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ABSTRACT

This paper describes probability of default (PD) analysis for Corporate Bonds, Debentures, Preference Shares of the Nature of Debt and Refinance Exposures to Banks. We have empirically shown that the historical data on credit spreads published by FBIL are the appropriate basis for extracting the market-implied default probabilities associated with credit instruments like bonds and debentures issued by corporates and financial institutions. The methodology delineated in the paper and the resultant rating wise PD estimates would enable Banks, Financial Institutions and Investors to understand the portfolio credit risk positions. The derived PDs will be useful for estimating the forward-looking expected credit loss based provisioning under IFRS for exposures to market based credit instruments and also for exposures to banks and refinance portfolios where historical default incidents are very low.

Keywords: Credit Risk, Bond Spreads, Expected Loss, Emerging Markets

JEL Classification Code: G12, G13 and G20

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1. Introduction

Events of the global financial crisis in 2007 – 2008, led to the criticism of "too little, too late" for the accounting recognition of impairment losses on financial instruments under IAS 39. As a consequence, the International Financial Reporting Standards 9 (IFRS 9) has introduced fundamental changes in credit impairment standards and assessment of loss allowances, which are expected to have a significant impact on the financial statements of Banks and FIs. In India, as in many other countries, IFRS implementation has become imperative. India has adopted Indian Accounting Standards (Ind AS) that are based on and substantially converged with International Financial Reporting Standards (IFRS). The Reserve Bank of India has extended the implementation deadline for commercial banks beyond the original date of 1 April, 2018. Many NBFCs however, have already migrated to IFRS financial statements. In line with IFRS 9, Ind AS 109 has introduced a forward-looking approach for identification of credit impairment and estimation of expected credit loss (ECL) that will provide a timely and adequate accounting treatment of loss provisions. The first step in the ECL computation is the estimation of the risk of default (alternatively, the Probability of Default – PD) of the counterparties to which the Bank has the exposures. In cases where standard historical default rate models for PD estimation for the portfolios under consideration cannot be applied, alternative approaches based on market data, for example credit spreads, can be very useful. Credit spread based PDs can be used by Banks which have substantial exposure in Bonds, Debentures and Preference Shares and exposure to other banks through refinance of loans, which are typically low default portfolios. In this paper, we compute the PDs for different external rating grades using credit spreads published by FBIL (Financial Benchmarks India Ltd.), which can then be applied for the estimation of ECL for exposures in bonds, debentures, preference shares and refinance exposures to Banks and FIs.

The Ind AS 109 accounting standards focus on the classification and measurement of financial assets and liabilities. The objective of Ind AS 109 is to establish principles for the financial reporting of financial assets and financial liabilities that will present relevant and useful information to users of financial statements for their assessment of the amounts, timing and uncertainty of an entity's future cash flows. Investments in bonds, debentures classified in the Held-to-Maturity (HTM) and Available For Sale (AFS) portfolios are equivalent of debt instruments classified as Amortized Cost and under Fair Value through Other Comprehensive Income (FVOCI) respectively under Ind AS 109. The exposure to these instruments will therefore be subject to ECL provisioning under Ind AS 109. Similarly, Refinance exposures of the Bank will be classified as Amortized Cost and subject to ECL provisioning under Ind AS 109.

Debt securities issued by Corporates, Banks and FIs are rated by External Rating Agencies. These Rating Agencies periodically publish external rating based default probabilities using historical data of bond defaults out of the total rated bonds issued in the market. However, the use of the External Rating based PDs for ECL computation of the Bank's portfolio of Bonds, Debentures, Preference Shares and Refinance exposures have three issues. First, the Rating Agencies publish long-run average default probabilities which are through-the-cycle (TTC) whereas for the purpose of IndAS 109 ECL, we require point-in-time (PIT) PDs. Second, these default probabilities are publicly available with a significant time lag – for example, the last published CRISIL bond default probabilities are available only till 2018. These lagged PDs cannot be applied for the ECL estimation for reporting dates 2019 onwards. Third, the Rating Agency published PDs are for the overall pool of bonds issued by corporates, banks and NBFCs and are not available separately for each of these sub-portfolios and as such, do not provide enough granularity. Given the above limitations, PDs implied by published credit spreads associated with external ratings delineated in this paper may be useful.

