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IFRS 9 Compliant Adjustment of CDS Implied Point-in-Time PDs to Through-the-Cycle Default Frequencies

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Abstract

This paper presents an economically justified International Financial Reporting Standard 9 (IFRS 9) compliant solution around the impairment component related to Expected Credit Loss (ECL) modeling. Under IFRS 9 the probabilities of default (PDs) employed in ECL calculation must be real-time estimates, i.e., the PDs must be point-in-time and incorporate forward-looking information. While market indicators of future debt performance, as credit default swap (CDS) spreads and yield curves, are frequently available in the market, at least for large issuers, they cannot be used directly for PD estimates, as non-default risks, such as liquidity, transparency, and other, explain a relevant part of a fixed-income issue´s credit spread. Still, IFRS 9 requires a neutral character of PD estimations. We demonstrate how to calibrate single-name CDS implied PDs by examining the relationship between individual point-in-time forward-looking credit spreads and historically observed long-term average default frequencies. As CDS spreads are individual measures corresponding to a concrete reference entity while default frequencies represent aggregate measures across homogeneous groups of issuers, to make an economically meaningful calibration possible the CDS data must be averaged over time and rating, sector and/or geography to allow for comparison of comparable metrics. Our easy-to-implement solution specifically targeting IFRS 9 purposes is illustrated on a sample of corporate issuers. The proposed adjustment framework permits to reach better understanding by banks and financial institutions of complex ongoing interactions between the impairment and economic capital requirements in relation to credit losses.

Keywords: Expected Credit Loss; IFRS 9; Point-in-Time Probability of Default; Term Structure of Probability of Default; Components of CDS Spreads.

JEL classification: G21, G28, G32, K29, M40, M41, M49

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1. Introduction

The global financial crisis had uncovered hidden systemic costs of the delayed recognition of credit losses experienced by banks and other financial institutions. The pre-crisis accounting standards became seen as a weakness existing in the global financial system, as they required measuring the impairment loss provision based on an incurred loss accounting.

Such worldwide spread practice lacked an economic sense as it prevented financial institutions from an appropriate provisioning for potential credit losses from emerging and thus not already crystallized risks. Therefore, to provide a response to the financial crisis, the accounting standard setters represented by the International Accounting Standards Board (IASB) had required banks and other lenders to switch from the incurred loss provisioning to expected-loss impairment model allowing for timely recognition of expected credit losses.

On July 24, 2014, the IASB issued the final version of International Financial Reporting Standard 9 (IFRS 9), bringing together three phases of the financial instrument project: (*i*) classification and management; (*ii*) impairment (expected credit losses); and (*iii*) hedge accounting, see IASB (2014). Starting with the aftermath of the global financial crisis and especially since the publication of the final version of IFRS 9 this subject has attracted a great attention from academia, financial players, and regulators (Reitgruber, 2013; Beerbaum, 2015; Pǎşcan, 2015; Novotny-Farkas, 2016; Vaněk, 2016; and references therein).

On November 29, 2016, the European Union (EU) published a Commission Regulation endorsing IFRS 9 "Financial Instruments", and thus confirmed the decision to adopt the standards. The EU effective date is the same as the IASB's effective date, January 1, 2018, with earlier application permitted (European Commission, 2016). This has strengthened a flow of research in the field (Cohen and Edwards Jr., 2017; and Onalia et al., 2017).

In respect to the newly introduced expected credit loss (ECL) model, the new Standard requires banks and financial institutions (i) to account for ECL from the moment when financial instruments are first recognized on the balance sheet and (ii) to register duly quantified ECL in a timelier manner, see Basel Committee on Banking Supervision (2015) and European Banking Authority (2017). For additional details on this subject see for instance Bischof and Daske (2016), Petrov and Rubtsov (2016), and Yang (2017).

However IFRS 9 does not provide specific methodologies to account for ECL. The purpose of this paper is to fill this gap and to arrive at a kind of a consensus basis between regulatory bodies and financial institutions on the ECL calculation issue.

On the part of impairment, IFRS 9 expected loss model requires recognition of ECL if a security is measured as Amortized Cost or Fair Value through Other Comprehensive Income. However, this paper does not address the issues of classification into different accounting categories, as it focuses on ECL assessment including the credit loss parameters estimation, especially for low default portfolios

The IFRS 9 makes banks and other lenders to base their calculations of ECL on reasonable and supportable data, which incorporate historical default rates, current position in the economic cycle, and also forecast information. The new model requires financial institutions to report ECL in three stages of impairment considering changes in credit quality since initial recognition of an instrument and according to the observed deterioration of its creditworthiness.

At the Stage 1 of the IFRS 9 impairment model, the 12-month ECL is recognized as an expense and the respective provision is constituted for each financial instrument. This loss allowance represents a part of lifetime ECL that may result from default occurrences within 12 months after the reporting date, see IASB (2014). The Stage 1, or so-called performing stage, means that no significant increase in credit risk was observed up to the date. In other words, the owner of the security is adequately compensated for the risk taken at the moment of origination or purchase of the asset. I.e., performing assets are recognized in the Stage 1.

When significant increase in credit risk of a financial instrument is detected by a bank, it means that the risk subjacent to the holding this assets is not any longer compensated by the generated proceeds. In other words, this asset becomes underperforming. Thus, the asset must be moved into the Stage 2, or so-called under-performing stage. At this moment, the lifetime ECL must be recognized and the respective augmented loss allowance must be reported. The lifetime ECL is but the present value of default losses that may result from a crystalized default event during all the lifetime-constituting periods summed over these periods with the probability of default within the period used as the respective weight.

The Stage 3 according to the IFRS 9 staging model occurs when the creditworthiness of an asset deteriorates in such manner that the asset becomes impaired. Similarly to the Stage 2, for credit-impaired assets, recognized in the Stage 3, lifetime ECL ought to be reported though in this case, the interest income part is calculated based on the carrying amount adjusted for the loss allowance.

The asset transition between the three above described ECL stages is possible in both directions, from Stage 1, to Stage 2, and further to Stage 3 (when the deterioration of creditworthiness occurs), and from Stage 2 to Stage 1 (when there is an evidence of improvement in asset credit quality). Although theoretically possible, exposures in Stage 3 are rather unlikely to move back to Stage 2 or 1, as the non-performing classification, i.e. default, often absorb losses and rarely expected to bounce back.

Though in this paper we mainly address the ECL calculation and not the three-stage model itself, we show that properly estimated forward-looking Point-in-Time (PiT) PDs used for ECL calculations can improve diverse trigger-based approaches to the three-stage asset recognition, for example, those based on changes in price, yield and/or credit ratings.

The remainder of the paper is divided into four parts. Section 2 discusses regulatory, theoretical, and empirical background. Section 3 describes the proposed calibration methodology for adjusting credit spreads used in PDs calculations. Section 4 presents the results of methodology application to a sample of corporate issuers. Section 5 concludes.

2. Regulatory, theoretical, and empirical background

2.1. Point-in-Time and Forward-Looking aspects of PDs assuring IFRS 9 compliance

The assessment of PDs for low default portfolios is one of the greatest hurdles for satisfying IFRS 9 requirements. Under IFRS 9 PDs, used in ECL calculation, must be real-time estimates, i.e., the PDs must be PiT and incorporate forward-looking information.

