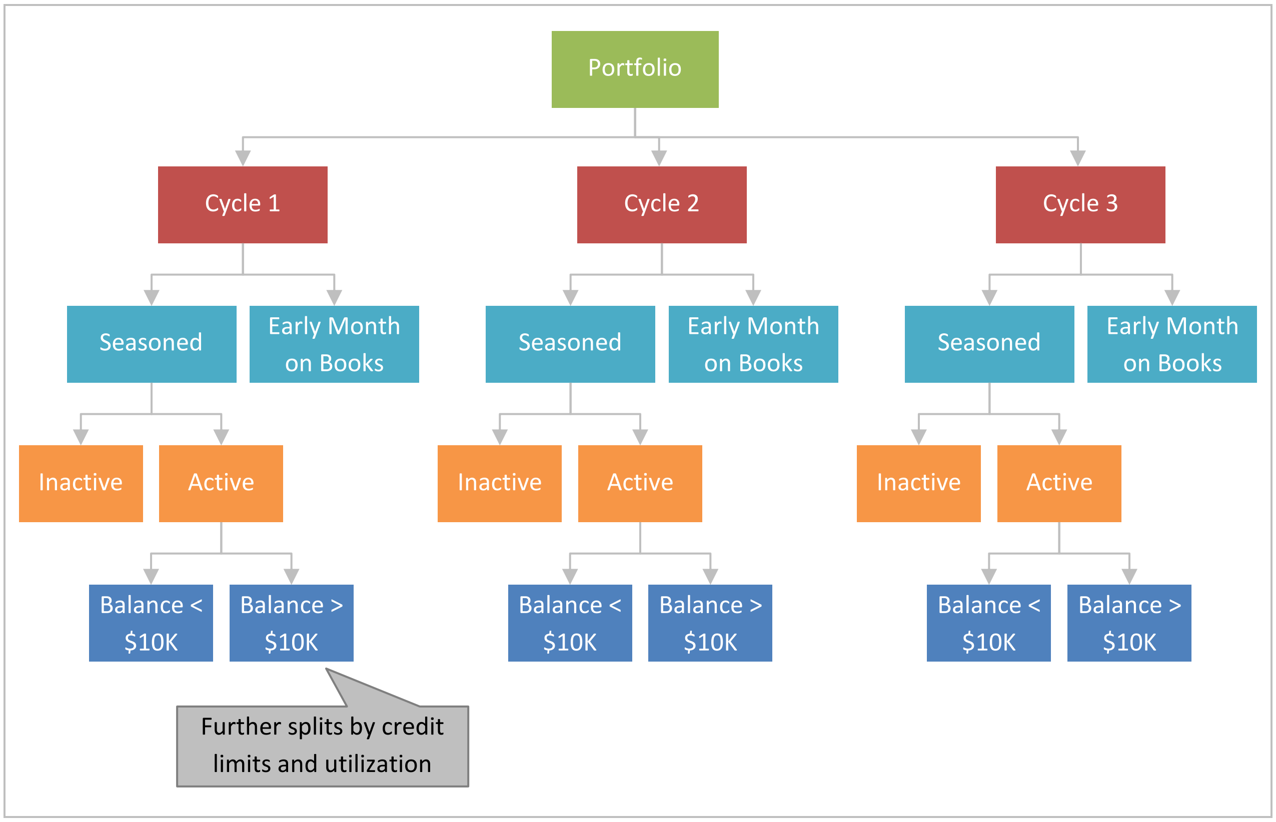
This leads to introduction of the post default work out window. Based on banks policies for various collection and recovery actions this window may vary from 12-24 months post month of default.

At Axtria, we conduct extensive discussions with the bank's experts and develop a 'decision tree' that sets out the right resolution paths for the loans in default, as shown in the chart below.



Once the resolution paths are delineated, the conditional probability of each is estimated. Typically, logistic regression is deployed to predict these conditional probabilities for end states. For each of the EAD segments a chain ladder based LGD is computed. An EAD weighted sum is performed to roll up the LGDs for non-debt sold node; Probabilities are then used to weight up the various LGDs derived for various other segments to compute a final end state probability weighted LGD for each account.