A wide variety of academic and empirical literature supports the use of market price implied Probability of Default for traded credit instruments and low default securities (Jarrow, Lando and Turbull, 1997; Duffie and Singleton, 1999; Hull et al., 2004 & 2005; Trück et al., 2004; Murthy, 2011; Gubareva, 2019). These studies alternatively use credit spreads derived from traded prices of credit risky bonds or traded Credit Default Swap (CDS) spreads.

In the context of India, the CDS market is non-existent and CDS spreads are not available. However, the corporate, NBFC and bank bond market (both primary and secondary) are fairly active and the market prices of these bonds are available. Furthermore, based on these traded market prices, FBIL publishes at fortnightly intervals, the annualized credit spreads (in basis points) associated with different bond credit ratings and maturities.

Jayadev and Jacob (2010) have found that credit spreads are largely determined by the proxies of default probability and recovery rate. Their paper has used structural models to establish relationship between spreads and important credit risk variables. The historical data on credit spreads published by FBIL are the appropriate basis for extracting the market-implied default probabilities associated with corporate bond/debenture exposures and Bank exposures in India.

Another advantage of the credit spread based PD estimates is that by definition, they are point-in-time and forward looking since they are associated with traded prices in which market participants have already built in current and future scenarios of change in credit risk of the issuer. Thus, these PDs do not need any further adjustment to be made PIT or forward looking for their application to ECL under IndAS.

2. Research Methodology: Estimating Market Implied Probability of Default from Rating-wise Bond Spreads

Corporate borrowers pay higher yields on the bonds they issue than governments pay on bonds of the same maturity. The difference between these yields is called the corporate bond spread. Part of this spread compensates investors for the expected default loss associated with holding corporate debt — arising from the possibility that corporate bonds may not be repaid in full. Thus, if we have information about the corporate bond spread and a Loss Given Default (LGD) for the bond, we can back out the default probability from the equations given below. The default probabilities derived from bond spreads are known as risk-neutral default probabilities.

Consider a zero coupon, credit risky bond with time to maturity T years, which has a current market value of B_0. Then we know from fixed income analytics that

$$B_0 = \frac{1}{(1+y_T)^T} \quad \text{..... (1)}$$

Where, y_T is the annualized yield to maturity of the credit risky bond and can be represented as the sum of the yield on an equivalent risk free security (r_T) and the annualized credit spread associated with the default risky security (s_T).

$$y_T = r_T + s_T \quad \text{..... (2)}$$

Alternately, assume that the credit risky bond has a cumulative probability of default any time over T years (CPD_T) and an expected recovery rate under default as R. Then, the value of the bond B_0 can be represented as the present value of expected future cash-flows:

$$B_0 = \frac{(1-CPD_T)+R*CPD_T}{(1+y_T)^T} \quad \text{..... (3)}$$

Combining equations 1, 2 and 3, we can derive the following relationship between the CPD_T, the credit spreads and the recovery rate:

$$CPD_T = \frac{\left[1-\frac{(1+r_T)^T}{(1+r_T+s_T)^T}\right]}{(1-R)} \quad \text{..... (4)}$$

Similarly, CPD_2, CPD_3, CPD_4 for longer default horizons of 2,3 or 4 years can also be estimated if we have information for the risk free rate, corporate yield, credit spread associated with the corresponding horizon and recovery rate.

From equation 4, it is clear that if the term structure of risk-free yields r_T, the term structure of credit spreads s_T for different external rating grades, and the expected recovery rate R are available, we can extract the cumulative probability of default CPD_T for each external rating grade for different tenors T.