The use of credit default swap (CDS) resolve the issue of compliance with the IFRS 9 in a sense that information inferred from CDS spreads produces point-in time PDs incorporating forward looking information. This is in accordance with the "Guidelines on credit risk and accounting for expected credit losses" issued by the Basel Committee on Banking Supervision (2015), paragraph 36, point e). For advanced additional reading see also the "Guidelines on credit institutions' credit risk management practices and accounting for expected credit losses" issued by the European Banking Authority (2017), paragraph 38, point e).

In accordance with the above referenced documents, robust and sound credit risk methodologies should not rely only on subjective, biased overly optimistic/pessimistic assumptions, or to be based on purely hypothetic wishful-thinking considerations. The employment of CDS spreads turns unnecessary generating relevant scenarios´ projections for ECL estimation, as they already reflect a certain set of market scenarios properly discounted by market participants. That is why the above-mentioned regulatory bodies consider CDS spreads as valid market indicators of future debt performance: market price clears the battle of market participants´ perspectives.

The fact that PDs inferred from CDS comply with the IFRS 9 point-in-time requirement can be understood considering the fact that CDS spread quotes are available on daily and

even intraday, real-time basis. Hence, the PDs can be assessed at each moment. Therefore, each day they correctly reflect credit quality of obligors as a function of the current point in time in the economic cycle, thus representing truly point-in-time measures.

Despite the IFRS 9 requires the reporting of the ECL and the respective provisions only by the end of each reporting period (month, semester, quarter or year), the possibility to track the evolution of ECL with the daily frequency could be insightful for the drilling down of the changes occurred over the prudential reporting period.

Also the use of CDS spreads assures the full compliance with the IFRS 9 requirements regarding the forward-looking character PDs metrics to be used in ECL calculations.

We consider the CDS spread quotes for all the available tenors, which usually fully cover the interval between 6 months and 10 years rather than for just one tenor corresponding to the maturity, average life or duration of the instrument. Thus, we construct the credit spread term structure, which, in its turn, permits to derive the term structure of corresponding PDs.

This cumulative term structure of the point-in-time PDs allows determining marginal annual PDs to be used in the ECL calculations. Thus for each obligor, for which exist CDS quotes, we could see how marginal annual PDs behave into the future. For example, existing systemic or idiosyncratic stresses usually result in higher marginal PDs at the beginning and lower marginal PDs afterwards.

On the contrary, a relative macroeconomic or microeconomic calmness regarding the obligor commonly results in the lower annual marginal PDs for a few close years to come, and then in higher PDs revealing growing degree of uncertainty in the mid- or long term future.

Thus, PDs inferred from credit spread term structure are in fact forward looking. It is completely different from the case when having a price of an instrument one deduces a yield and then assumes the flat term structure to calculate ECL. Hence, our approach, based on point-in-time PDs term structure is capable of overcoming such deficiencies by providing forward- looking market-based PD estimates.

At this point, let us recall that IFRS 9 requires a neutral character of PDs estimations. It means that to calculate the expected losses, the IFRS 9 would expect banks and financial institution to use PDs commensurate in scale with historically observed default rates.

2.2. Default vs. non-default component in credit spreads

In order to address a neutral character of PDs metrics, envisaged by IFRS 9, we develop a methodology to convert usually inflated PDs estimates, implied by single-name CDS quotes, into the PiT forward-looking PDs, which resemble observed default frequencies.

This is because CDS spread contains considerable non-default component, see for example Lin et al. (2011). Thus, if one would use the CDS quotes information without adequately sustained adjustment, the presence of a non-default component in CDS spreads would result in an inflationary bias while estimating default compensation premia and subjacent PDs.

Not surprisingly, the issue of inferring PDs and ratings from credit spreads has been recently addressed in many other research papers, see for example, Tang and Yan (2010), Benzschawel and Assing (2012), Heynderickx et al. (2016), Jansen and Fabozzi (2017) and references therein.

While market indicators of future debt performance, as CDS spreads and yield curves, are frequently available in the market, at least for large issuers, they cannot be used directly for PD estimates, as non-default risks, such as liquidity, accounting transparency, bond holding uncertainty, taxation and other risks, explain a relevant part of the credit spread. Below we mention several examples, selected to illustrate an important portion of non-default components in credit spreads.

First, the evidence that credit risk can be divided into a default and non-default components has been widely acknowledged in many papers on the subject. For example, the importance of liquidity risk component is considered in Longstaff et al. (2005), Chen L. et al. (2007), Chen H. et al. (2014 and 2016), Okou et al. (2016), among many other works.

Second, Yu (2005) researches the non-default spread component relative to the influence of accounting information transparency on credit spreads. It is documented that companies with transparent accounting information have lower credit spreads.

Third, as for uncertainty, credit spread contains an additional premium demanded by bond investors or protection sellers, which is related to the unpredictable changes in the default risk environment. This premium is frequently called as a distress risk premium; see for example Berndt et al. (2008) and Campbell et al. (2001) and references therein.

Forth, pension information derived from accounting disclosures is also priced in credit spreads of corporates (Cardinale, 2007; Gallagher and McKillop, 2010; among others). This relationship between pension liabilities, on one hand, and credit spreads, on the other hand, however, is not a linear monotonic function. The sensitivity of bond spreads to deficits relative to both, funded and unfunded pension liabilities is substantially higher for high-yield than for investment-grade bonds. Gallagher and McKillop (2010) observe also that influence of pension liabilities on credit spreads depends upon obligors´ geography.

In addition, another non-default risk component present in credit spreads is related to a political risk (Block and Vaaler, 2004; Bekaert et al., 2013; Rosado-Buenfil, 2016; and references therein). These studies come to similar conclusions, acknowledging for example that credit spreads are wider in the lead-up to an election, with spreads narrowing

postelection. Thus, such widening and narrowing are not related to the creditworthiness of obligors, and hence should not affect the default related portion of spread and respective PDs estimates.

Therefore, the question is not whether PDs inferred from CDS spreads must be adjusted, but how to calibrate them in an adequate manner, i.e., to produce PDs commensurate in scale with historically observed default frequencies, while maintaining obligor specific information present in CDS spread quotes.

2.3. Empirical evidence of PD adjustment necessity and its economic rationale

We consider a sample portfolio composed by equally weighted credit exposures to 250 constituents of the two most liquid CDS indices: Markit iTraxx Europe (iTraxx), and Markit CDX North America Investment Grade Index (CDX). Each of them comprises 125 equally weighted CDS on investment grade European (iTraxx) and North American (CDX) entities.

The composition of these two indices is determined by the respective Index Rules. The ratings of the constituents belong to the range from AAA down to BBB-. Both iTraxx and CDX indices roll every six months in March and September. Because of each roll, a few names are added to and removed from the indices. Such rebalancing of the indices allows for maintaining the average creditworthiness of the index constituents stable along the time.

To assure the validity of the posited above statement, we assess the average long-term cumulative PD for 3, 5, 7, and 10 years horizon of the chosen 250 entities portfolio, consisting of the constituents of the iTraxx and CDX indices. At least along the last 10 years, the average PD of the iTraxx and CDX constituents is always contained in the range between the observed long-term default frequencies corresponding respectively to BBB+ e BBB ratings.