The outstanding balance at the time of default represents Exposure at Default (EAD). The segmentation for calculating EAD is dependent on the approach adopted. Typically, using Credit Conversion Factor (CCF) based approach does not require segmentation per se. However, given the 'bimodal distribution of predicted values' challenge in this approach (which causes unnecessary over prediction of EAD since quite a few CCFs can be negative and hence need to be floored to zero), we normally recommend regression based approach to directly predict EAD. Under regression based approach, segmentation is adopted on similar lines as PD segmentation (It has to be noted it's not exactly same as PD segmentation). Typical EAD segmentation schema is driven by level of activity, credit line, outstanding balance and loan age on books. The chart below represents the EAD segmentation schema graphically.



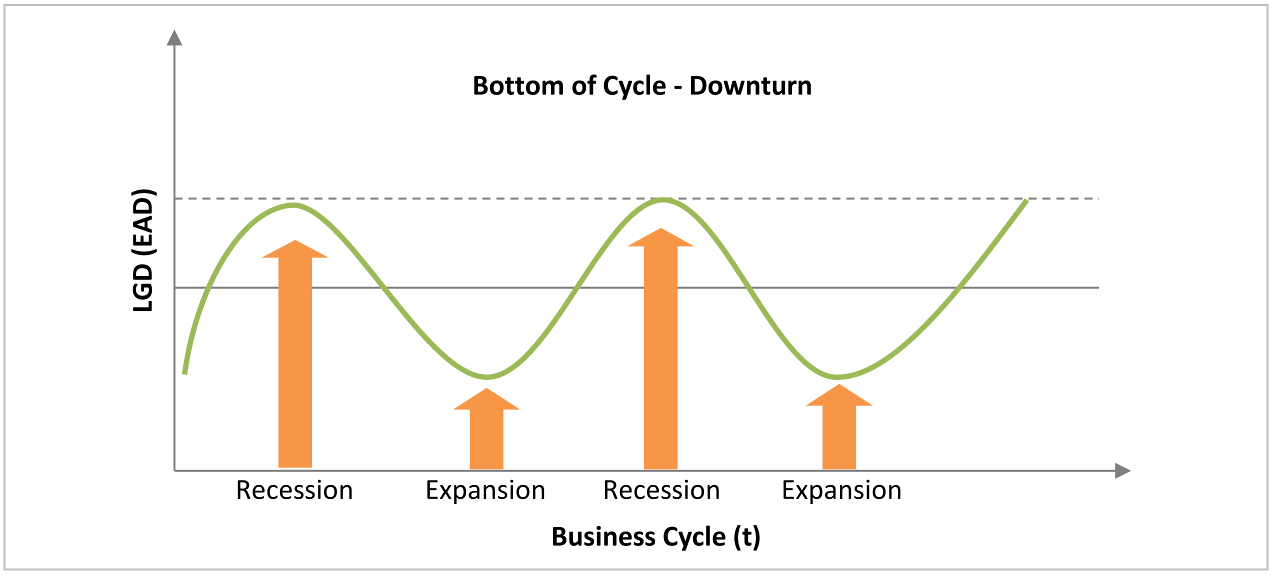
As one would have observed from above, segmentation across PD, LGD, EAD is not just pure science of segregating homogenous risk pools – it's an art which demands relevancy from business usage perspective while meeting regulatory compliance objectives.

Downturn Assessment

With regards to the occurrence of systemic risks and their impact on LGD and EAD, Basel requires the calculation not only of the average expected LGD (EAD), but also of a 'downturn' LGD (EAD). Banks are to use downturn LGD (EAD) estimates in regulatory capital calculations. Basel has elaborated on the "downturn LGD (EAD)" standard and suggested a principles-based approach. It required the banks to

- Identify the appropriate downturn conditions and the adverse dependencies between default rates and recovery rates
- Incorporate them to produce LGD (EAD) parameters for the bank's exposures, which are consistent with the identified downturn conditions.