For the first year (T = 1), the Marginal 1-yr PD (MPD_1) is

$$MPD_1 = CPD_1 \quad \text{..... (5)}$$

The marginal 1-year PD (MPD_T) for longer tenors T= 2,…. n are then iteratively extracted as

$$MPD_T = CPD_T - CPD_{T-1} \quad \text{..... (6)}$$

The market spread implied marginal and cumulative probabilities derived from the above formulae are known as risk-neutral default probabilities. These risk-neutral

PDs are relevant for the valuation of credit risky securities, but are not directly applicable for the ECL computation under IndAS 109.

In contrast, the PDs for credit risky securities derived from historically observed default rates are what are known as real-world (or physical default probabilities). Real-world default probabilities are usually lower than risk-neutral default probabilities. This means that bond traders earn more than the risk-free rate on average from holding corporate bonds than what would be justified by purely a compensation of expected loss. Why are the two estimates of the probability of default so different? The answer is that bond traders do not base their prices for bonds only on the actuarial probability of default. They build in an extra premium to compensate for the other risks they are bearing – for example liquidity risk, uncertainty of default etc. and for other factors like differences in tax and regulatory treatment for risk-free and default risky securities. Thus, risk-neutral PDs extracted from market spreads over-estimate the pure risk of default that would otherwise be captured by the real-world PDs. This is known as the ***"Credit Risk Puzzle***" (Hull, Pedescru and White, 2005).

In order to derive the real-world equivalent PDs, the risk-neutral PDs have to be adjusted with an appropriate scaling factor "**w"**, also known as the weight of the default component in credit spreads. This scaling factor, which can vary both by tenor (T) of the risk-neutral PDs and by the external rating category (G) to which the risk neutral PDs are associated, is estimated as the ratio of the historical time series average of Risk Neutral CPDs and the historical time-series average Real World CPD for each tenor and rating grade.

$$w_T^G = \frac{Avg.Risk\ Neutral\ CPD_T^G}{Avg.Real\ World\ CPD_T^G} \quad \text{..... (7)}$$

The scaling factors derived as above measure the proportion by which Risk Neutral PDs are higher than Real World PDs due to all other risk factors considered by market participants trading on these securities.

For any other risk neutral probabilities derived based on current market spreads, the real-world equivalent PDs can be backed out by using the appropriate scaling factor.

$$Real\ World\ CPD_T^G = \frac{Risk\ Neutral\ CPD_T^G}{w_T^G} \quad \text{..... (8)}$$

3. Data and Variables

We have obtained historical, FBIL published data on the term structure of GSec par yields (as representative of risk-free yields) and the term structure of credit spreads associated with different credit ratings (AAA to BBB-) for PSU/Bank/FI, NBFCs and Corporates. The spread tenors available are 0.5 years, 1 year, 2 year, up to 10 year. The data is available on monthly intervals over a period of March 2016 till February 2020.

Furthermore, we also have the CRISIL published data on average real-world cumulative probabilities of default (for T = 1 year, 2 years and 3 years) associated with different credit ratings as on Dec 2018 (Table 1).

The data available is adjusted and applied as follows:

1. **Estimation of Scaling Factors:** the monthly risk-free yields and credit spreads from March 2016 to December 2018 are used to derive the average risk-free yields and credit spreads for different rating grades and tenors and then back out the average Risk Neutral CPDs (as per equation 7). Using the CRISIL published average real-world cumulative default probabilities, the scaling factors are estimated for each tenor and rating grade.

2. **Estimation of Point-in-Time Real World PDs:** the monthly risk-free yields and credit spreads from Jan 2019 to December 2019 are used to derive the average risk-free yields and credit spreads for different rating grades and tenors and then back out the Point-in-Time Risk Neutral CPDs relevant for reporting period Dec 2019. The scaling factors calibrated in the previous step are then applied to estimate the Point-In-Time Real World cumulative and marginal probabilities that would be applicable for ECL computation for the particular portfolio (Banks/FIs or NBFCs or Corporates) as on December 2019.