We perform this assessment by considering the iTraxx and CDX on-the-run compositions changing twice a year due to the rebalancing during the rolls. Then, we attribute to each of the 250 constituents of the iTraxx plus CDX portfolio a long-term through-the-cycle PD. To do so we look these long-term PDs up according to the individual credit rating through our master-scale matrix of long term PDs, i.e., observed cumulative default frequencies.

Our PD master-scale matrix contains the average PDs obtained from the default rates reported by S&P Global (2017) and Moody´s Investors Service (2017). For S&P default rates we use the matrix of Global Corporate Average Cumulative Default Rates by Rating Modifier (1981-2016) as available in the S&P rating agency report on Default, Transition, and Recovery: 2016 Annual Global Corporate Default Study and Rating Transitions

(S&P Global, 2017). For Moody´s default rates we use the matrix of Average Cumulative Issuer-Weighted Global Default Rates By Alphanumeric Rating, 1983-2016. These cumulative PDs for the BBB/Baa2 rating grade are 0.17%, 0.73%, 1.50%, 2.28%, and 3.51% for 3, 5, 7, and 10-year periods, respectively. Later on, we use these long-run averages of cumulative default frequencies to anchor median values for calibrated spread implied PDs.

The economic sense of such average PD for 1, 3, 5, 7, and 10 years is quite simple and indicates what is a percentage part of one monetary unit exposure, which is expected to default over the corresponding time horizon. This time horizon represents a typical long-term "average" of respective n-year long time intervals occurred over the last 30 years plus history. The five chosen time horizons, namely 1, 3, 5, 7, and 10 years, correspond to the points in the iTraxx and CDX indices term structures for which CDS spread quotes are available through Bloomberg terminals.

For the years 2007-2017 we use the available CDS quotes time series for iTraxx and CDX and calculate the average over the period for the four chosen point in the term structure. Their values are 39 bps, 63 bps, 89bps, 105bps, and 119 bps for 1, 3, 5, 7, and 10-year periods, respectively. Our dataset comprises the end-of-the-day mid-spread quotes as per CMAN (New York office of CMA Datavision) provider on a daily basis.

At this point considering the widely used relationship between CDS spread, maturity and loss given default (see, for example, Choudhry (2006), page 155) we calculate implied cumulative PDs, i.e., PDs implied by CDS spread. The relationship has the following form:

$$PD_{cum}(T) = \{ 1 - \mathrm{EXP}(-Spread * T) \} / LGD \qquad (1)$$

where PD_{cum} stands for cumulative PD, $Spread$ represents CDS spread for the maturity T, and LGD stands for loss given default.

Following the market consensus subjacent to the CDS quotes for senior unsecured debt, which is the case for the debt seniority of iTraxx and CDX, we use the LGD value of 60% corresponding to the recovery rate of 40%. Using Equation 1 we receive the following figures for the implied cumulative PDs: 3.10%, 7.26%, 11.78%, and 18.73% for 3, 5, 7, and 10-year periods, respectively.

Notice that the CDS spread implied cumulative PDs are several times higher than the respective default rates observed by the rating agencies. Table 1 below summarizes our findings.

Table 1. Average CDS-spread implied PDs vs. average BBB observed default rates.

Long term average ITRAXX CDX metrics (2007-2017)					
Maturity (years)	1	3	5	7	10
Long terms spread average (bps)	39,1	64,3	90,3	103,5	121,6
Spread implied cumulative PD	0,65%	3,18%	7,36%	11,64%	19,08%
Avg. SP-Moody´s cumulative PD	0,17%	0,73%	1,50%	2,28%	3,51%

Table 1 demonstrates that the CDS-spread implied PDs on average are inflated in relation to the respective observed default frequencies. In this manner, we document an empirical evidence of a necessity to adjust cumulative spread-implied PDs to make them on average commensurable with the range of the respective cumulative default rates figures.

In other words, in order to assure a neutral character of PDs estimations, the default and non-default components in credit spread should be distilled, and then solely the default-related component is to be employed to calculate the PDs implied by the term structure of credit spreads.

3. Calibration methodology for adjusting credit spreads used in PDs calculations

This section provides description of our methodology on how to calibrate credit spread implied PDs by examining the relationship between individual point-in-time forward-looking CDS spreads and historically observed long-term average default frequencies. Our technique allows for assuring the unbiased nature of the resulting point-in-time forward-looking PDs.

Banks and other financial institutions usually convert their PDs, calibrated on through-the-cycle basis by means of employing long-term average default frequencies, into point-in-time forwards looking PDs taking into consideration current and future economic conditions. Frequently this is done through assessment of the current phase of the credit cycle accompanied by implementation of subjective probability-weighted scenarios for lifetime ECL based on expectations about future performance of financial assets, commonly linked to macroeconomic drivers. Figure 1 below illustrates this approach, following which the point-in-timeliness and forward-looking features are introduced to the original through-the-cycle metrics.
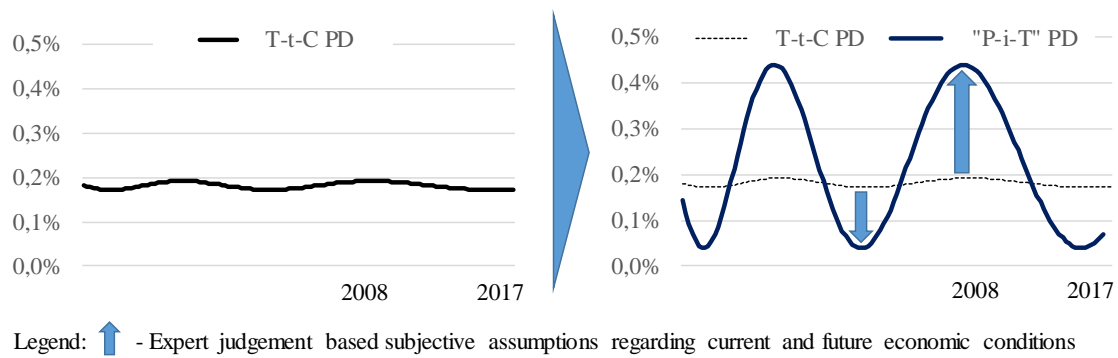
Figure 1. Conversion of Through-the-Cycle PD into Point-in-Time forward-looking PD

Although Figure 1 serves for illustrative purposes only, a certain care is taken to make it look the most resembling to the "real" situation of 1Y PD for a BBB/Baa2-rated debt exposure. For this example, the median of long-run default frequencies observed by S&P and Moody´s rating agencies equals to 0.174%. This anchor level for Through-the-Cycle (T-t-C) PDs is complied with the left chart of Figure 1.

The cumulative PDs, i.e., PD_{cum} nY, corresponding to other points of the PD term structure, are usually obtained following a similar T-t-C PD nY conversion process, as illustrated in Figure 1. Annual, i.e., marginal forward PDs, for the year-long periods in future, are obtained as a difference between the two cumulative "point-in-time" PDs corresponding to any of two consecutive maturities. That is:

$$PD_{n-1,\, n} = PD_{cum}\ n\mathbf{Y} - PD_{cum}\ (n\text{-}1)\mathbf{Y} \qquad\qquad (2)$$

Differently from such approach, from the very beginning we operate with PDs implied by term structure of credit spreads, thus assuring that our PD metrics is both, point-in-time and forward-looking, as term structure of credit spreads for a given obligor at any current date reflects price levels that clear the market for different debt maturities far into the future.