Essentially, Basel II requires bottom-of-the-cycle LGD (EAD), estimated from a sufficiently stressed (market downturn) period during which high LGDs (EADs) are observed. The chart below explains the downturn approach graphically.



There are three critical challenges to be overcome while assessing downturn values:

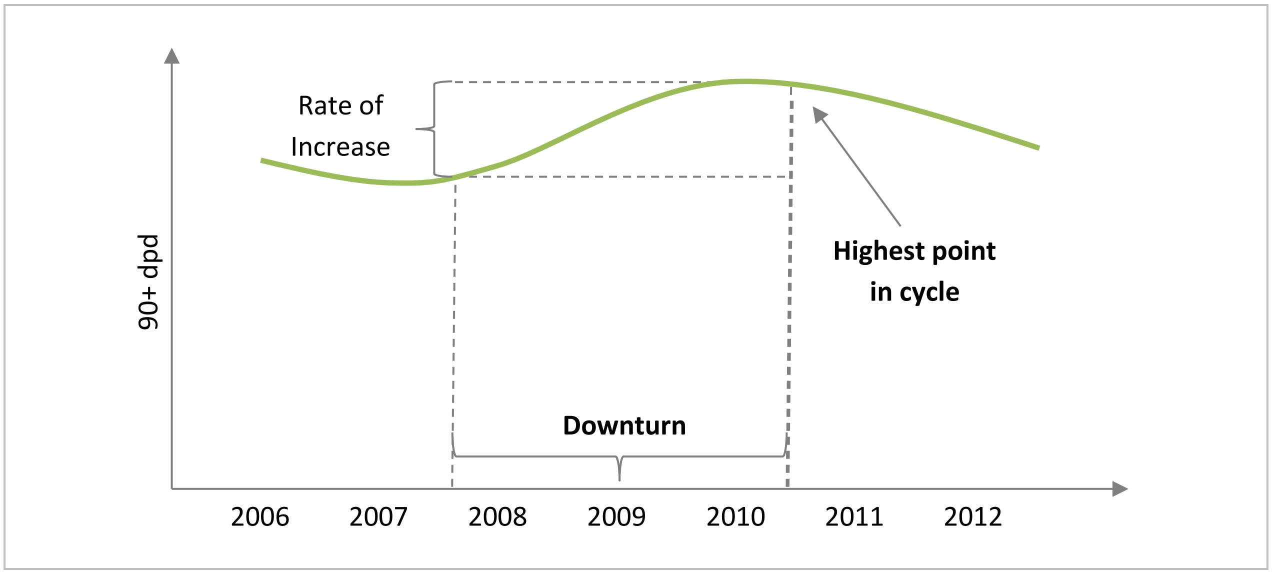
- LGDs of different portfolios may be driven by different risk factors thus following their own cycles. This could result in LGD diversification among different portfolios and different countries.
- PD and LGD have a lagging relationship, depending upon a bank's collection practices. The accurate correlation between the two is critical to be captured.
- Turning points in credit cycle need to be captured fast enough and with high degree of accuracy.

We adopt the following approach to adequately address the above challenges:

Downturn LGD (EAD) = Maximum of the following -

- LGD (EAD) estimated through annual snapshots of Point in Time methodology (Point in Time methodology is detailed later in the paper).
- Long term average LGD (EAD) – This is typically a default weighted average of Point in Time estimates over a long duration (5-7 years).

LGD (EAD) during 'stressed' scenario. The stressed scenario is typically defined as the time period when the default rates peaked within the portfolio. For EAD (credit cards or revolving products), the stressed scenario can also be derived by observing the peaking of line utilization rates across annual snapshots of data. The chart below depicts the stressed scenario graphically.



Once the downturn LGD (EAD) has been estimated, the account level values are appropriately adjusted by a multiplier (LGD (EAD) Downturn / LGD (EAD) Average estimated at Point in Time). Interestingly, if the time period available does not contain default rates (utilization rates) which reflect a downturn, additional adjustments might be required to 'estimate' downturn LGD (EAD).