   In this exercise, the following important data adjustments/assumptions are made.

   (a) The CRISIL CPDs are available for broad rating grades (AAA, AA, A, BBB, BB, and C) whereas the FBIL credit spreads are available for rating grade notches (AAA, AA+, AA, AA-, A+, A, A-, BBB+, BBB, and BBB-). In order to harmonize the data, the FBIL credit spreads for each rating grade are first derived as average of the credit spreads across all notches of that rating grade. For example, the credit spread for AA is measured as the average credit spread of AA+, AA and AA- and so on.

   (b) The CRISIL CPDs are available for BB and C grades whereas the market spreads are not. So, the spreads for BBB- in FBIL data is used as the nearest representative of spreads that would otherwise be applicable to BBB- and below (that is, BB and C grades).

   (c) The CRISIL CPDs are published separately for grades BB and C. We group these two grades and estimate a weighted average CPD for the combined grade of BB and below.

   (d) The Real World CPDs for AAA rating category for all 3 tenors as per CRISIL is 0%. Using this to determine the scaling factors for AAA would generate an error in equal 7. Furthermore, using a default probability of 0% would possibly be questioned by the regulator. Thus, we assume the Real World AAA CPDs to be equal to a small (Basel specified minimum) positive percentage equal to 0.03%. Similarly, the 1-Yr Real world PD for AA category as per CRISIL is 0.02%. We assume it to be equal to 0.05% (to ensure that monotonicity of PD).

   (e) Neither CRISIL nor FBIL publish CPD / spread data for unrated categories, whereas in real –life portfolios, there may be securities which are externally unrated. Thus, the real-world CPDs for unrated category are estimated as the weighted average CPD for all rated accounts in CRISIL

data, where the weight is the number of issuer-months for each rated category. The credit spreads for unrated category are estimated as the simple average of the credit spreads for each FBIL rating category.

(f) While longer tenors for FBIL credit spreads are available, CRISIL Real World CPDs are only published for 3 tenors. Thus, we can estimate the scaling factors for each rating grade, only for annual tenors up to 3 years. The scaling factors associated with the 3-yr tenor are then applied to longer tenor (4 years onwards) spread implied risk neutral cumulative probabilities to generate the real world cumulative probabilities.

(g) The spread implied real world cumulative probabilities are estimated only up to a 5-yr tenor. The assumption is that the marginal PDs beyond the fifth year will be flat and equal to the MPD for T = 5.

(h) The Recovery Rate R is assumed to be equal to 35% (that is, the Loss Given Default is assumed to be 65%) as per the RBI (2011) IRB Approach prescription for unsecured exposures.

4. Empirical Results & Findings

In this section, we describe the results of implied real world cumulative and marginal default probabilities derived from market based credit spreads associated with bonds and debentures issued by Banks/FIs and corporates.

Based on the data adjustments specified in points c, d and e above, the adjusted cumulative default probabilities from CRISIL matrix are given in (Table 2).

Analysis 1: Spread Implied Real World Default Probabilities for Exposures to Banks and FIs

Table 3 provides the estimated Scaling Factors between Spread Implied Risk Neutral PDs and CRISIL adjusted Real World PDs. Up to tenor Year 3, these are derived using the methodology specified above. For Year 4 and 5, these are assumed to be equal to the scaling factors associated with the 3-yr tenor. As can be seen, for any tenor, the scaling factors are highest for the best rating category and reduce to less than 1 for the worst rated category. This implies that the real world default probabilities are typically lower than the spread implied risk neutral default probabilities for higher rated securities and this relationship reverses for lower rated categories.