Instead of performing T-t-C to P-i-T conversion of PDs, based on subjectivity involving assumptions about current and future states of economy, we progress from spread-implied P-i-T forward-looking PDs to solely default component implied P-i-T forward-looking PDs. As it is explained below our approach to distilling default component in the credit spread of an obligor is methodologically robust and data supported. It does involve neither subjective assumptions nor inevitably biased expert judgment. Figure 2 below illustrates our methodology.

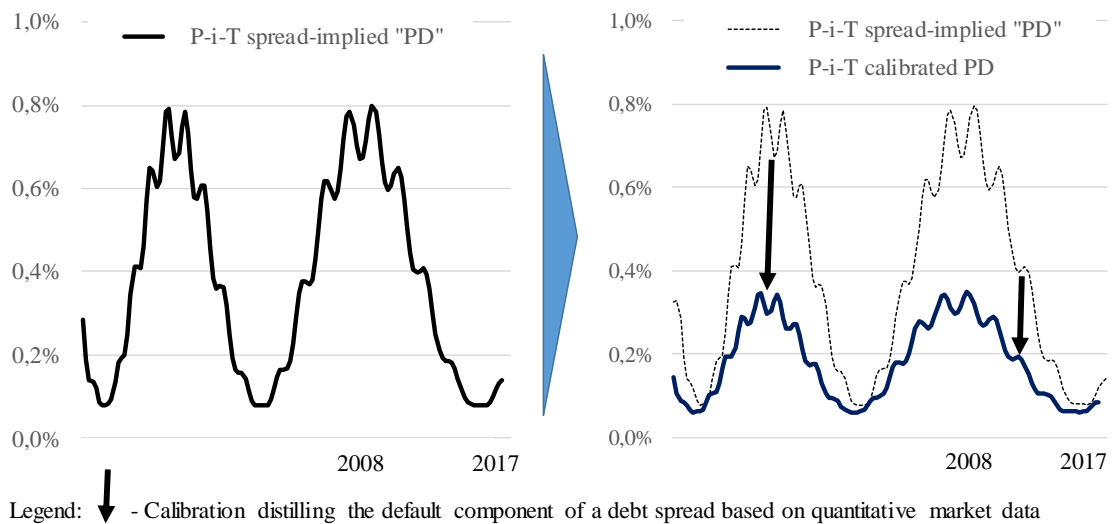Legend: ↓ - Calibration distilling the default component of a debt spread based on quantitative market data

Figure 2. Calibration of spread-implied Point-in-Time forward-looking PD

Figure 2 serves for illustrative purpose only: several important differences of the proposed calibrated spread-implied PD approach can be observed in relation to the T-t-C PD conversion into the P-i-T PD.

Following the spread-implied PD calibration methodology, we do not introduce the forward-looking character or point-in-timeliness in our PD estimation, but just keep them along the process of the calculation as they are intrinsically and inherently present in our metrics from the very beginning. What we need is to bring term structure implied PDs to the anchor levels commensurate on average with long-run observed default frequencies.

Being based on the market information in a form of a CDS spread quotes, the proposed here approach is more sensitive to the current state of economy, as credit spread undergo continuous changes, even on intraday basis. So, for each reporting date credit spreads have a well-defined end-of-the day value. The volatility patterns are then expected. They are schematically reproduced in Figure 2 through the short-run disruption of long-run trends in the behavior of the curves. Hence, such behavior reflects both, the influence of a current point within the cycle, and the discounted future scenarios relative to the current date, as CDS price subjacent to the spread quote clears the market.

During the preparation of Figure 2, a certain care is also taken to make it look the most resembling to the typical situation of 1Y PD for a BBB/Baa2-rated debt exposure. As in Figure 1, the long-run default frequency of 0.174%, observed by S&P and Moody´s rating agencies, is taken into consideration. As could be seen in Figure 2 the spread-implied PDs are superior to this anchor level of observed default frequencies. The proportions depicted in Figure 2 correspond to typical relations verified in reality.

The cumulative PDs, i.e., PD_{cum} nY, corresponding to other points of the PD term structure are obtained following a similar nY spread-implied PD calibration process, as illustrated in Figure 2. Similarly to the T-t-C to P-i-T PD conversion approach, in the

proposed spread-implied PD calibration process, the annual, i.e., marginal forward PDs, for the yearlong periods in future, are obtained as a difference between the two cumulative P-i-T PDs corresponding to any two consecutive maturities. Equation 2 is applicable in this case too.

Next we present the details of calibration methodology, which permits to compare apples with apples, i.e., the long-run average of the mean default frequency observed for a chosen homogenous group of debt issuers with the long-run average of mean PD, as implied by the credit spreads of the same homogeneous group of obligors. This is the corner stone of our approach.

As CDS spreads are individual measures corresponding to a particular entity while default frequencies represent aggregate measures across homogeneous groups of issuers, in order to allow for economically meaningful comparison of comparable metrics, the CDS data must be averaged over time and rating, sector and/or geography.

The main question we need to answer is how to distill solely the default-related component from the credit spread. To perform this task we employ the reverse engineering. The long-run average of the mean default frequency observed for a chosen sample of issuers with similar creditworthiness corresponds, through Equation 1, to default spread or default component in the credit spread. Henceforth, the expression for long-run average of mean, hypothetical exclusively default-compensating spread of a selected sample of obligors is:

$$Spread_{LR\_D} = -ln\{\ 1 - ODF_{cum}(\ T\ ) * OLGD\ \}\ /\ T \tag{3}$$

where spread $Spread_{LR\_D}$ stands for a pure would-be default spread, ODF_{cum} stands for cumulative long-run observed default frequency over diverse periods of T consecutive years, contained within the analyzed data history, T, and $OLGD$ stands for the mean observed loss given default.

On the other hand, long-run average of mean observed credit spread for a sample of obligors may be found by double averaging procedure; by the sample and by the length of the analyzed long-run interval. This is:

$$Spread_{LR\_AVG} = AVERAGE_{LR}\ [\ AVERAGE_{Sample}\ \{\ Spread_i\ (d, T)\ \}\ ] \tag{4}$$

where $Spread_{LR\_AVG}$ stands for long-run across-sample average of individual credit spreads ($Spread_i\ (d, T)$) observed for maturity T at each available date d within the long-run interval. But as it was already discussed, this $Spread_{LR\_AVG}$ represents a sum of two distinct default and non-default components.

Therefore now we approach the very essence of the issue and can empirically filter out the non-default component and stay with the pure default compensation part. On average,

for the ratio R_{Sample} of the default component to the credit we can write the following expression:

$$R_{Sample} = Spread_{LR\_D} / Spread_{LR\_AVG} \qquad (5)$$

Thus, we are able to perform calibration of a current value of credit spread in order to distil just the pure default-related compensation. We multiply this point-in-time forward-looking current credit spread $Spread_i(d, T)$ of an issuer i from a chosen sample by the R_{Sample} ratio calculated for the sample to which the selected issuer belongs. Thus, for the pure default compensation $Spread_{i\_D}(d, T)$ we have:

$$Spread_{i\_D}(d, T) = Spread_i(d, T) \text{ x } R \qquad (6)$$

This default component, $Spread_{i\_D}(d, T)$, ought to be used for calculating spread-implied cumulative, and then annual marginal point-in time forward-looking PDs.