Point-In-Time versus Through-The-Cycle

The approach to develop PD models using Point in Time (PIT) or Through the Cycle (TTC) methodology has been an important topic (of debate) in Basel model development and implementation initiatives. Let us first understand each methodology in more details, before deep diving into the merits – demerits of each.

PIT credit risk measure is one which utilizes all available and pertinent information as of a given date to estimate expected probability of default over next 12 months. The information set includes not just expectations about the entity's own long-run credit risk trend, but sectoral, geographic, macroeconomic, and macro-credit trends as well. PIT ends up giving dynamic capital requirements for the bank.

TTC credit risk measure, on the other hand, primarily reflects the entity's long-run, enduring credit risk trend. Modelers tend to stack 6 monthly data over long duration while building these models. Transient, short-run changes in credit risk that are likely to be reversed with the passage of time are filtered out. The predominant features of TTC credit risk measures are their high degree of stability over the credit cycle and the smoothness of change over time. Compared to PIT, TTC risk measures display much less volatility over the business cycle.

As can be sensed, each methodology has its own utility across different scenarios. PIT PDs react immediately to all news that affects the entity's risk of default, making them timely signals of credit risk, but also highly volatile and pro-cyclical. TTC measures demonstrate higher degree of stability. However, the high degree of stability comes at the cost of reduced timeliness and default prediction accuracy relative to PIT risk measures. More conservative banks have tended to favor TTC methods of modeling so that pricing and exposure decisions are taken on a more accurate view of the risk over the life of the loan. Another factor to consider in selection of the methodology is whether the bank wants to hold capital against RWAs which fluctuate more often (PIT) than not (TTC).

It is thus critical is to understand the objective of prediction more granularly. If the bank is trying to choose a snapshot which resembles time foreseeable in near future, then PIT approach makes more sense. PIT PDs are useful for applications in which the early detection of changes in credit risk at both the single name and portfolio level is important. Investors concerned about losses due to defaults or credit spread widening require the early warning of credit risk changes that PIT PDs provide. However, these very same attributes make PIT PDs less desirable for other types of applications in which the costs of adjustment – which may arise due to transactions costs, regulatory compliance costs, change of contractual terms, etc. – exceed the expected costs of negative credit events (such as default). Further, PIT PD does not identify the true risks of loan when it is made in good times. In those situations, TTC approach works better.

Given these conflicting needs (of providing estimates (as specified by Basel) in line with long run averages and also ensuring short term sensitivity of models is not low); at Axtria, we have developed a hybrid approach. In this, we first calculate PD using PIT methodology and then (re) calibrate PD values at account level using TTC approach to capture long term effects.

The TTC calibration models are time series models of default rates at segment / portfolio level which regress default rates against exogenous pertinent drivers of default, over a longer time horizon. Using the calibration model estimates at segment / portfolio level, the PIT measure is 'scaled' (at account level) to capture long term effects.

Bibliography

1. McKinsey Working Papers on Risk, Number 26 - Basel III and European Banking – Its impact, how banks might respond, and the challenges of implementation, Nov 2010.
2. Ernst & Young - The impact of the Basel III capital & liquidity requirements: Balance Sheet Optimization
3. Basel Committee on Banking Supervision - Frequently asked questions on Basel III monitoring, September 2012
4. The Journal of Credit Risk (81-102), Volume 8 / Number 2, Summer 2012, Modeling exposure at default and loss given default: empirical approaches and technical implementation.

Our experience of Basel model development and implementation shows that the devil is in the details and there is ample to be lost in the maze. A careful and well-crafted approach in Basel model development and implementation is crucial.

We, at Axtria strongly recommend upfront investment in detailing of methodologies, getting buy-in and sponsorship from executive management, doing early pilots and having strong governance mechanisms (internal and external) to clarify methodology issues/ interpretations in a timely manner.

We hope this paper helps you get some answers to select technical and interpretive challenges around the Basel model development methodology. We wish you good luck in your Basel journey!

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