Table 4 summarizes the spread implied risk neutral cumulative probabilities derived as an average over the most recent one-year period (Jan 2019 – Dec 2019). As expected, probabilities are monotonically increasing as the rating worsens. Also for a given rating grade, the cumulative PDs are higher for longer tenors. These risk-neutral probabilities are then scaled by the factors depicted in Table 3 to obtain the real-world cumulative PDs shown in Table 5. From these real-world cumulative PDs, we derive the forward-looking Marginal 1-Yr. PDs shown in Table 6, which are relevant for Expected Credit Loss (ECL) computation for exposures (Investments / Loans / Refinance) to Banks and FIs.

We recommend that the Marginal Default Probabilities as shown in Table 6, be used for ECL computation for Investments in bonds / debentures issued by Banks and FIs and the Refinance Exposures to Banks and FIs. This will enable the banks to more accurately estimate their future loan loss provision requirements.

Analysis 2: Spread Implied Real World Default Probabilities for Exposures to Bonds, Debentures and Preference Shares issue by Corporates

Similar to the analysis of real world default probabilities derived from published credit spreads of Banks and FIs, this section presents the results of the implied real world default probabilities based on corporate spreads in Tables 7 – 10. From Table 9, we see that the default probabilities demonstrate monotonicity that is they are increasing with lower credit ratings. Also, for a given rating, the longer tenor cumulative PDs are higher.

It is quite evident there is a significance difference between Risk Neutral and Real CPDs. Such difference has also been observed in Berg (2010), Bohn (2000), Coval et al. (2008), and Murthy (2011) which use the importance of news or systematic risk in explaining the difference. Berg (2010) shows that in a Merton Model, credit risk premia are a significant portion of model spreads and the difference between risk neutral and real default probability increases as credit quality improves.

We recommend that the Marginal Default Probabilities as shown in Table 10, be used for ECL computation for investment in bonds, debentures, preference shares in the nature of debt, issued by Corporates given that these are real-world, point-in-time and forward looking best estimates of the risk of default required for ECL based loss allowance under IndAS.

Concluding Discussions

For credit exposures in the Investment Portfolio (corporate bonds, debentures and preference shares in the nature of debt) which are not internally rated but have external ratings associated, and for exposures to Banks / FIs in the refinance portfolio, where the bank has no history of defaults to model PD, we have developed External Rating based PD model using credit spreads published by FBIL. Since FBIL published spreads are extracted from traded market prices of securities, these spreads implicitly carry forward-looking information about macroeconomic factors. The model generates 1-yr marginal PDs and cumulative PDs which can be used for the purpose of Stage 1 and Stage 2 Expected Credit Loss (ECL) computation for exposures to corporate bonds, debentures and preference shares and for refinance exposures to other banks.

In order to estimate loss allowances under IndAS, Financial Institutions and Banks which hold substantial investments in market traded credit instruments in their HTM or AFS portfolios and who may have exposures to the refinance portfolios of other banks, may require to consider the alternative PD estimation methodologies which do not rely on internal history of defaults. The credit spread based PD methodology described in this paper provides a convenient and efficient alternative. FBIL publishes traded credit spreads for different entities (corporates / Banks and FIs / NBFCs) by external ratings and tenors. Real world TTC PDs for corporate bonds and debentures are also updated by External Rating agencies, albeit annually, which can be used to derive the scaling factors. The two data sets come together as per our methodology, to provide updated forward-looking PIT marginal and cumulative PDs, which are most suitable for ECL based provisioning under Ind AS.

References

Berg, T. (2010). "From Actual to Risk-neutral Default Probabilities: Merton and beyond", *Journal of Credit Risk*, Vol. 6, Issue 1, pp. 55-86.

Bohn, J. (2000). "An Empirical Assessment of a Simple Contingent-Claims Model for the Valuation of Risky Debt", *Journal of Risk Finance*, Vol. 1, pp. 55-77.