The next section provides an example on how to derive the calibration parameters, i.e. pure default compensation expressed in percentage of credit spread used for PiT forward-looking PDs calculations.

4. Application of calibration methodology

4.1. Calibration parameters for an investment grade sample

In order to access the weight of pure default compensation part in spread of investment grade (IG) sample, we start with the long-term average spread and the average SP-Moody´s cumulative PD data (see the respective rows in Table 1). By means of Equation 3, we calculate the default component, which is purely due to the compensation of default risk, for each maturity point chosen in the term structure. The ratio of the default component over the total spread represents the relative weight of the default compensation. The term structure of default component weights in IG credit spreads per maturity is presented in Table 2.

Table 2. Term structure of the default compensation in percentage of IG credit spread.

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Weight of Default Component in IG Credit Spread per Maturity					
Maturity (years)	1	3	5	7	10
Long terms spread average (bps) (A)	39,1	64,3	90,3	103,5	121,6
Avg. SP-Moody´s BBB/Baa cumulative PD	0,17%	0,73%	1,50%	2,28%	3,51%
Spread derived from cumulative PD (bps) (B)	10,4	14,5	18,1	19,7	21,3
Default component ($C = B$ /A), %	**26,7%**	**22,6%**	**20,0%**	**19,0%**	**17,5%**

The last row of Table 2 evidences that the weight of default component for all the point of the spread term structure is below 30%. This result contrasts the findings of Arakelyan and Serrano (2016) for the period 2004-2011. Authors report that, on average, the default risk premium accounts for 40% of CDS. Our empirical data suggests that the default risk premium for IG entities, on average, is centered at 20% of credit spread, as per the last row of Table 2.

Table 2 proves that the major part of a credit spread is not related to compensation of default risk, but represents a sum of non-default components of different nature. From qualitative point of view this result is in line with outcomes of other research on credit spread components (Longstaff et al., 2005; Chen L. et al., 2007; Gallagher and McKillop, 2010; Lin et al., 2011; Chen H. et al. 2014 and 2016; Okou et al., 2016; and Arakelyan and Serrano, 2016).

Form quantitative point of view the numerical results presented in the bottom row of Table 2 are a new frontier in the empirical research on the matter in a sense that our figures are based on daily empirical data subjacent to a decade long time window 2007-2017, comprising distinct phases of the business cycle. The fact that the analyzed data history spreads over both, distress and normal economic conditions, assures robustness of the outcomes especially for being employed in calculating life-long ECL.

The bottom row of Table 2 demonstrates that the shorter maturity, the bigger is a part of spread, which compensates against default, i.e. the higher is the percentage expressing relative size of the default component. Given the IG rating of the exposures, this result is expectable and intuitive as for shorter maturities the uncertainty levels are inferior to the uncertainty levels for the long end of the term structure.

A risk premium, present in credit spreads, apart from liquidity, interest rate and volatility risk, is associated also with uncertainty about the future value of cash flows, which grows with maturity for yield curves with positive slope. I.e., investors tend to price uncertainty into the yield curve by demanding higher risk premium for maturities further into the future. We posit that liquidity component does not represent relevant changes per maturity, as trading related to IG exposures is characterized the investment rather than speculative features, free of fire sales, generalized sell-offs, and other distress patterns. For additional reading we on these topics we recommend Berg (2010) and Muir (2013 and 2017).

Next subsection considers a sample containing debt issuers with credit ratings belonging to the non-investment grade range.

4.2. Calibration parameters for a non-investment grade sample

By analogy with an IG case, we select a sample consisting of 75 non-investment grade (HY) obligors with credit ratings ranging within the BB/Ba grade and whose CDS quotes histories cover the period 2007-2017. In order to have the homogeneous sample from the extensive initial sample, we filter out those names that have been downgraded to BB/Ba grade from the IG range, and those that had been downgraded from BB/Ba grade to single B and/or CCC/Caa grades, even if they eventually have been upgraded back to BB/Ba grade within the considered time window. We perform such cleansing with the purpose to average spreads corresponding to the BB/Ba grade only.

Similarly to IG case, to calculate the weight of pure default compensation part in spread of HY debt, we start with the long-term average spread and the average SP-Moody´s cumulative PD data for BB/Ba grade, see the respective rows in Table 3 below.

Table 3. Term structure of the default compensation in percentage of HY credit spread.

Weight of Default Component in HY Credit Spread per Maturity					
Maturity (years)	1	3	5	7	10
Long terms spread average (bps) (A)	144,7	217,3	267,7	285,8	316,3
Avg. SP-Moody´s BB/Ba cumulative PD	0,67%	3,52%	6,60%	8,89%	12,22%
Spread derived from cumulative PD (bps) (B)	40,4	71,2	80,8	78,3	76,1
Default component ($C = B/A$), %	**27,9%**	**32,7%**	**30,2%**	**27,4%**	**24,1%**

By the means of Equation 3, using average cumulative PDs, i.e., the observed default frequencies, we calculate the default component, which is purely due to the compensation of default risk, for each maturity point chosen in the term structure. The ratio of the default component over the total spread represents the relative weight of the default compensation. The term structure of default component weights in HY credit spreads per maturity is presented in the bottom row of Table 3.

As in the IG case, it is worth noting that the weight of default component in HY spreads for all the points of the term structure is below 33%. It means that on, average, more than

two thirds of a credit spread are not related to compensation of default risk, but represents a sum of non-default components of different nature.

Our result for HY entities also contrasts the findings of Arakelyan and Serrano (2016) who state that, on average, the default risk premium accounts for 40% of CDS. Our empirical data suggests that the default risk premium for HY entities, on average, is centered at 30% of credit spread (see the last row of Table 3).

Performing the comparison of the bottom rows of Tables 2 and 3, we can observe that the weight of default component in HY spread is larger than the weight of default component in IG spread for all the points in the term structure. This is an intuitive outcome, as credit quality of obligors in IG range is never considered by investors to be really important, as overall quality of debt is good for investment. On the contrary, for HY grade exposures, the credit quality of issuers gains more importance in comparison to the IG case.

Differently, from the IG case, the behavior of default component in HY spreads is not monotonous with maturity, reaching a local maximum at 3 years point of the spreads term structure. We ascribe this fact to the severely jeopardized liquidity at 1-year point, as in fact very limited volumes are traded in non-investment grade names with such a short residual maturity. This means that the liquidity component has its maximum at 1-year point, while the local minimum of liquidity component is attributed to the 5-year maturity, which is in accordance with Berg (2010) and also in line with market consensus, as most trading takes place in 5-year maturity point.

On the other hand, the term structure of non-default future uncertainty related risk premium during the last decade, on average, was positively sloped. Thus, the superposition of a positively sloped non-default uncertainty related risk premium curve and a V-shaped liquidity premium curve with minimum at 5-year point makes it plausible to observe the minimum of non-default spread component, i.e., the maximum at default spread component at 3-year point, as we empirically evidence in Table 3.