Coval, J., Jure, J., and Stafford, E. (2008). "Economic Catastrophe Bonds", *The American Economic Review*, Vol. 99, Issue 3, pp. 628-666.

Duffie, D., and Singleton, K. J. (1999). "Modeling Term Structures of Defaultable Bonds", *Review of Financial Studies*, Vol. 12, pp. 687-720.

Gubareva, M. (2019). "Weight of the Default Component of CDS Spreads: Avoiding Procyclicality in Credit Loss Provisioning Framework", *Complexity,* pp. 1-19, URL: https://doi.org/10.1155/2019/7820618

Hull, J., Predescu, M., and White, A. (2004). "The Relationship between Credit Default Swap Spreads, Bond Yields and Credit Rating Announcements", *Journal of Banking and Finance*, Vol. 28, Issue 11, pp. 2789-2811.

Hull, J., Predescu, M., and White, A. (2005). "Bond Prices, Default Probabilities, and Risk Premiums", *Journal of Credit Risk*, Vol. 1, Issue 2, pp. 53-60.

Jarrow, R. A., Lando, D., and Turnbull, S. M. (1997). "A Markov Model for the Term Structure of Credit Risk Spreads", *The Review of Financial Studies*, Vol. 10, Issue 2, pp. 481-523.

Jayadev, M., and Jacob, J. (2010). "", *Journal of Emerging Market Finance*, Vol. 9, Issue 1, pp. 51-70.

Murthy, S. (2011). "Market-implied Risk-neutral Probabilities, Actual Probabilities, Credit Risk and News", *IIMB Management Review*, Vol. 23, pp. 140-150.

Table 1: CRISIL's Average Cumulative Default Probabilities for Long-Term Ratings (2008-2018)

Rating Category	*Issuer-Months*	*1-Year*	*2-Year*	*3-Year*
AAA	10,851	0.00%	0.00%	0.00%
AA	26,815	0.02%	0.09%	0.18%
A	50,012	0.20%	0.95%	1.91%
BBB	159,514	0.86%	2.13%	3.83%
BB	262,180	3.54%	7.47%	11.21%
B	236,578	8.01%	15.91%	21.98%
C	8,353	20.56%	33.64%	41.16%
Total	754,303			

Source: CRISIL Default Study, 2018

Table 2: Adjusted CPDs for Long Term Ratings (2008 - 2018)

Rating Category	*Issuer-Months*	*1-Year*	*2-Year*	*3-Year*
AAA	10,851	0.03%	0.03%	0.03%
AA	26,815	0.05%	0.09%	0.18%
A	50,012	0.20%	0.95%	1.91%
BBB	159,514	0.86%	2.13%	3.83%
BB and Below	507,111	5.91%	11.84%	16.73%
Unrated		4.17%	8.48%	12.19%
Total	754,303			

Note: Yellow Cells represent adjustments

Table 3: Scaling Factor = Risk Neutral PD / Real World PD (Dec 2018)

– Banks and FIs

Tenor→ *Rating Category*	*1*	*2*	*3*	*4*	*5*
AAA	32.79	60.01	82.27	82.27	82.27
AA	31.90	34.08	24.91	24.91	24.91
A	15.72	6.45	4.73	4.73	4.73
BBB	5.09	4.01	3.28	3.28	3.28
BBB- and Below	0.79	0.77	0.80	0.80	0.80
Unrated	0.68	0.65	0.67	0.67	0.67

Table 4: Risk Neutral Cum. Default Prob.

(based on Avg spread Jan 2019 - Dec 2019) – Banks and FIs

Tenor→ *Rating Category*	*1*	*2*	*3*	*4*	*5*
AAA	1.34%	2.33%	3.21%	3.81%	3.95%
AA	2.14%	4.02%	5.73%	7.02%	8.12%
A	4.00%	7.66%	11.07%	14.02%	16.72%
BBB	5.64%	10.85%	15.71%	20.04%	24.06%
BBB- and Below	5.98%	11.49%	16.64%	21.25%	25.52%
Unrated	3.68%	7.04%	10.17%	12.86%	15.29%

Table 5: Spread Implied Real Work Cumulative Default Probabilities (Dec 2019)

– Banks and FIs

Tenor→ *Rating Category*	*1*	*2*	*3*	*4*	*5*
AAA	0.04%	0.04%	0.04%	0.05%	0.05%
AA	0.07%	0.12%	0.23%	0.28%	0.33%
A	0.25%	1.19%	2.34%	2.97%	3.54%
BBB	1.11%	2.71%	4.79%	6.12%	7.34%
BBB- and Below	7.53%	14.89%	20.74%	26.48%	31.80%
Unrated	5.40%	10.78%	15.25%	19.29%	22.93%

Table 6: Spread Implied Real World Marginal Default Probabilities

(Dec 2019) – Banks and FIs

Tenor→ ***Rating Category***	***1***	***2***	***3***	***4***	***5***
AAA	0.04%	0.00%	0.00%	0.01%	0.00%
AA	0.07%	0.05%	0.11%	0.05%	0.04%
A	0.25%	0.93%	1.15%	0.62%	0.57%
BBB	1.11%	1.60%	2.09%	1.32%	1.23%
BBB- and Below	7.53%	7.36%	5.85%	5.74%	5.32%
Unrated	5.40%	5.39%	4.47%	4.04%	3.64%

Table 7: Scaling Factor = Risk Neutral PD / Real World PD (Dec 2018)

- Corporates

Tenor→ ***Rating Category***	***1***	***2***	***3***	***4***	***5***
AAA	38.32	70.80	101.92	101.92	101.92
AA	37.47	40.52	30.18	30.18	30.18
A	21.22	8.76	6.45	6.45	6.45
BBB	7.31	5.76	4.71	4.71	4.71
BBB- and Below	1.14	1.11	1.15	1.15	1.15
Unrated	0.93	0.89	0.92	0.92	0.92

Table 8: Risk Neutral Cum. Default Prob.

(based on Avg spread till Dec 2019)- Corporates

Tenor→ ***Rating Category***	***1***	***2***	***3***	***4***	***5***
AAA	1.63%	3.12%	4.62%	5.71%	6.91%
AA	2.63%	5.10%	7.50%	9.52%	11.41%
A	5.33%	10.35%	15.13%	19.37%	23.34%
BBB	7.65%	14.79%	21.51%	27.54%	33.18%
BBB- and Below	8.19%	15.82%	22.98%	29.40%	35.40%
Unrated	4.88%	9.48%	13.89%	17.79%	21.49%

Table 9: Spread Implied Real World Cum. Def. Prob. (Dec 2019) – Corporates

Tenor→ *Rating Category*	***1***	***2***	***3***	***4***	***5***
AAA	0.04%	0.04%	0.05%	0.06%	0.07%
AA	0.07%	0.13%	0.25%	0.32%	0.38%
A	0.25%	1.18%	2.35%	3.00%	3.62%
BBB	1.05%	2.57%	4.57%	5.85%	7.05%
BBB- and Below	7.16%	14.24%	19.91%	25.47%	30.67%
Unrated	5.26%	10.64%	15.14%	19.39%	23.42%

Table 10: Spread Implied Real World Marginal Default Probabilities (Dec 2019) - Corporates

Tenor→ *Rating Category*	***1***	***2***	***3***	***4***	***5***
AAA	0.04%	0.00%	0.00%	0.01%	0.01%
AA	0.07%	0.06%	0.12%	0.07%	0.06%
A	0.25%	0.93%	1.16%	0.66%	0.62%
BBB	1.05%	1.52%	2.00%	1.28%	1.20%
BBB- and Below	7.16%	7.08%	5.67%	5.57%	5.19%
Unrated	5.26%	5.37%	4.50%	4.26%	4.03%