For the long end of the term structure, i.e., for the 5-year plus maturities, the weight of default component keeps decreasing in line with increasing into the future both, liquidity premium and uncertainty risk premium.

The next subsection exemplifies an application of our ready-to-use methodology to calculate IFRS 9 compliant ECL for selected IG and HY exposures.

4.3. Application of calibration methodology to the IFRS 9 compliant ECL calculation

For the sake of illustration of the applicability of our calibration approach to low default portfolios we select four different investments in corporate bonds. The chosen debt issues

are the following: Hewlett Packard Enterprise bond with maturity September 15, 2022 (ISIN US428236BX09); Staples Inc. bond with maturity January 12, 2023 (ISIN US855030AM47); Olin Corporation bond with maturity September 15, 2027 (ISIN US680665AJ53); and Windstream Services LLC bond with maturity on August 01, 2023.

All these bonds have a semiannual coupon frequency. The end date of the reporting period, used as a reference date for ECL calculation, is chosen to be June 30, 2017. For the Windstream Services LLC we also present a calculation of ECL as for September 30, 2017 in order to illustrate how our approach works when the exposure experiences financial stresses.

We calculate ECL following the requirements established by IFRS 9:

$$ECL = \sum_{t=1}^{T} \frac{PD(t) \times LGD \times EAD(t)}{(1 + EIR)^t}$$

(7)

where *PD*(*t*) is a marginal point-in-time forward-looking PD and *EAD*(*t*) is an exposure at default relative to a time interval *t*, *LGD* is a loss given default, and *EIR* stands for original effective interest rate when the asset was first recognized.

In the four considered below examples for simplicity reasons we use *LGD* value of 60%, which is a market consensus for senior unsecured debt. We also assume that the bond assets were purchased at their issue, allowing us to use the initial yield at issue as a proxy for *EIR*.

In its turn, regarding *EAD*, the IFRS 9 requires the calculation to be linked to the amortized cost. And thus it depends upon initially recognized book value and the *EIR*. But as our work is not focused on algorithms of IFRS 9 compliant *EAD* calculations, we employ an assumption that the assets used in our example were originally recognized at par, and hence we calculate *EAD* as a sum of the nominal value of the position and of the coupon to be paid during the period *t*.

The first considered example is related to the Hewlett Packard Enterprise, which is rated as BBB by SP and Baa2 by Moody´s. Over the preceding quarters there was no observations that could be interpreted as signaling on deteriorating credit quality. Thus, we classify this bond as Stage 1. In this case only 12-month ECL must be calculated. Table 4 presents the result of the calculations.

Table 4. 12-months ECL for Hewlett Packard IG debt exposure as of June 30, 2017

12-months ECL for HP exposure as of June 30, 2017		
Date (mm.yyyy)	12.2017	06.2018
Maturity horizon (years) (A)	0,5	1
Spread quotes (bps)	8,9	11,5
Weight of default component for IG	26,7%	26,7%
Default compensation (bps)	2,4	3,1
Point-in-Time cumulative PD (Equation 1)	0,02%	0,05%
Point-in-Time marginal PD (Equation 2) (B)	0,02%	0,03%
Coupon	4,05%	4,05%
Initial Yield (C)	4,08%	4,08%
LGD (D)	60%	60%
EAD/Nominal (p.p.) (E)	102,03	102,03
Marginal ECL (p.p.) ($F = B*D*E/(1+C)^A$)	0,01	0,02
ECL 12-month (p.p.)	**0,03**	

For the presented above calculations we use the two points of the HP credit spread term structure: 0.5-year and 1-year. The respective quotes, as per Bloomberg terminal, are calibrated by using the weight of default component of 26.7% (see Table 2). Although, this percentage was calculated for 1-year point, we apply it for 0.5-year point too. The purely default compensation spread parts are transformed in marginal point-in-time forward-looking PDs. The coupon of 4.05% results in *EAD* per half-year period of 102,025, rounded in Table 4 to 102.03. Finally, summing marginal ECL for the two half-year long period, we arrive at 12-months ECL of 0.03 percentage points.

The second obligor considered for the calibration methodology application is the Staples Inc., rated BBB- by SP and Baa2 by Moody´s as of June 30, 2017. As IG securities represent an elevated credit quality, IG exposures are usually classified as Stage 1 positions, and, hence, only 12-months ECL is supposed to be calculated. Still, decaying credit quality leading to a substantial increase in credit risk, which could be evidenced, for example through credit spread widening, eventually allows to classify position as Stage 2. Therefore, lifetime ECL must be computed. We assume that this is the case of Staples Inc. debt, and present the respective calculations in Table 5.

Table 5. Lifetime ECL for Staples Inc. IG debt exposure as of June 30, 2017

Lifetime ECL for Staples Inc. exposure as of June 30, 2017								
Date (mm.yyyy)	122 017	06.2018	06.2019	06.2020	06.2021	06.2022	01.2023	06.2024
Maturity horizon (years) (A)	0,5	1	2	3	4	5	5,54	7
Spread quotes (bps)	30,8	36,5	58,0	112,0	196,4	293,9	n.a.	414,1
Weight of default component for IG	26,7%	26,7%	24,7%	22,6%	21,3%	20,0%	19,8%	19,0%
Default compensation (bps)	8,2	9,8	14,3	25,3	41,9	58,9	64,6	
Point-in-Time cumulative PD (Equation 1)	0,07%	0,16%	0,48%	1,26%	2,77%	4,83%	5,86%	
Point-in-Time marginal PD (Equation 2) (B)	0,07%	0,09%	0,31%	0,79%	1,51%	2,06%	1,02%	
Coupon	4,375%	4,375%	4,375%	4,375%	4,375%	4,375%	5,375%	
Initial Yield (C)	4,40%	4,40%	4,40%	4,40%	4,40%	4,40%	4,40%	
LGD (D)	60%	60%	60%	60%	60%	60%	60%	
EAD/Nominal (p.p.) (E)	102,19	102,19	104,38	104,38	104,38	104,38	102,69	
Marginal ECL (p.p.) ($F = B*D*E/(1+C)^A$)	0,04	0,06	0,18	0,43	0,79	1,04	0,50	
ECL lifetime (p.p.)				**3,04**				

The spread for maturity and the respective weight of default component are obtained by linear interpolation of the figures relative to 5-year and 7-year points. The step coupon of 5.375% during the last semiannual period is reflected accordingly in Table 5. Summing all marginal ECL until maturity, presented in the second from the bottom raw of Table 5, we arrive at lifetime ECL of 3.04 percentage points. The downgrades of the Staples Inc. had occurred later on in August. Thus this fact corroborates with the plausibility of this final figure.

The rows of Table 5 containing Point-in-Time cumulative PD and Point-in-Time marginal or forward PD are used below for graphic representation of the respective term structures, derived from the spread quotes as of June 30, 2017.
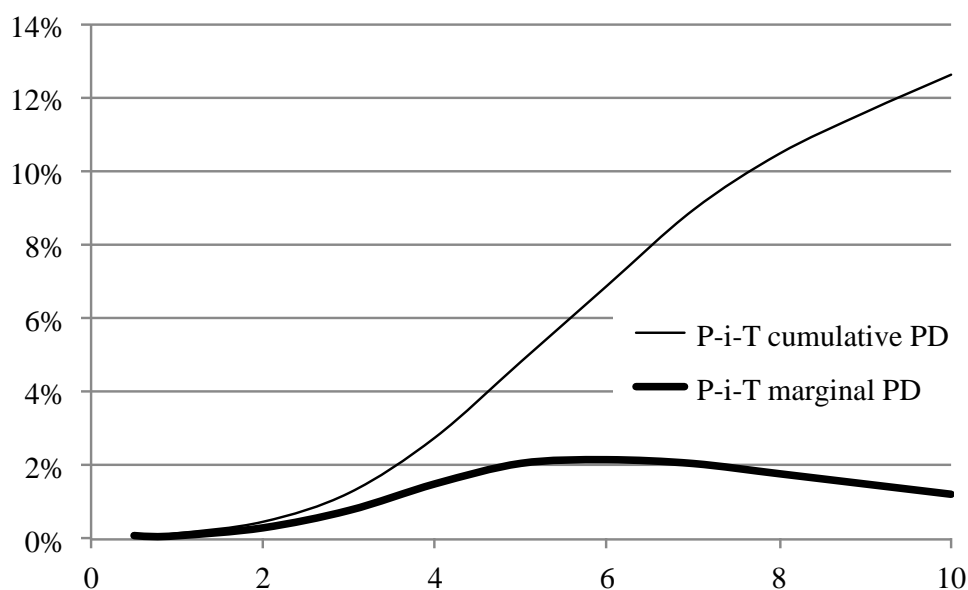
Figure 3. Term structure of P-i-T cumulative and marginal PD for Staples Inc.

As could be seen in this example, the ECL calculations were performed using the points of the PD term structure, located within the positive slope of the curve, which means that the issuer, although somewhat stressed, is not at an imminence of default.

At this point we apply our methodology to calculate ECL for non-IG exposure. For this purpose in our third example we employ the Olin Corporation, rated BB by SP and Ba1 by Moody´s as of June 30, 2017. This corporation represents a stable credit risk profile with no observations of any kind that could be interpreted as signaling on deteriorating credit quality. Thus, we classify this bond as Stage 1. Only 12-month ECL must be calculated in this case. Table 6 demonstrates the related calculations.

Table 6. 12-months ECL for Olin Corporation HY debt exposure as of June 30, 2017

12-months ECL for Olin Corp exposure as of June 30, 2017		
Date (mm.yyyy)	12.2017	06.2018
Maturity horizon (years) (A)	0,5	1
Spread quotes (bps)	27,5	34,3
Weight of default component for HY	27,9%	27,9%
Default compensation (bps)	7,7	9,6
Point-in-Time cumulative PD (Equation 1)	0,06%	0,16%
Point-in-Time marginal PD (Equation 2) (B)	0,06%	0,10%
Coupon	5,125%	5,125%
Initial Yield (C)	5,125%	5,125%
LGD (D)	60%	60%
EAD/Nominal (p.p.) (E)	102,56	102,56
Marginal ECL (p.p.) ($F = B * D * E/(1+C)^{\wedge}A$)	0,04	0,06
ECL 12-month (p.p.)	**0,09**	

For the results presented in Table 6 above, we use two points of the Olin Corporation credit spread term structure: 0.5-year and 1-year. Similarly to the HP case, the Olin Corporation quotes, as per Bloomberg terminal, are calibrated by the weight of default component of 27.9%, (see Table 3). Then, the purely default compensation spread parts are transformed into marginal point-in-time forward-looking PDs. The coupon of 5.125% results in *EAD* per half-year period of 102.5625, rounded in Table 6 to 102.56. Finally, summing marginal ECL for the two half-year long period, we arrive at 12-months ECL of 0.09 percentage points.

In addition, going from simple to complex, we continue with the forth example related to the Windstream Services LLC debt, rated BB- by Fitch and B1 by Moody´s. Deteriorating credit quality, evidenced through wide credit spreads, suggests that this exposure needs to be classified as Stage 2. Thus, lifetime ECL must be computed. We present our calculation in Table 7 for the reporting date June 30, 2017.

Table 7. Lifetime ECL for Windstream Services HY debt exposure as of June 30, 2017

Lifetime ECL for Windstream Services LLC exposure as of June 30, 2017								
Date (mm.yyyy)	12.2017	06.2018	06.2019	06.2020	06.2021	06.2022	08.2023	06.2024
Maturity horizon (years) (A)	0,5	1	2	3	4	5	6,1	7
Spread quotes (bps)	168,1	181,1	305,1	513,5	753,0	882,9	n.a.	967,2
Weight of default component for HY	27,9%	27,9%	30,3%	32,7%	31,5%	30,2%	28,7%	27,4%
Default compensation (bps)	47,0	50,6	92,6	168,1	236,9	266,4	259,7	
Point-in-Time cumulative PD (Equation 1)	0,39%	0,84%	3,06%	8,20%	15,07%	20,78%	24,36%	
Point-in-Time marginal PD (Equation 2) (B)	0,39%	0,45%	2,22%	5,14%	6,87%	5,72%	3,57%	
Coupon	6,375%	6,375%	6,375%	6,375%	6,375%	6,375%	6,375%	
Initial Yield (C)	6,375%	6,375%	6,375%	6,375%	6,375%	6,375%	6,375%	
LGD (D)	60%	60%	60%	60%	60%	60%	60%	
EAD/Nominal (p.p.) (E)	103,19	103,19	106,38	106,38	106,38	106,38	106,92	
Marginal ECL (p.p.) ($F=B*D*E/(1+C)^A$)	0,23	0,26	1,25	2,73	3,42	2,68	1,57	
ECL lifetime (p.p.)				**12,15**				

Summing all the marginal ECL until maturity, presented in the second from the bottom raw of Table 7, we arrive at lifetime ECL of 12.15 percentage points.

We select the Windstream Services debt under financial stress, on purpose to demonstrate a capacity of our approach to timely address the ever-changing real creditworthiness of obligors. During the third quarter of 2017, the credit quality of Windstream Services LLC suffered a lot, and the spreads widened considerably, although these changes were not reflected in rating downgrades.

For sake of comparison, in Table 8 we present our calculation of lifetime ECL for Windstream Services LLC for the reporting date September 30, 2017.

Table 8. Lifetime ECL for Windstream Services HY debt exposure as of Sept 30, 2017

Lifetime ECL for Windstream Services LLC exposure as of September 30, 2017								
Date (mm.yyyy)	03.2018	09.2018	09.2019	09.2020	09.2021	09.2022	08.2023	09.2024
Maturity horizon (years) (A)	0,5	1	2	3	4	5	5,8	7
Spread quotes (bps)	3055,1	2604,4	2012,6	2058,9	1960,9	1871,0	n.a.	1761,0
Weight of default component for IG	27,9%	27,9%	30,3%	32,7%	31,5%	30,2%	29,0%	27,4%
Default compensation (bps)	853,6	727,6	610,7	674,2	616,9	564,5	534,3	
Point-in-Time cumulative PD (Equation 1)	6,96%	11,70%	19,16%	30,52%	36,44%	40,99%	44,63%	
Point-in-Time marginal PD (Equation 2) (B)	6,96%	4,73%	7,46%	11,36%	5,93%	4,54%	3,64%	
Coupon	6,375%	6,375%	6,375%	6,375%	6,375%	6,375%	6,375%	
Initial Yield (C)	6,375%	6,375%	6,375%	6,375%	6,375%	6,375%	6,375%	
LGD (D)	60%	60%	60%	60%	60%	60%	60%	
EAD/Nominal (p.p.) (E)	103,19	103,19	106,38	106,38	106,38	106,38	106,92	
Marginal ECL (p.p.) ($F=B*D*E/(1+C)^A$)	4,18	2,75	4,21	6,02	2,95	2,13	1,63	
ECL lifetime (p.p.)				**23,88**				

Comparing spread quotes of Table 7 and Table 8, we can observe the considerable spreads widening for the September 30, 2017. Such spread dynamics results in augmented lifetime ECL, which now equals 23.88 percentage points, which we consider to be plausible with the fair value of the asset whose spreads break the level of 3000 bps.

The inverted term structure of credit spreads, which is considered to warn about eventually approaching default or debt restructuring, as per Table 8, results in a complex Point-in-Time term structure of marginal PD, exhibiting the short-term and long-term parts with negative slope, see Figure 4. The term structure of cumulative PD for September 30, 2017 is also depicted, along with the term structures of cumulative and marginal PDs as of June 30, 2017, jointly placed in Figure 4 for comparison.
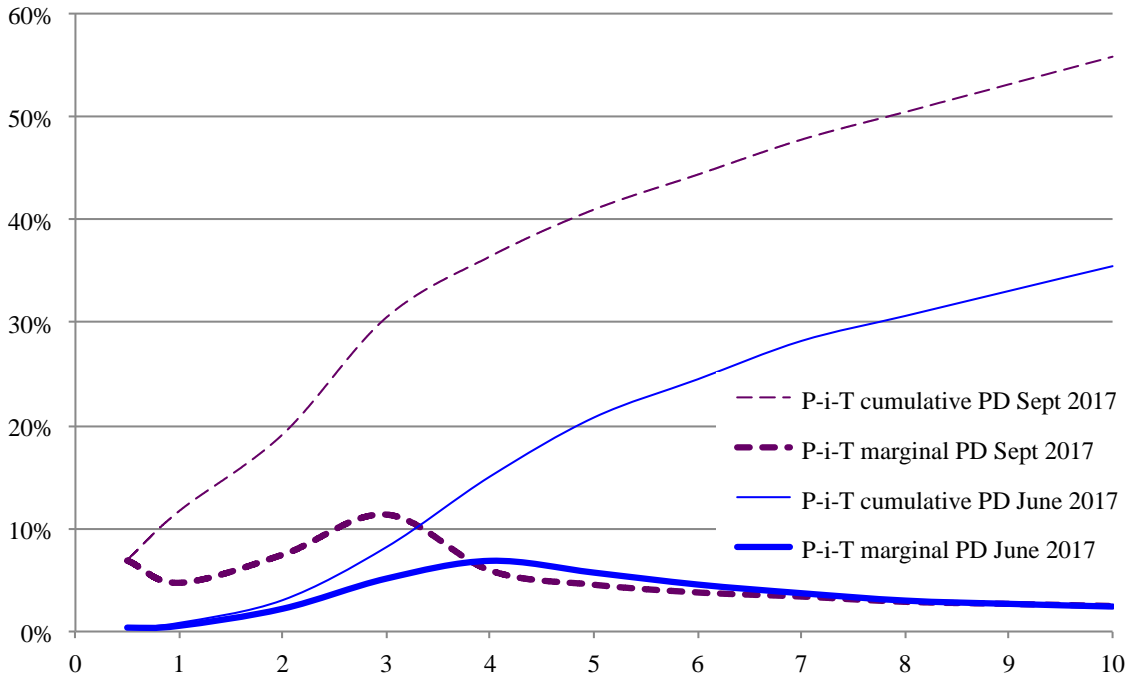
Figure 4. Changes in the term structures of P-i-T PDs from June to September 2017 for Windstream Services LLC

Such a complex term PD term structure results from the point-in-time spread quotes for diverse points in the term structure of credit spreads, which are representative of prices at which market clears every day, and which represent all future scenarios, duly weighted and discounted by market participants.

It is rather difficult to imagine that the widely practiced conversion of T-t-C PDs into P-i-T measures by employment of hypothetic scenarios could allow for such detailed description of forwards marginal values of the PD, as our approach characterized by point-in-timeliness from its very inception.

Our approach could be additionally coupled with scenario analyses and macroeconomic considerations, in order to see how ECL will behave under additional or diminished stress. This issue will be addressed in further research.

5. Conclusions

We present an economically justified and IFRS 9 compliant solution related to ECL modeling. The multi-period PDs used in ECL calculation under our approach are real-time estimates, i.e., they are point-in-time measures and incorporate forward-looking information. It is so, as our PDs are based on CDS market quotes, which provide forecasts on default risk of reference entities.

Differently from commonly employed approaches, which employ the through-the-cycle default rates and then convert them by means of scenario analyses into the point-in-time PDs, our methodology incorporates the point-in-timeliness from the very beginning as it starts with point-in-time forward-looking credit spreads and then calibrates them distilling solely the default compensation part.

In order to reach such neutral character of PDs estimations we compare the long-run average of the CDS spreads, averaged over the sample of a homogeneous group of issuers, to the default spread derived from the long-run observed default frequencies, reported by rating agencies. Such comparison allows calculating the average weights of default compensation part present in credit spread for each forwards term.

Our results related to average weights of default component in a credit spread, 20% for IG and 30% for HY, contrast with the findings of Arakelyan and Serrano (2016) which argue that the default risk premium accounts for 40% of CDS spreads. Differently from previous studies, we provide weights of default component for each forward term.

As a framework based on point-in-time parameters, the IFRS 9 ECL calculations result in cyclicality in provisions. The important issue is to avoid an eventual procyclicality, i.e., an amplification of cycle-related fluctuations in the financial systems. Our calibration procedure, using as PD anchor levels the long-run through-the-cycle observed default frequencies, assures that fluctuations under our approach are controlled by construction.

Our easy-to-implement solution specifically targeting IFRS 9 purposes is illustrated on a sample of corporate issuers. We give examples of calculation both 12-months and lifetime ECL for both IG and HY debt exposures. We also illustrate how the increasing financial stress could be treated within our framework by providing a comparative analysis of lifetime ECL for the same issuer at two different reporting dates.

Our results are innovative, meaningful, plausible, and convincing. The proposed adjustment framework permits to reach better understanding by banks and financial institutions of complex ongoing interactions between the impairment and economic capital requirements in relation to credit losses. The developed calibration methodology enlightens how to deal with an aspired one day in the future convergence between prudential Basel accord and accounting treatment of credit risk parameters.

We believe that our research will be of use for practitioners, regulators, and members of scientific community during the implementation of IFRS 9 requirements as well as along the coming post-IFRS 9 era of further sophistication of already, though in haste, implemented IFRS 9 compliant processes and methodologies of ECL calculation.

Funding

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